BEHAVIORAL MECHANISM DESIGN: EVIDENCE FROM THE MODIFIED FIRST-PRICE AUCTIONS*

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Abstract. This paper tests the behavioral equivalence of a class of strategically-equivalent mechanisms that also do not differ in terms of their procedures. In a private value setting, we introduce a family of mechanisms, so-called Mechanism (α), that generalizes the standard first-price sealed bid auction. In Mechanism (α), buyers are asked to submit a value which will then be multiplied by α to calculate the bids in the auction. When $\alpha = 1$, Mechanism (α) is the standard first-price sealed-bid auction. We show that for any α, calculated bids should be identical across mechanisms. We conduct a laboratory experiment to test the behavioral equivalence of this class of mechanisms under different values of α. Even though the procedure and environment do not change across auctions, we do not observe same bidding behavior across these strategically-equivalent mechanisms. Our research can inform mechanism design literature with respect to the design of optimal mechanisms.

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1. Introduction

Mechanism design is the modern economic analysis of institutions and markets. It has changed the way economists think about optimal institutions when governments are unaware of individual preferences. In the mechanism design literature, the focus is on designing optimal mechanisms (Jackson 2001; Jackson 2003). For example, designing the optimal mechanism is an extremely important problem in the auction literature, where the objective is to increase efficiency by ensuring the object goes to the bidder with the highest value. Experimental research is useful in testing whether constructed mechanisms generate the predicted outcomes (Chen and Ledyard 2008; McFadden 2009).[1]

The aim of this paper is to investigate whether seemingly equivalent mechanisms generate the same outcomes in a laboratory setting. An understanding of this issue is crucial, since mechanism design theory is a standard toolkit for many economists and has affected virtually all areas of policy including regulation, auctions, and environmental policy. An important finding in this literature is that theoretically revenue-equivalent mechanisms do not necessarily lead to the same outcome (Kagel 1995; Kagel and Levin 2011). Indeed, the auction literature provides remarkable evidence that even strategically equivalent mechanisms do not generate equal revenues: the first-price sealed-bid and Dutch auctions perform differently in laboratory settings (Coppinger, Smith and Titus 1980; Cox, Roberson and Smith 1982; Turocy, Watson and Battalio 2007; Katok and Kwasnica 2008).[2] Note that strategic-equivalence is stronger than revenue-equivalence since for every strategy in the Dutch auction, there is another strategy in the first-price auction which results in the same outcome; hence one could be tempted to conclude that both auction formats are identical.

While these results are initially striking, one might argue that these are fundamentally different institutions. They differ in the way that they are implemented: the Dutch auction is progressive and open, while the first-price auction is static and sealed (Vickrey 1961; Krishna 2002). Indeed, these procedural differences are vital for an

[1]In particular, experiments help us observe behavior in auctions (Kagel 1995; List 2003; Filiz-Ozbay and Ozbay 2007; Kagel and Levin 2009), optimal contracting (Healy, Ledyard, Noussair, Thronson, Ulrich and Varsi 2007), prediction markets (Healy, Ledyard, Linardi, and Lowery 2010), matching (Niederle, Roth and Sonmez 2008) and public goods (Attiyeh, Franciosi, Isaac and James 2000; Kawagoe and Mori 2001; Chen 2004; Healy 2006).

[2]Lucking-Reiley (1999) shows that these auctions are not revenue equivalent in a field setting.

agent whose risk preference is outside of the standard expected utility model. Even though these institutions are strategically-equivalent, the revenue equivalence result holds only when the agents are expected utility maximizers (Karni 1988).[3]

The novelty of this paper is to design and experimentally contrast mechanisms that are strategically-equivalent *and* share exactly the same structure/procedure.[4] We consider an auction environment with a single indivisible object and buyers with independent private values. We introduce a class of mechanisms, so-called Mechanism (α), that generalizes the standard first-price sealed bid auction. In Mechanism (α), buyers are asked to submit a value which will then be multiplied by α to calculate the bids in the auction. As in the first-price sealed-bid auction, the buyer with the highest bid gets the good and pays his/her bid. Note that, in equilibrium, the "calculated bids" in the Mechanism (α) are identical for any α, thus yielding strategic-equivalence. In addition, Mechanism (α) has the same structure under different α's with a small change in how the outcome function translates the values to the bids, giving the desired procedural-equivalence. As a consequence, this family of mechanisms generate identical bid functions (and, hence, identical revenues) without the need for particular assumptions, such as on risk preferences.

We use the first-price sealed-bid auction as our base mechanism. There are two reasons for this choice. First, the first-price sealed-bid auction is commonly used both in the mechanism design literature and in the real world. Second, we can construct an environment with exactly the same structure across auctions. As a further control, we provide a "bid calculator" to the subjects so that in all mechanisms, calculating the bids (transformations of submitted values to bids) does not create any additional complexity to the auctions than would be inherent in the standard first-price auction. This is in line with Jackson (2001) who argues that complexity may explain why some outcome-equivalent mechanisms do not perform the same way.

In order to address the question of whether individuals behave equivalently in these strategically and procedurally equivalent mechanisms, we run an experiment considering three treatments: Mechanism (0.9), Mechanism (1), and Mechanism (1.1), where

[3] For both the first-price and Dutch auctions, Nakajima (2011) characterizes an equilibrium when bidders have non-expected utility preferences, particularly exhibiting the Allais paradox.

[4] We say two mechanisms are procedurally-equivalent if for every extensive form representation of one of them, one can construct an identical extensive form representation for the other mechanism (with the exception of labeling).

Mechanism (1) corresponds to the standard first-price sealed-bid auction. We pick α's close to 1 on purpose to keep the mechanisms as similar as possible. In addition, we pick α's symmetrically around 1 so that the behavioral differences will not be attributed to the distance from the standard first-price auction.

In contrast with what theory predicts, we observe differences across mechanisms. We establish the following conclusions: (i) we find that the subjects bidding behavior differed most notably between Mechanism (0.9) and Mechanism (1), where those participating in Mechanism (0.9) shaved their bids by approximately 5% more, and (ii) the revenue equivalence does not hold; the standard first-price auction generated higher revenue than the Mechanism (0.9)–subjects who participated in Mechanism (0.9) earned approximately 20% more compared to Mechanism (1).

Our findings provide new challenges for auction theory as well as mechanism design theory in general. In order to design optimal mechanisms, one needs to consider the behavioral aspects of mechanisms. The behavioral anomalies might then be taken into account to provide better theories and more efficient mechanisms. The next section describes the Mechanism (α) and shows the correspondence between the first-price sealed-bid auction. In Section 3, experimental design and procedures are explained. Section 4 presents the data analysis. Section 5 concludes.

2. Mechanism (α)

There is a single indivisible good for sale and there are N bidders with private valuations, v_i. The private values are distributed uniformly over the range $V = [0, 100]$. In Mechanism (α), each potential buyer is asked to submit a sealed-value s_i instead of a sealed-bid. The submitted-values are multiplied by α to calculate the bids in the auction. The potential buyer with the highest calculated-bid gets the good and pays his/her calculated-bid.

This family of mechanisms have the same set of equilibria. Formally, given an equilibrium in Mechanism (α_1), there exists a corresponding equilibrium generating the same outcome in Mechanism (α_2). This observation is independent of how the risk preferences are modeled and of the utility representation. In addition, it does not require identical agents. To see the equivalence, assume that there exists an equilibrium in Mechanism (α_1). In Mechanism (α_2), consider a strategy profile where agents submit $\frac{\alpha_1}{\alpha_2}$ times their original strategies. Indeed, this is an equilibrium in Mechanism (α_2). If there is no incentive to unilaterally deviate from the original strategies in Mechanism (α_1), then no one would gain by deviating unilaterally from the described strategy in Mechanism (α_2). Hence for any $\alpha_2 > 0$, $\frac{\alpha_1}{\alpha_2}$ times the original strategies constitute an equilibrium generating the same outcome in Mechanism (α_2).

Now, for the illustration purposes, we derive the unique symmetric equilibrium strategy when bidders are assumed to have the same von-Neumann-Morgenstern utility function $u(.)$ with $u(0) = 0$, $u^{'} > 0$ and $u^{''} \leq 0$. Given $\alpha > 0$, assume all other players $j \neq i$ follow symmetric, increasing and differentiable equilibrium strategy $S_\alpha : V \to V$. Bidder i is facing a trade off between the winning probability and the gain of winning. Bidder i's maximization problem is:

$$\max_s \; u(v_i - \alpha s) \left[\frac{S_\alpha^{-1}(s)}{100}\right]^{N-1}$$

At a symmetric equilibrium, $s = S_\alpha(v_i)$. Together with the first order condition, this gives

$$(N-1)\frac{u(v_i - \alpha S_\alpha(v_i))}{u^{'}(v_i - \alpha S_\alpha(v_i))} = \alpha S_\alpha^{\prime}(v_i) v_i \tag{2.1}$$

where $S_\alpha(0) = 0$.

If agents have Constant Relative Risk Aversion (CRRA) utility functions with risk aversion coefficient equal to $1 - r$, the unique symmetric equilibrium strategy is:

$$S_\alpha(v_i) = \frac{N-1}{\alpha(N-1+r)} v_i. \tag{2.2}$$

In equilibrium, the submitted-value function, given by equation (2.2), multiplied with α gives the calculated-bid function. Therefore, it is easy to see that the bids are no longer a function of α and, therefore, Mechanism (α) generates the same bid function regardless of the α. That is,

$$\alpha S_\alpha(v_i) = \frac{N-1}{(N-1+r)} v_i.$$

In addition, note that $\alpha = 1$ corresponds to the standard first-price sealed-bid auction.

3. Experimental Procedure

The experiments were performed in the RCGD experimental lab at the Institute for Social Research at the University of Michigan during September 2011. The experiment was programmed and conducted with the software z-Tree (Fischbacher, 2007).[5] Subjects were recruited from the students of the university (through the ORSEE recruitment program which sends an E-mail to all university students who are enrolled to the program).

The experiment consisted of three treatments, each consisting of three sessions. In each session, there were 8 to 16 subjects and 20 rounds. In each round, groups of 4 subjects were formed randomly. Each subject participated in only one of the sessions. The sessions took approximately one hour. Subjects earned laboratory currency (points) which was then converted into cash at the end of the session. A conversion rate of .30 cents per point earned was used.

We follow a between-subjects design. The treatments are shown in the table below.

	# subjects	# subjects in each auction	# rounds	α
Mechanism (1)	36	4	20	1.0
Mechanism (0.9)	32	4	20	0.9
Mechanism (1.1)	36	4	20	1.1

Table 1. Experimental Design

In the three treatments, we chose mechanisms with different α's corresponding to the different treatments. Notice that Mechanism (1) is simply a first-price sealed-bid auction. Mechanism (0.9) and Mechanism (1.1) are strategically and procedurally equivalent to Mechanism (1), but we would like to see whether they are behaviorally equivalent as well.

In our experiment, participants were seated individually in visually isolated cubicles with computers in front of them. Then, they received instructions on the computer

[5]Pilot experiments were run at New York University at the CESS Laboratory with pen and paper. We do not see any qualitative differences between the pilot experiments and computerized experiments reported here.

screen (see Appendix A). Instructions were also read aloud in order to make sure that the information was common knowledge. We follow a between subjects design, so each subject participated in only one of the treatments. Subjects were told that there would be 20 rounds and each period they would be randomly re-grouped with 3 other people in the room without knowing the identities of these people. In each period, the value of the object for each subject was determined by a random number generator program in front of them. The values were between 1 and 100 where every number of two decimal places was equally likely.[6] At each period, subjects viewed a screen that showed their value and contained three sections: a "bid calculator" for testing submitted values,[7] a "value submission" section where submitted values were to be entered, and a history sheet indicating results from previous rounds. The subject with the highest calculated bid, which was equal to the submitted value multiplied with the α corresponding to that treatment, won the object in his/her group. The profit of the winner was determined by the difference between his/her value and the calculated bid. In all treatments, the winner was determined randomly with equal probability in case of a tie. At the end of each round, subjects could view the outcome of the auction (whether they won and their profit in points) and review their submitted value and calculated bid.

The main aim of this paper is to see if there is any behavioral difference between these strategically and procedurally equivalent mechanisms. We designed the experiment and Mechanism (α), so that the different auctions were implemented in an uncomplicated way. Some may argue that any behavioral difference may be attributed to the difference in the complexity of the mechanisms; that is, the reason for different outcomes could be because the subjects failed to recognize the equilibrium of the new game. However, complications of this sort are prevented with the use of the "bid calculator." Also, notice that the Mechanisms (0.9) and (1.1) are not complicated in the sense that if one can solve the equilibrium in the first-price sealed-bid auction, then one can solve it in these mechanisms as well.[8]

[6]We allowed them to enter decimal places to enable a continuous strategy space.

[7]A bid calculator calculates what would be the bid of the subject for a given submitted value.

[8]We do not expect Mechanisms (0.9) and (1.1) to have different levels of complexity even if one argues Mechanism (1) has less cognitive load.

4. Results

As we have demonstrated earlier, for any α_1 and α_2 not equal to zero, the Mechanisms (α_1) and (α_2) are strategically-equivalent. In addition, they are procedurally-equivalent due to the design of the Mechanism(α); the auction follows the same procedure under different α's with only a minimal change in how bids are calculated. However, if the mechanisms are not behaviorally equivalent, then this may open up a new dimension for designing mechanisms.

4.1. Bidding Behavior in the Mechanisms.

If individuals have CRRA utility functions with risk aversion coefficient equal to $1 - r$, equation (2.2) implies linear bidding behavior. In order to test for linearity, we run the following regression for each treatment:[9]

$$Bid_i = \beta_0 + \beta_1 value_i + \beta_2 value_i^2 + u_i.$$

We cannot reject the null hypothesis that β_2 equals zero in all treatments at the 5% level, which provides support for linearity of the bid function.[10]

Next, for each mechanism, we regress bids on values and a constant term (see Table 2); we find that the slope (robust standard error) of the estimated bid function of Mechanism (1) is 0.886 (0.016). The constant term (robust standard error) is equal to -0.225 (0.513). However, the constant term is not significant at the 5% level. If we repeat the regression without a constant term, the slope coefficient (robust standard error) is 0.882 (0.008).

We observe that subjects are shaving their bids approximately 5% more in Mechanism (0.9). Indeed, we find that, in Mechanism (0.9), the coefficient (robust standard error) of the estimated bid function is 0.829 (0.011). For Mechanism (1.1), the observed behavior is similar to Mechanism (1). The coefficient (robust standard error) of the estimated bid function is 0.874 (0.010). To make the comparisons easier, Table 2 summarizes the estimated bid functions, both with and without constants.

[9] Throughout the paper we cluster observations at the session level.

[10] The associated p-value for β_2 is 0.277 for Mechanism (1), 0.223 for Mechanism (0.9), and 0.202 for Mechanism (1.1). In addition, we tried higher order polynomials, and we cannot reject linearity.

	With constant		Without constant	No. of
	constant	value	value	observations
Mechanism (1)	-0.225	0.886***	0.882***	720
	(0.513)	(0.016)	(0.008)	
Mechanism (0.9)	0.215	0.829***	0.832***	640
	(0.539)	(0.011)	(0.006)	
Mechanism (1.1)	-0.615	0.874***	0.865***	720
	(0.475)	(0.010)	(0.006)	

Standard errors are in parenthesis, *** 1% significance level.

Table 2. Estimated Bid Functions

4.2. **Are differences significant?** Although Mechanism (0.9) and Mechanism (1) are strategically and procedurally equivalent, our data suggests that there is a behavioral difference between mechanisms. In order to test for the equivalence of the two bid functions, we have used the dummy variable approach. We run the following regression:

$$Bid_i = \beta_0 + \beta_1 D_i + \beta_2 value_i + \beta_3 value_i * D_i + u_i$$

where D_i is equal to 1 if data point is coming from the Mechanism (0.9), 0 otherwise. We reject that the two bid functions have the same slope coefficients at the 5% significance level ($p - value = 0.022$). We also repeat the same regression without a constant and we still conclude that the interaction term is significantly different than zero at the 1% significance level ($p - value = 0.008$). Therefore, we reject the null hypothesis that the estimated bid functions are the same.

Pair-wise comparisons of the regressions show that the estimated bid function of Mechanism (1.1) is significantly different (at the 5% significance level) than Mechanism (0.9), but is not significantly different from Mechanism (1.0). Table 3 documents these findings.

The most dramatic difference across the mechanisms is seen in the earnings made by those subjects participating in Mechanism (0.9) compared to Mechanism (1). Those who participated in the former treatment made approximately 20% more in earnings, as seen by comparing the average earnings in points of 39.73 in Mechanism (0.9) to

	With constant		Without constant	No. of
	β_1	β_3	β_3	observations
Mechanism (1) to (0.9)	0.441	-0.057**	-0.050***	1360
	(0.666)	(0.017)	(0.009)	
Mechanism (1) to (1.1)	-0.390	-0.012	-0.018	1440
	(0.626)	(0.017)	(0.009)	
Mechanism (0.9) to (1.1)	-0.830	0.045**	0.032***	1360
	(0.643)	(0.014)	(0.008)	

Standard errors are in parenthesis, ***1% significance level and **5% significance level.

Table 3. Pair-wise Comparison of Estimated Bid Functions

32.47 in Mechanism (1).[11] Of course, this intriguing difference indicates a revenue difference across the mechanisms where one would have expected equivalence; this empirical anomaly suggests that one should be careful in picking the optimal mechanism even among the theoretically equivalent class of mechanisms.

4.3. **Time Trends.** Studying for adjustments in bidding over time for each mechanism is not only interesting but also necessary in order to conclude that these mechanisms differ. It may be the case that bidding behavior in Mechanism (0.9) is getting similar to the bidding behavior in the other mechanisms over time. Therefore, for each mechanism, we first look at the average bid as a fraction of value over the periods to get an insight. Figure 1 suggests that, in fact, the differences across mechanisms are getting larger.

We therefore repeat our regression analysis by adding one more explanatory variable, "iro," which is equal to the inverse of round. A nonlinear adjustment process is preferred over a linear adjustment process, since this allows for rapid learning in the first rounds.[12] In any case, results do not depend on this specification. We get the same results if we instead add "round."

Table 4 reports the coefficients of the regressions. The time trend coefficient is not significant in the Mechanism (1.1). In the Mechanism (0.9) and (1.0), the time trend

[11]The average earnings of Mechanism (1.1) was 35.22, which is in line with the fact that the estimated bid function for subjects participating in this treatment was slightly less than those participating in Mechanism (1) but higher than those participating in Mechanism (0.9).
[12]See Kagel (1995, pages 521-523) for a discussion on this issue.

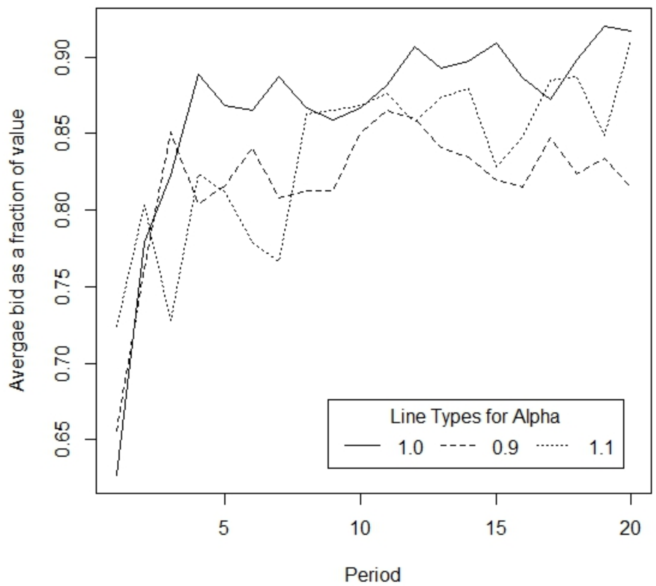

FIGURE 1. Average Bid as a Fraction of Value

coefficient is negative and significant at the 5% significance level. The negative time trend coefficient suggests higher bidding over time. However, we see that even if bids are increasing in Mechanism (0.9), subjects do not bid as aggressively as in Mechanism (1).[13] Therefore, the regression results confirm our observation from Figure 1.

4.4. **Can Heterogeneity be an Explanation?** As we have already shown, CRRA model itself is not enough to explain the different bids in different mechanisms. The risk aversion coefficient implied by Mechanism (1.0), $1 - r = 0.60$, is not consistent with the risk preferences observed in the other two treatments where $1 - r = 0.39$ for $\alpha = 0.9$ and $1 - r = 0.53$ for $\alpha = 1.1$. In this section, we explore the possibility that individuals have heterogeneous risk preferences.

Bidding theory has been extended to agents with heterogeneous risk preferences (see Cox, Smith and Walker (1982, 1983, 1985, 1988)). The heterogeneous constant relative risk aversion model (CRRAM) assumes that each bidder has a different risk aversion coefficient which is drawn from some distribution Φ on (0,1]. Each bidder

[13]To see this compare the coefficients of *value* in the regressions: 0.909 with 0.859.

	Value	Iro	No. of observations
Mechanism (1)	0.909***	-10.632**	720
	(0.007)	(1.100)	
Mechanism (0.9)	0.859***	-9.536**	640
	(0.009)	(1.026)	
Mechanism (1.1)	0.886***	-8.046	720
	(0.005)	(2.839)	

Standard errors are in parenthesis, *** 1% significance level and **5% significance level.

Table 4. Time Trends

is assumed to know only his/her own risk aversion parameter and that other bidders' risk aversion parameters are randomly drawn from the distribution Φ. We now study whether heterogeneity can also explain the differences we observe across treatments.

We repeat the analysis in Section 4.2 by adding subject dummies to control for heterogeneity across individuals. None of our qualitative results change. In fact, the difference between Mechanism (0.9) and Mechanism (1.0) and between Mechanism (0.9) and Mechanism (1.1) are now larger and there is stronger statistical evidence, i.e., lower p-values (p-values are 0.010 and 0.017, respectively).[14] In addition, we do not find a difference across Mechanism (1.0) and Mechanism (1.1) ($p-value = 0.552$). Our results indicate that even controlling for heterogeneity across individuals, different mechanisms generate different behavior.

In addition, we can check whether the CRRAM model provides meaningful risk aversion coefficients. The CRRAM model implies that each individual has a linear bid function for bids that do not exceed an upper bound (cutoff point) as defined by the maximum bid that would be submitted by the least risk averse bidder in the population. After that cutoff point, the bid function for that agent would be nonlinear. Cox and Oxaca (1996) demonstrate that each cutoff point uniquely determines the risk parameter of individuals. Following Cox and Oxaca, we have estimated the individual bid functions, cutoff points and risk parameters of subjects.[15]

[14] These estimations are available upon request.

[15] The average risk aversion coefficients, $1-r$, are 0.51, 0.63 and 0.56 for alpha = 0.9, 1.0, and 1.1, respectively. As expected, the risk aversion parameters are lowest for Mechanism (0.9), and highest for Mechanism (1.0). We use the non-parametric Mann-Whitney (Wilcoxon Rank Sum) test for each

We then compare these risk aversion coefficients estimated from the bidding behavior with risk preferences elicited by using a lottery choice task (based on Holt and Laury (2002)). In part 2 of our experiment, the subjects were presented with 15 situations, each of which introduced the choice between a fixed payoff of a specific amount (the "safe choice") or a 50-50 lottery between a payoff of \$4.00 and of \$0.00. When the subjects submitted all of their choices, the computer randomly selected a situation for each subject, and they received the payoff from whichever option they selected from that situation.[16]

If CRRAM provides meaningful risk aversion coefficients, one would expect to see a strong relationship between these two sets of risk preferences. We find a correlation coefficient of 0.105, which is extremely small. In addition, when we regress the number of safe choices on the risk aversion coefficients estimated from bids in part 1, we do not see any significant relationship for any of the treatments (p-values are 0.794, 0.808, and 0.173 for $\alpha = 0.9$, 1.0 and 1.1, respectively).[17] Given these two pieces of evidence—first, when we run regressions with individual dummies the differences across mechanisms only got stronger and, second, the risk preferences estimated from individual bids are not very meaningful—we suspect that the behavioral differences cannot be consistently explained by the CRRAM model, or at the very least this model fails to provide a satisfactory explanation.

5. Conclusion

We study the behavioral difference between strategically-equivalent mechanisms that share the exact same environment. In order to do this, we construct the Mechanism

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possible pair of treatments in order to test the hypothesis that the risk parameters are drawn from the same population against the alternative hypothesis that one treatment has systematically lower values. There is weak evidence that risk aversion parameters from Mechanism (0.9) and Mechanism (1.1) are systematically lower than the risk aversion parameters from Mechanism (1.0) (p-values are 0.176 and 0.203). In order for CRRAM to explain the differences across mechanisms in a consistent way, we expect to observe these risk preferences to be drawn from the same population. This is due to the fact that we have performed all our treatments by using the same subject pool and subjects were randomly assigned into different treatments.

[16]The average number of safe choices (robust standard deviation) for each treatment is 8.688 (2.468), 8.611 (2.831) and 8.306 (2.724) out of 15 possible choices for Mechanisms 1.0, 0.9 and 1.1, respectively. We cannot reject the hypothesis that the number of safe choices are the same across any pairwise comparisons (p-values are all larger than 0.531).

[17]Hence, there is no significant relationship between individuals' bidding behavior and the risk aversion coefficients estimated in part 2.

(α), where the bid functions are identical across different α's. In general, we observe differences across the mechanisms in terms of estimated bid functions: Mechanism (0.9) differs significantly compared to Mechanism (1) and to Mechanism (1.1). Therefore, we also see that revenue equivalence between the mechanisms does not hold.

While we cannot pin down what might cause this significant difference, we conjecture that this might be explained by the anchoring and adjustment heuristic (Slovic and Lichtenstein 1971; Tversky and Kahneman 1974).[18] We observe that, for $\alpha = 0.9$, individuals do not adjust their bids sufficiently. In our experiment, on average, individuals submit 88% of their values in Mechanism (1). If they also submit the 88% of their values in Mechanism (0.9), this corresponds to a bid function with a slope of 0.79. Instead we see that individuals bid 83% of their values. Clearly, individuals make an adjustment but the adjustment is not enough. The reason we do not see a similar insufficient adjustment in Mechanism (1.1), which would imply a higher bid function, might simply be due to the small margin of earnings in that region. Individuals realize insufficient adjustment corresponds to very little earnings, so the adjustment is (almost) complete. We see this to our advantage since this shows that mechanisms are not different in their complexity, i.e., subjects are able to make full adjustments.

An alternative explanation for our result is that the subjects interpret α as a suggestion. Since α is common knowledge among subjects, they can coordinate to submit lower calculated bids. At least bids will be bounded by α*100. Some subjects strategically lower their bids given that the bids are bounded by α*100. Hence, the average bid/value ratio will be less than α. This line of reasoning only applies when α is equal to 0.9. When $\alpha = 1$ or 1.1, this has no information or it is not a reasonable suggestion. One way to separate out different explanations may be to run a treatment where α is not commonly known.

These findings open up a new research agenda for mechanism design theory. We provide strong evidence that the behavior of individuals is different even under strategically-equivalent mechanisms that are also procedurally the same. This is suggestive that while searching for the optimal mechanism, theory should incorporate the behavioral aspects of mechanisms. As such, these findings have overriding consequences for the

[18]Anchoring and adjustment is defined as different starting points yielding different actions, since adjustments are typically insufficient.

parts of theory which relate to implementation and equivalence, including the Revelation Principle.

Appendix A. Instructions for the Mechanism (0.9)

Instructions

Thank you for agreeing to participate in this experiment. Please make sure your mobile phones are turned off to avoid interruptions during the meeting. This is an experiment in the economics of decision making. Your participation in this experiment is voluntary but we hope that you will also find the experiment interesting. You will be compensated for your participation. You will be given $7 for showing up. You can earn an additional amount of cash which will be distributed at the end of the experiment. The instructions are simple and you will benefit from following them carefully.

Part 1

In the first part of the experiment there will be a series of auctions. In each round you will participate in an auction with three other participants, for a total of 4 people. Between rounds the people in your group will change randomly. However, you will not know the identities of these people. There will be 20 rounds. In each round, your earnings will depend of your choice and the choices made by the 3 other people in your group. We use points to reward you. At the end of the experiment we will pay you 30 cents for each point you won.

In each round, a fictitious good will be auctioned and each of you will have different values for this good. Each round, your value for the good will be determined by a random number generator. The number will be between 1 and 100 where every number (of two decimal places) is equally likely.

At the beginning of Round 1 you will be shown your value for the good. You will participate in an auction for the good, where your final earnings will be the difference between your value and your bid if you win the auction. However, in this auction you will not directly submit a bid. Instead, you will be asked to enter a "submitted value" for the good and a bid will then be calculated for you. You are allowed to enter a "submitted value" that is different from your actual value. The server will collect each participants "submitted value" from Round 1, and your "submitted values" will be multiplied by .9 to determine your calculated bid. For example, say your submitted value is 60, then a calculated bid of .9*60 = 54 will be submitted for you. Please note that each round a bid-calculator will be provided for you so you may test out different submitted values before you make your final decision.

The computer randomly forms groups of four participants. Within each group, the calculated bids will be compared. The results of Round 1 will then be displayed. You will be informed whether or not you held the highest calculated bid in your group. Only those of you with the highest calculated bid in their group will get the good, and his/her earnings will be equal to the difference between his/her value and calculated bid. In the case of a tie, the winner will be determined randomly with equal probability. If you are the winner, your earnings will be:

Earnings = Your value for the good - .9 * your submitted value

If the highest calculated bid is not yours (or if you lose in the case of a tie), then you earn nothing in the auction. So, your earnings will be:

Earnings = 0

That will end Round 1, and then Round 2 will begin. The same procedure will be used for all 20 Rounds. After each round you will be able to see whether you have won the auction and your earnings in that round on your computer screen. Your final earnings at the end of the experiment will be the sum of earnings over the 20 rounds. Remember that at the end of the experiment you will receive the show-up fee and your total points/earnings will be multiplied by 30 cents to calculate your final payment.

Part 2

You will now be presented with several Situations. Each Situation will present you with the choice between a Fixed Payoff of a specific amount, or a 50-50 Lottery between a payoff of $4.00 and of $0.00. When you have made all of your choices, the computer will randomly select a Situation, and you will receive the payoff from whichever option you selected. You will then be asked to answer questions from a quick and confidential survey. (See Table 6.)

Survey Questions

Please answer ALL of the questions in this brief survey as accurately as you can. All answers are confidential, and in fact your answers are linked only to your participant ID for today's experiment, and not your name or student ID.

TABLE 5. Situations for Risk Elicitation

Situation	Lottery	Fixed Payoff
1	50% chance of $4.00 and 50% chance of $0.00	$0.25
2	50% chance of $4.00 and 50% chance of $0.00	$0.50
3	50% chance of $4.00 and 50% chance of $0.00	$0.75
4	50% chance of $4.00 and 50% chance of $0.00	$1.00
5	50% chance of $4.00 and 50% chance of $0.00	$1.25
6	50% chance of $4.00 and 50% chance of $0.00	$1.50
7	50% chance of $4.00 and 50% chance of $0.00	$1.75
8	50% chance of $4.00 and 50% chance of $0.00	$2.00
9	50% chance of $4.00 and 50% chance of $0.00	$2.25
10	50% chance of $4.00 and 50% chance of $0.00	$2.50
11	50% chance of $4.00 and 50% chance of $0.00	$2.75
12	50% chance of $4.00 and 50% chance of $0.00	$3.00
13	50% chance of $4.00 and 50% chance of $0.00	$3.25
14	50% chance of $4.00 and 50% chance of $0.00	$3.50
15	50% chance of $4.00 and 50% chance of $0.00	$3.75

1. What is you age in years? (Enter: Integer.)
2. What is your gender? (Enter: Male, Female.)
3. What is you major? (Enter: String.)
4. What strategy did you use in the auctions? (Enter: String.)
5. Have you ever participated in an auction before? (Enter: Yes, No.)
6. How often have you gambled or purchased lottery tickets in the past year? (Enter: Very frequently, Frequently, Sometimes, Rarely, Never.)

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