Behavioral Differences between Direct and Indirect Mechanisms: Evidence from First Price Auctions*

Yusufcan Masatlioglu
University of Michigan

Neslihan Uler†
New York University

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Abstract

The Revelation Principle depends on a seemingly innocuous assumption that theoretically outcome-equivalent (TOE) direct and indirect mechanisms are behaviorally equivalent as well. We use the first-price sealed-bid auction as our indirect mechanism and construct corresponding TOE direct mechanisms.

In contrast with what theory predicts, subjects behave significantly differently under direct and indirect mechanisms: (i) The revenue equivalence does not hold - the indirect mechanism generated higher revenue than the direct mechanisms, (ii) subjects behaved as if they were less risk averse in the direct mechanisms, (iii) moreover, we observed different bids across direct mechanisms. We show that a reference-dependent model explains the behavioral differences.

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1 Introduction

The well-known Revelation Principle states that for any equilibrium of a mechanism, there exists an incentive compatible direct mechanism in which truth telling generates outcomes that are equivalent to the given equilibrium of the original mechanism. This suggests that, without loss of generality, a designer could restrict his/her attention to direct mechanisms and, therefore, in the search for optimal mechanism design, does not need to consider indirect mechanisms.

Invoking the Revelation Principle may be problematic in some situations. The restrictions necessary for truthful revelation in equilibrium may result in a complicated direct

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†New York University, Department of Economics, 269 Mercer Street, 7th Floor, New York, NY 10003; Tel: 1-212-998-8038; E-mail: nu221@nyu.edu.

mechanism. In this case, it is hard to expect that the truth revealing equilibrium will be played. One should also check whether the corresponding direct mechanism is as robust as the original one. If the payoff structure of the incentive compatible direct mechanism is very sensitive to slight deviations of other players from the equilibrium strategy, individuals may choose safer strategies in reality unlike the theoretical prediction of the truth revealing equilibrium (see Jackson (2001)). There are some other instances where the Revelation Principle cannot be applied if its basic underling assumptions are not satisfied. For example, Parkes (2003) introduced a new variation of the Revelation Principle in which agents do not have complete information over their preferences. The usual Revelation Principle was not applicable since it assumes costless preference elicitation. Laffont and Martimort (1997) mention another weakness of the Revelation Principle. It assumes costless communication and Bayesian Nash behavior between agents. However, they believe that collusion cannot be considered as an exception when it applies to groups. In this paper, we construct direct mechanisms, which do not suffer from the problems above.

Designing the optimal mechanism is a very important problem in public goods literature, where the aim is to provide incentives to prevent free riding. During the 1970's the main challenge was to design a mechanism, such as the well known Vickrey-Clarke-Groves mechanism, where revelation of the true preferences is a dominant strategy. Attiyeh, Franciosi, Isaac (2000) tested the pivotal mechanism, which is a special case of the Vickrey-Clarke-Groves mechanism, to see if it actually induced truth telling. They showed that subjects did not reveal their true preferences although reporting true preferences was a dominant strategy. Kawagoe and Mori (2001) then tested to check if the misrevelation is due to the complex payoff structure and they show that when subjects are provided with detailed payoff tables, they tend to reveal their preferences. For a detailed survey on incentive compatible mechanisms for pure public goods, see Chen (2004).

However, these papers do not compare the behavioral aspects of the direct and indirect mechanisms. Our aim is to test the behavior of individuals facing outcome equivalent direct and indirect mechanisms to see if these mechanisms are behaviorally equivalent as well. To our knowledge, there have not been experiments testing the behavioral equivalence of direct and indirect mechanisms. However, the Revelation Principle relies on the assumption that there is no behavioral difference between them. This implies that the applicability of the Revelation Principle may be questioned if these mechanisms are not behaviorally equivalent.

To explore this question, we use the first-price sealed-bid auction as our indirect mechanism. There are several reasons for this choice. First, it is commonly used both in the mechanism design literature and in the real world. Second, it is easy to construct a theoretically outcome-equivalent (TOE) direct mechanism simple enough to be tested in a laboratory environment. Moreover, the direct mechanism we use, called Direct(α) Mechanism, has very similar properties to the standard first-price sealed-bid auction.

In a Direct(α) Mechanism, each potential buyer is asked to submit a sealed-value s_i instead of a sealed-bid b_i. The submitted values are then opened by a mediator who does not know the true values of the buyers. He multiplies them by α to determine the "calculated bids" of the buyers. The buyer with the highest calculated bid gets the good and pays her/his calculated bid.

As we show below, the first-price sealed-bid auction is TOE to any Direct(α) Mechanism, $\alpha \neq 0$. By this we mean that, in equilibrium, the bids in the first-price sealed-bid auction is equal to the "calculated bids" in the Direct(α) Mechanism for any α, $\alpha \neq 0$. Therefore, for each direct mechanism, we will compare the "calculated bids" with the "bids" observed in the indirect mechanism.

In contrast with what theory predicts, subjects behave significantly differently under direct and indirect mechanisms. We establish the following conclusions: (i) The revenue equivalence does not hold - the indirect mechanism generated higher revenue than the direct mechanisms, (ii) subjects behaved as if they were less risk averse in the direct mechanisms, (iii) moreover, we observed different bids across direct mechanisms. We show that a reference-dependent model explains the behavioral differences.

The next section describes the Direct(α) Mechanisms 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 demonstrates a behavioral explanation for the data and the conclusions follow.

2 The Setup

We will first derive the equilibrium bid function of the first-price sealed-bid auction. Then, we will demonstrate that the first-price sealed-bid auction is TOE to the Direct(α) Mechanism for any α, $\alpha \neq 0$.

2.1 First-Price Sealed-Bid Auction (Indirect Mechanism)

There is a single good for sale and there are N bidders with private valuations, v_i. Hence, bidder i only knows his own value. The private values are distributed uniformly over the range $V = [0, 100]$. Bidders are assumed to have the same von-Neumann-Morgenstern utility function $u(.)$ with $u(0) = 0$, $u^{'} > 0$ and $u^{"} \leq 0$.[1]

In a first-price sealed-bid auction, the highest bidder gets the good and pays his own price. Therefore, bidder i is facing a trade off between the winning probability and the gain of winning. Suppose all other players $j \neq i$ follow symmetric, increasing and differentiable equilibrium strategy $\beta : V \to V$. Then the winning probability of bidder i with value v_i and bid b is $\left[\frac{\beta^{-1}(b)}{100}\right]^{N-1}$, so in the equilibrium b maximizes $u(v_i - b)\left[\frac{\beta^{-1}(b)}{100}\right]^{N-1}$. At a symmetric equilibrium, $b = \beta(v_i)$. Together with the first order condition, this gives

$$(N-1)\frac{u(v_i - \beta(v_i))}{u'(v_i - \beta(v_i))} = \beta'(v_i)v_i \tag{1}$$

[1] Homogeneity assumption simplifies the illustration of the model, however, our results are independent of it, as shown in Section 5.1.

where $\beta(0) = 0$.

If agents have Constant Relative Risk Aversion (CRRA) utility functions with risk aversion coefficient equal to $1 - r$ (i.e., $u(x) = x^r$), then (1) simplifies to

$$(N-1)(v_i - \beta(v_i)) = r\beta'(v_i)v_i. \tag{2}$$

Given the initial condition, this equation has a unique solution:

$$\beta(v_i) = \frac{N-1}{(N-1+r)}v_i. \tag{3}$$

These computations simply show that the bidding strategy of the players will be to bid $\frac{N-1}{(N-1+r)}$ of their value.[2]

Note that the first-price sealed-bid auction is an indirect mechanism. For simplicity we will refer to the first-price sealed-bid auction as the "Indirect Mechanism".

2.2 Direct(α) Mechanism

In a Direct(α) Mechanism, each potential buyer is asked to submit a sealed-value s_i instead of a sealed-bid. The submitted values are then opened by a mediator who does not know the true values of the buyers. He multiplies them by α to find out the calculated bids of the buyers, where $\alpha \neq 0$. The potential buyer with the highest calculated bid gets the good and pays her/his calculated bid.

Similarly, suppose all other players $j \neq i$ follow symmetric, increasing and differentiable equilibrium strategy $S : V \to V$. Given α, player i will then choose s to maximize $u(v_i - \alpha s)\left[\frac{S^{-1}(s)}{100}\right]^{N-1}$. At a symmetric equilibrium, $s = S(v_i)$. Together with the first order condition, this gives

$$(N-1)\frac{u(v_i - \alpha S(v_i))}{u'(v_i - \alpha S(v_i))} = \alpha S'(v_i)v_i \tag{4}$$

where $S(0) = 0$.

If agents have CRRA utility functions with risk aversion coefficient equal to $1 - r$, the unique equilibrium strategy is:

$$S(v_i) = \frac{N-1}{\alpha(N-1+r)}v_i. \tag{5}$$

In equilibrium, the submitted value function, given by equation (5), multiplied with α should be equal to the bid function, given by (3). Now, note that, this is not only true for CRRA utility functions but for any form of utility functions. It is easy to see that when $S(v_i) = \frac{\beta(v_i)}{\alpha}$, equation (4) is equivalent to equation (1). Therefore for any α and utility function $u(.)$, the Direct(α) Mechanism is outcome-equivalent to the first-price sealed-bid auction.[3]

[2] For a detailed overview on auction theory, see Krishna (2002).

[3] In Section 5.1, we also show that the same result holds for heterogenous bidders.

3 Experimental Procedure

The experiments were performed at the Center for Experimental Social Science (C.E.S.S.) at New York University from July through November 2003. Subjects were recruited from the undergraduate students of the university (through the C.E.S.S. recruitment program which sends E-mail to all university students who are enrolled to the program at the same time). The experiment consisted of four treatments. In each treatment, there were 15 subjects and 20 rounds. In each round 3 groups of 5 subjects were formed randomly. Each subject participated in only one of the treatments. The treatments took approximately one hour. Subjects earned laboratory currency (points) which is then converted into cash at the end of the session. Conversion rates (in cents) of the treatments differed in order to balance the average earnings among them.[4,5]

The treatments are shown in the following table:

Experimental Design

Treatments	No. of Subjects	No. in each Auction	No. of periods	α	Subject pool	conversion rate (in cents)
Indirect	15	5	20+(1)	-	NYU	55
Direct(0.95)	15	5	20+(1)	0.95	NYU	35
Direct(0.90)	15	5	20+(1)	0.90	NYU	35
Direct(1.00)	15	5	20+(1)	1.00	NYU	55

Table 1: Treatments

In the first treatment, the standard first-price sealed-bid auction is tested. In the other three treatments, Direct(α) Mechanism is tested with three different α corresponding to each treatment. In the following sections, the reasons of choosing these direct mechanisms will be clarified.

In our experiment, participants were seated individually in visually isolated cubicles with computers in front of them. Then, they received instructions (see Appendix A) with their ID numbers on them. Instructions were also read aloud in order to make sure that the information was common knowledge. Subjects were told that there would be 20 periods and each period, they would be randomly paired with 4 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 integer was equally likely. In the first treatment, at each period, after receiving their values, subjects were asked to fill in the appropriate sections in their record sheets and their bid cards with the bid cards numbered from 1,2,...,20. The cards were then collected in a box and 5 cards were drawn

[4] We had run a pilot experiment before the real experiments. Under the same incentives (movie tickets), we witnessed that a direct mechanism generates higher earnings (in points) to the subjects than the indirect mechanism.

[5] Cox et al. (1988), Smith and Walker (1993) has shown that multiplicative transformations of the payoffs does not have significant effects on bids.

randomly to generate the first group. This procedure was repeated once more to generate the other two groups. The subject with the highest bid won the object in his/her group. The profit of the winner was determined by the difference between his/her value and the bid. In the other treatments, instead of bid cards, subjects were provided with submitted value cards and were asked to fill in the corresponding submitted value cards at each period. Similarly, the submitted value cards were collected in a box and the groups were randomly formed. In every group the subject with the highest calculated bid, which is equal to submitted value multiplied with the α corresponding to that treatment, won the object. His/her profit was determined by the difference between his/her value and the calculated bid. In all treatments, the winner was determined by flipping a coin in case of a tie. The winners' IDs were projected on a blackboard after each round. However, no extra information, such as the winning bids, were provided to the subjects.[6]

The main aim of this paper is to see if there is any behavioral difference between direct and indirect mechanisms. We designed the experiment in such a way that the direct mechanism is not complicated since any behavioral difference may be attributed to the difference in the complexity of the mechanisms, i.e., the reason for different outcomes could be simply because the subjects failed to recognize the equilibrium of the new game due to its complexity. In order to prevent any complication, we supplied the subjects with multiplication tables which showed the calculated bids for any possible choice of submitted values. Notice that the Direct(α) Mechanism is 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 the Direct(α) Mechanism as well.

4 Results

4.1 Indirect Mechanism

If individuals have CRRA utility functions with risk aversion coefficient equal to $1 - r$, equation (3) implies linear bidding behavior. In order to test for linearity, we run the following regression using the last 15 rounds (225 data points):

$$Bid_i = \alpha_0 + \alpha_1 Value_i + \alpha_2 Value_i^2 + u_i.$$

We found that α_2 (corrected standard error) is equal to -0.0006 (0.0005).[7] We cannot reject the null hypothesis that α_2 equals to zero, which provides a support for linearity of the bid function. This suggests a homogeneous CRRA model explains the behavior well in the Indirect Mechanism at the aggregate level for some risk aversion coefficient $1 - r$, which will also be derived from the data below.

[6] Dufwenberg and Gneezy (2002) showed that information disclosure has a significant overbidding effect.

[7] Note that, in order to account for repeated observations for a given individual, we are correcting the variance-covariance matrix, by using Stata "cluster" command.

Next, we regressed bids on values and a constant term; we found that the slope (corrected standard error) of the estimated bid function of the Indirect Mechanism is 0.945 (0.012). Constant term (corrected standard error) is equal to -0.66 (0.52). However, the constant term is not significant at the 5% level. If we repeat the regression without a constant term, the slope coefficient (corrected standard error) is 0.935 (0.007). We see that the risk aversion coefficient is 0.72 with a standard deviation of 0.033.[8]

As we have demonstrated earlier, for any α, $\alpha \neq 0$, the Indirect Mechanism and the Direct(α) Mechanism are TOE. However, if the mechanisms are not behaviorally equivalent, then the indirect mechanism may be superior to the corresponding incentive compatible direct mechanism. Therefore, we would like to test if direct and indirect mechanisms are behaviorally equivalent or not. For this purpose, we pick the Direct(0.95) and Direct(0.9) Mechanisms. Direct(0.95) Mechanism is the corresponding incentive compatible direct mechanism, where bidding the true values is the equilibrium. In Direct(0.9) Mechanism, truth telling is not an equilibrium; however, it is still TOE to the Indirect Mechanism.

4.2 Direct(0.95) Mechanism

We compare the mechanisms by using a simple transformation of the raw data. Remember that, the submitted value function, $S(v)$, multiplied with α should be equal to the bid function, $\beta(v)$. Therefore, we convert submitted values into calculated bids in order to test the theoretical prediction that the bid functions should be the same.[9]

Although the Indirect Mechanism and the Direct(0.95) Mechanism are TOE, our data suggests that there is a behavioral difference between mechanisms. Indeed, we found that, in the Direct(0.95) Mechanism, the coefficient (corrected standard error) of the estimated bid function is 0.9 (0.011)[10], i.e., subjects are shaving 5% more. In order to test for the equivalence of the two regressions, we have used the dummy variable approach. We run the following regression:

$$Bid_i = \alpha_0 + \alpha_1 D_i + \alpha_2 Value_i + \alpha_3 Value_i * D_i + u_i$$

where D_i is equal to 1 if data point is coming from the Direct(0.95) Mechanism, 0 otherwise. We reject that: (i) the two regressions have the same slope coefficients (at 1% level), (ii) they have the same intercepts (at 5% level). Therefore, we reject the null hypothesis that the estimated bid functions are the same.[11]

[8] Risk aversion coefficients are computed with the slope coefficients, that come from the regression of bids on values, without a constant.

[9] We have eliminated Subject 9 and 12, in Direct(0.95), from our analysis since they did not understand the mechanism. (Throughout the session, their expected profits were negative for many rounds.) Our results do not change much if we have not eliminated them.

[10] The constant (robust standard error) in the regression equation is equal to 0.77 (0.37) and is significant at the 10% level. We have also tested for linearity and we cannot reject the null hypothesis that the bid function is linear.

[11] If we force constant term to be zero in the regressions, the estimated bid function is 0.91. Furthermore, the difference between the two mechanisms is still significant (p=0.028 for a one-tailed test).

In fact, when we compare the subjects' earnings (points), we see that in the Direct(0.95) Mechanism subjects have earned 19.67 points on average compared to the Indirect Mechanism where subjects earned only 14.07 points on average. The difference between the earnings is approximately 40%. Indeed, the expected increase in earnings from shaving 5% to 10% is approximately 42% if we restrict ourselves with values greater than 50.

The differences between the earnings of subjects may be due to how risky the subjects considered the mechanisms to be. We derived the risk aversion coefficient implied from the data. In the Direct(0.95), the risk aversion coefficient is 0.61 with standard deviation 0.045. An important observation is that subjects behaved as if they are less risk averse when they were faced with the direct mechanism compared with the indirect one.

4.3 Direct(0.9) Mechanism

In the Direct(0.9) Mechanism, we have observed that subjects bid even lower. The coefficient (corrected standard error) of the estimated bid function is 0.86 (0.012); subjects are shaving 14% of their values.[12] To make the comparisons easier, Table 2 summarizes the estimated bid functions.[13] In order to test for equality of these regressions, we repeat the dummy variable approach. Pair-wise comparisons of the regressions show that the estimated bid function of the Direct(0.9) Mechanism is significantly different (at the 5% significance level) than both the Indirect and Direct(0.95) Mechanisms.[14]

As one can guess, subjects' behavior was even less risk averse in the Direct(0.9) Mechanism. Indeed, we found that the risk aversion coefficient associated with this mechanism is 0.4 with a standard deviation of 0.048. This is a huge difference when compared with the one estimated for the Indirect Mechanism and there is still a big difference when compared with the estimated coefficient of the Direct(0.95) Mechanism. Since this bidding behavior is not as aggressive as the others, this treatment has generated the lowest revenue for the seller and, therefore, the highest earnings for the subjects. Subjects earned 30.81 points on average (i.e., subjects' revenue more than doubles if the Direct(0.9) Mechanism is used

[12] To test for linearity, we repeat the following regression:

$$Bid_i = \alpha_0 + \alpha_1 Value_i + \alpha_2 Value_i^2 + u_i.$$

We found that α_0 (corrected standard error) is equal to -1.1 (0.45), α_1 (corrected standard error) is equal to 0.98 (0.42), α_2 (corrected standard error) is equal to -0.0013 (0.0004). We reject the null hypothesis that the bid function is linear (p=0.01). However, since the quadratic bid function is very similar to the linear one, for comparison purposes, we find it more convenient to work with a linear model.

[13] Table 2 presents an important observation that the standard errors in the regressions are very similar among the treatments, which helps to argue that the individuals did not get confused in the direct mechanisms. The standard errors decrease even further if we conduct random or fixed effect regressions. However, the coefficients and the p-values do not change much. The results of these regressions are available from the authors upon request.

[14] Since the bid function of the Direct(0.9) Mechanism is not linear, a nonparametric approach for testing equality of the bids may be prefered over a parametric one. Therefore, we run Kolmogorov-Smirnov equality of distributions test. In order to do that we first normalize bids by values and then we compute the average bid for each subject since Kolmogorov-Smirnov test requires independent observations. Kolmogorov-Smirnov test also rejects the null hypothesis of: i) equal distributions of bids in the Indirect and Direct(0.9) Mechanisms (one-sided p=0.02). ii) equal distributions of bids in the Direct(0.95) and Direct(0.9) Mechanisms (one-sided p=0.005).

instead of the Indirect Mechanism).

Linear Regressions[a]					
		with constant		without constant	# of observations
		constant	Value	Value	
Indirect		-0.657 (0.515)	**0.945**** **(0.012)**	**0.935**** **(0.007)**	225
Direct (α)	α = 0.95	**0.765*** **(0.370)**	**0.900**** **(0.011)**	**0.912**** **(0.009)**	195
	α = 0.90	**0.880*** **(0.423)**	**0.856**** **(0.012)**	**0.869**** **(0.009)**	225

[a] Corrected standard errors are in parenthesis
* 10% significance level, ** 5 % significance level

Table 2: Summary of regression results

4.4 Direct(1) Mechanism

The reader may dismiss the above results by simply saying that they are the results of framing. To check if there is a framing effect, we ran another treatment with the Direct(1) Mechanism. Notice that the only difference between these two mechanisms is that in the Direct(1) Mechanism subjects are asked to submit a value instead of a bid. However, note that submitting a value is not as natural as bidding. This may create the possibility that subjects will consider these two mechanisms differently. Also, if the subjects think that the experimenter actually knows their true values, they may be disinclined to misreport.

We found that the coefficient (corrected standard error) of the estimated (calculated) bid function of the Direct(1) Mechanism is 0.934 (0.017).[15] Moreover, we cannot reject the hypothesis that the estimated bid functions of the Direct(1) and Indirect Mechanisms are the same. The generated bid functions are not statistically different, which suggests that we do not have framing effect here. Therefore, we see that subjects do not consider these two mechanisms differently.

This finding strengthens our results on behavioral differences of the mechanisms above since discrepancy is unlikely to be due to an error in the experimental procedure that we have followed. At this point, one may argue that different conversion rates between direct and indirect mechanisms might have created the different bidding behavior. However, it has been shown that multiplicative transformations of the payoffs does not have significant effects on bids (see Cox et al. (1988), Smith and Walker (1993)). Also, although the conversion rates are same, we still observe a significant difference between the Direct(0.95) and the Direct(0.9). So, different conversion rates cannot be an explanation for the

[15] The constant, -0.4, in the regression is not significant (p=0.34). In our econometric analysis, we have eliminated subject 2 as an outlier.

observed discrepancies.[16]

4.5 Time Trends

Testing 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 behaviors in the direct mechanisms are getting similar to the bidding behavior in the Indirect Mechanism over time. We, therefore, repeat our regression analysis by adding one more explanatory variable, "iro", which is equal to inverse of round. A nonlinear adjustment process is preferred over a linear adjustment process, since this allows for a rapid learning in the first rounds.[17] In any case, results do not depend on this specification. We get the same results if we instead add "round".

Table 3 reports the coefficients of the regressions. The time trend coefficient is not significant in the Indirect Mechanism and the Direct(0.95) Mechanism. In the Direct(0.9) Mechanism, time trend coefficient is significant only at 10% significance level. Although a negative time trend coefficient suggests higher bidding over time, bidding in the Direct(0.9) Mechanism does not get as aggressive as the Indirect Mechanism. Except for very small values, the bids in the Indirect Mechanism are higher than the bids in the direct mechanisms.[18]

		Constant	Value	Iro	# of observations
Indirect		-0.794 (0.884)[a]	**0.945**** **(0.012)**	1.534 (7.008)	225
Direct (α)	α = 0.95	**1.640**** **(0.519)**	**0.900**** **(0.010)**	-10.361 (7.913)	195
	α = 0.90	**2.165**** **(0.912)**	**0.856**** **(0.012)**	**-14.444*** **(7.129)**	225

[a] Corrected standard errors are in parenthesis
* 10% significance level, ** 5 % significance level

Table 3: Regressions with a time trend variable

5 What explains the observed data?

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 the first treatment (corresponding to the Indirect Mechanism) is not consistent with the behavior observed

[16] Furthermore, in a pilot experiment where we keep the monetary incentives constant (the reward is free movie tickets for the winners), we observe that an indirect mechanism generates higher bids compared to a direct mechanism.

[17] See Kagel (1995, pages 521-523) for a discussion on this issue.

[18] Adding individual specific variables do not affect these results. Fixed and random effect regressions provide very similar coefficients. Also, we get the same results without eliminating the first 5 periods.

in the other two treatments where $\alpha = 0.95$ and $\alpha = 0.9$. Next, we will show that, although extending the model to heterogenous agents also fails to explain these differences, a reference-dependent model can be an explanation.

5.1 Can Heterogeneity be an Explanation?

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 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. CRRAM model can explain the overbidding behavior observed in the first-price sealed-bid auctions and the heterogeneity between the agents.

In Appendix B, we show that, for any α, Direct(α) Mechanism is still TOE to the Indirect Mechanism for each type even when we allow for the possibility of heterogeneous agents. Therefore, for each individual i, the bid function of the Indirect Mechanism and the calculated bid functions of the direct mechanisms would be the same.

We followed the same empirical analysis used in Cox and Oxaca (1995) to estimate the individual risk aversion coefficients. Then, we used the non-parametric Mann-Whitney (Wilcoxon Rank Sum) test for each possible pair of treatments in order to test the hypothesis that the two sets of individual risk aversion parameters come from the same distribution against the alternative hypothesis that one has systematically larger values. Table 4 presents the results. At the 5% significance level, we can reject the hypothesis that the parameters come from the same distribution for the Indirect Mechanism and the Direct(0.9), and, at the 10% significance level, for the Indirect Mechanism and the Direct(0.95). As a result, CRRAM model cannot consistently explain the observed data.

A Pair-wise Comparison of Risk Aversion Coefficients[a]

	Direct (0.95)	**Direct (0.90)**
Indirect	1.635 (0.051)	3.256 (0.001)
Direct (0.95)		1.82 (0.034)

[a] Mann-Whitney U-test (one-tail) based on ranks is used. The null hypothesis is that two sets of coefficients come from the same distribution. The numbers in the cells are the z-statistics and the p-values are given in brackets.

Table 4: Nonparametric Regressions

5.2 A Reference-Dependent Model

Much experimental evidence suggests that preferences depend on what is perceived to be the reference point and that losses are weighted more than the corresponding gains, where gains and losses are defined relative to this reference point. Although the reference point is generally interpreted as the endowment point or status quo, it has also been argued that, it can be interpreted in terms of expectations (Tversky and Kahneman (1991), Koszegi and Rabin (2004)). The following is taken from Koszegi and Rabin (2004): "Some evidence does indicate that expectations are more important than the status quo or lagged consumption in determining a person's sensation of gain or losses."

We conjecture that bidders interpret α as the proposed bidding coefficient and therefore, they take $(v - \alpha v)$ as a reference earning.[19] We assume that individuals have the same S-shaped utility function $u(.)$ with $u(0) = 0$, $u^{'}(x) > 0$ and $u^{"}(x) \leq 0$ for $x \geq 0$, and $u(-x) = -ku(x)$ where k is the loss aversion coefficient, $k \geq 1$. Suppose that $u(.)$ is a CRRA utility function with risk aversion coefficient equal to $1-r$. Suppose all other players $j \neq i$ follow symmetric, increasing and differentiable equilibrium strategy $\beta : V \to V$. Then the winning probability of bidder i with value v_i and bid b is $\left[\frac{\beta^{-1}(b)}{100}\right]^{N-1}$. In the equilibrium the bidders maximize their expected utility with respect to their expectations. Therefore, we have the following maximization problem:

$$u(\alpha v_i - b)\left[\frac{\beta^{-1}(b)}{100}\right]^{N-1} - ku((1-\alpha)v_i)(1 - \left[\frac{\beta^{-1}(b)}{100}\right]^{N-1}).$$

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

$$r(\alpha v_i - \beta(v_i))^{r-1} v_i = \frac{N-1}{\beta'(v_i)}[(\alpha v_i - \beta(v_i))^r + k((1-\alpha)v)^r] \tag{6}$$

where $\beta(0) = 0$.

Although this equation does not have a closed form solution, it is easy to see that the bidding function is linear, i.e., $\beta(v_i) = f(\alpha, N, k, r)v_i$. When $\alpha = 1$, $f(\alpha, N, k, r)$ simplifies to:

$$f(\alpha, N, k, r) = \frac{N-1}{(N-1+r)} \tag{7}$$

which gives the same bid function as the Indirect. Next, we would like to compute the bidding coefficient at some specific values. Remember that in the Indirect Mechanism, we have derived a risk aversion coefficient of $1 - r = 0.72$, or equivalently $r = 0.28$, with a standard deviation of 0.033. For demonstration purposes, we pick $r = 0.28$ and $r = 0.3$ (both are in the 95% confidence interval of the estimated r) to show that the model we propose here can consistently explain the differences observed in the data. For example, when $r = 0.28$ and $k = 1$, we find the bidding coefficients as 0.934, 0.92 and 0.88 for α equals 1, 0.95 and 0.9 respectively. As another example, if $r = 0.3$ and $k = 1.5$, we find the bidding coefficients as 0.93, 0.926 and 0.88 for α equals 1, 0.95 and 0.9 respectively.[20]

[19] This is not the only way to formulate the expectations of bidders.For example, if everybody truthfully reveals their values, given α, a bidder would get $(v - \alpha v)$ with probability $\left[\frac{v}{100}\right]^{N-1}$. This amount may be viewed as a reference point as well. However, this only complicates the model without changing the main results of it.

[20] The coefficients estimated from the real data are not significantly different than the coefficients that are predicted by the model.

6 Conclusion

In order to study the behavioral differences between indirect and direct mechanisms, we construct TOE direct mechanisms corresponding to the standard first-price sealed-bid auction, which is an indirect mechanism itself. We find that individuals behave as if they are more risk averse in the first-price sealed-bid auction when compared to the direct mechanisms. This aggressive bidding raises the revenues for the seller in the indirect mechanism and therefore revenue equivalence between the mechanisms does not hold. We also observe different bids across direct mechanisms. There are significant differences between the bid functions and therefore the revenues generated.

The behavioral differences can be explained by a reference-dependent model, where bidders form expectations on their final payoffs depending on the announced shaving rate. If the gains and losses are defined relative to their expectations, then direct mechanisms will generate lower bids compared to the standard first-price auction.

These findings raises questions on the applicability of the Revelation Principle since we provide a strong evidence that behavior of individuals is affected from the institution itself. Therefore, while searching for the optimal mechanism, it may not be valid to restrict attention to the direct mechanisms alone.

Appendices

A Instructions for the Direct(0.95) treatment

This is an experiment in decision making. Various research centers have provided funds for this research and if you make good decisions you may be able to earn a good amount of money which will be paid to you at the experiment's completion.

In this experiment there will be a series of auctions. Each of you will have an ID number which is shown at the top of your record sheet. Please take out your record sheet now. Note that there is another record sheet on your computer, which is exactly the same as the record sheet that is given to you with the instructions. As we go on, you are asked to fill in the appropriate lines of these record sheets. In each auction you will be paired with 4 other people in this room randomly. So, there will be 3 groups of 5 people and 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 on your choice as well as the choices made by the 4 other subjects in your group. We use points to reward you. At the end of the experiment we will pay you 35 cents for each point you won.

In each auction, 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 on your computer. The number will be between 1 and 100 where every integer is equally likely.

At the beginning of Round 1, you will get your value for the good 1. Write down your value in the appropriate lines on both of your record sheets. Don't show your value to the other people in the room.

After you receive your value, you will be asked to submit a value for it. So you will be asked to write down your "submitted value" on your record sheet and on the "submitted-value card 1" (please note that the 20 submitted-value cards you have are numbered 1, 2,... , 20).

The experimental monitor will collect all the "submitted-value cards" of round 1 from the students in the room, and without knowing your value he will multiply your "submitted value" by 0.95 to find out your "calculated bid" and put all the bids in a box. For example, say your submitted value is 60, then the monitor will submit a calculated bid of 57(=0.95*60) for you. (Note that you are also provided with a multiplication table). Then he will randomly take five submitted-value cards out of the box to form the group of subjects you will be interacting with in Round 1. The people whose submitted-values are on these five cards will form one group. Within each group, the calculated bids on these will be compared. The monitor will then announce (on a blackboard) the ID's of the students in each group with the highest calculated bid. Only the students 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. If your ID is announced, it means that you are the winner of this round. In case of a tie, the winner will be determined by flipping a coin. So, if you are the winner, your earnings will be

Earnings = your value for the good - 0.95* your submitted value

If the highest calculated bid is not yours (or if you lose the flip in case of a tie), then you earn nothing in this 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 auction you will be able to see your earnings in your record sheet on your computer. Your final earnings at the end of the experiment will be the sum of earnings over the 20 rounds.

There will be one practice round which is followed by 20 real rounds. The practice round will not count towards your total earnings. (There is only one way to lose money in this experiment which is to submit a value which is more than 1.05 times your value and win. If your calculated bid is above your value for the good and win the auction, your earnings will be subtracted to determine the total). Remember that at the end of the experiment, your total points/earnings will be multiplied by 35 cents to calculate your final payment. Are there any questions? Please do not talk with others during the experiment.

B Can heterogeneity be an explanation?

We, now, adopt the CRRAM model presented in Cox, Smith and Walker (1988) to include the possibility of heterogenous risk averse bidders, in which the homogenous constant relative risk aversion model is a special case. Each bidder has von-Neumann-Morgenstern utility function $u(v_i - b_i, r_i)$, where r_i is randomly drawn from some distribution function Φ on (0,1]. Assume that $u(x, r)$ is twice continuously differentiable and strictly increasing with respect to the first component and $u(0, r) = 0$, for all $r \in (0, 1]$. Also, assume that $u(x, r)$ is strictly log-concave in r, for each $r \in (0, 1]$.

Assume that each bidder believes that his/her rivals will use the bid function $b(v, r)$, which is strictly increasing in v and $b(0, r) = 0$ for all $r \in (0, 1]$. If the bid function has a v-inverse function $\pi(b, r)$, that is differentiable and strictly increasing in b, then the probability of all $n-1$ rivals of bidder i will bid amounts less than or equal to b is

$$G(b) = [\int\limits_r H(\pi(b, r))d\Phi(r)]^{n-1} \tag{8}$$

where H is the uniform distribution on [0,100].

Therefore, the expected utility of bidding b_i to bidder i is

$$G(b_i)u(v_i - b_i, r_i) \tag{9}$$

The first order condition with respect to b_i is

$$G'(b_i)u(v_i - b_i, r_i) - G(b_i)u_1(v_i - b_i, r_i) = 0 \tag{10}$$

If $\pi(b, r)$ is the v-inverse of an equilibrium bid function, then it must be a best response for bidder i and, therefore, should satisfy the first order condition.

$$G'(b_i)u(\pi(b_i, r_i) - b_i, r_i) - G(b_i)u_1(\pi(b_i, r_i) - b_i, r_i) = 0 \tag{11}$$

This implies

$$\frac{d(G(b_i)u(\pi(b_i, r_i) - b_i, r_i))}{db_i} = G(b_i)u_1(\pi(b_i, r_i) - b_i, r_i)\pi_1(b_i, r_i) \tag{12}$$

Integrating (12) yields

$$G(b_i)u(\pi(b_i, r_i) - b_i, r_i) = \int\limits_0^{b_i} G(y)u_1(\pi(y, r_i) - y, r_i)\pi_1(y, r_i) \tag{13}$$

Cox et al. (1988) show that b_i maximizes bidder i's expected utility, when his/her value is $\pi(b_i, r_i)$, for any $b_i > 0$ in the domain of $\pi(., r_i)$. Hence, $\pi(b, r)$ given by (13) is the v-inverse of an equilibrium bid function. Next, they show that $(b_i, \pi(b_i, r_i))$ yields a global maximum of (9).

We will now show that, for any α, Direct(α) Mechanism is still TOE to Indirect Mechanism even when we allow for the possibility of heterogeneous agents. Assume that each bidder believes that his/her rivals will use a submitted value function $s(v, r)$, with v-inverse function $p(s, r)$. The probability that all $n-1$ rivals of bidder i will submit values less than or equal to s is

$$K(s) = [\int_r H(p(s, r))d\Phi(r)]^{n-1} \tag{14}$$

And, the expected utility of reporting a value s_i equals

$$K(s_i)u(v_i - \alpha s_i, r_i) \tag{15}$$

The first order condition is

$$K'(s_i)u(v_i - \alpha s_i, r_i) - \alpha K(s_i)u_1(v_i - \alpha s_i, r_i) = 0 \tag{16}$$

Now, it is easy to see $s(v_i, r_i) = \frac{b(v_i, r_i)}{\alpha}$ satisfies equation (16). First, note that, $p(\frac{b(v_i, r_i)}{\alpha}, r_i) = \pi(b_i, r_i)$ if $s(v, r)$ is an equilibrium bid function and, therefore, $K(\frac{b(v_i, r_i)}{\alpha}) = G(b_i)$ and $\frac{1}{\alpha}K'(\frac{b(v_i, r_i)}{\alpha}) = G'(b_i)$. Therefore, for each individual i, the bid function of the Indirect Mechanism and the calculated bid functions of the direct mechanisms are the same.

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