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

(preliminary draft)

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Abstract

The Revelation Principle depends on a seemingly innocuous assumption that theoretically outcome-equivalent (TOE) mechanisms are behaviorally equivalent as well. However, this strong assertion has not yet been tested in previous experimental studies. In this paper, we aim to fill this gap.

We settled on the first-price sealed-bid auction as our indirect mechanism and then constructed TOE direct mechanisms. In contrast with what theory proposes, the subjects behaved significantly different under direct and indirect mechanisms. We established the following conclusions: (i) The revenue equivalence did not hold - the indirect mechanism generated higher revenue than the direct mechanisms, (ii)the subjects behaved as if they were less risk averse in the direct mechanisms, (iii)moreover, we observed behavioral differences across direct mechanisms. The main implication of these findings is that the Revelation Principle may not be applicable and therefore, it may not be sufficient to focus on the direct mechanisms alone.

1 Introduction

The well-known Revelation Principle states that for any equilibrium in a mechanism, there exists an incentive compatible direct mechanism in which truth telling strategy generates

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equivalent outcomes as the given equilibrium of the original mechanism. It 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.

The mechanism design literature is based on the Revelation Principle and, therefore, is often restricted to direct mechanisms. However, invoking the Revelation Principle may be problematic in some situations. The restrictions necessary for truthful revelation in equilibrium may result in a complicated direct 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 will go one step further. We will construct direct mechanisms, which do not suffer from the problems above, in order to see whether the Revelation Principle is applicable in this basic setting. To our knowledge, there have not been experiments in the literature testing the behavioral aspects of direct and indirect mechanisms. However, the Revelation Principle relies on the assumption that there is no behavioral difference between them. Our aim is to test if the behavior of individuals show variations when they are faced with direct and indirect mechanisms by using experimental techniques. We would like to argue that the Revelation Principle may not be applicable at all if there is a behavioral difference between direct and indirect mechanisms.

To explore this question, we settled on 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 where one can control types (values) of the subjects by the value inducing method. Moreover, direct mechanisms that we have constructed, say Direct(α) mechanisms, have very similar properties to the standard first-price sealed-bid auction.[1]

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

[1] Direct(α) mechanisms are not complicated mechanisms; the rules and the payoff structures of Direct(α) mechanisms are very similar to standard first-price sealed-bid auctions.

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.

Any Direct(α) mechanism, $\alpha \neq 0$, should generate the same bidding behavior as the first-price sealed-bid auction. Therefore, for each direct mechanism, we will compare the "calculated bids" with the "bids" observed in the indirect mechanism in order to test the hypothesis that the two data sets are not statistically different. In Section 4, we will also be comparing the "calculated bids" of direct mechanisms in order to see if there is a significant deviation from the theoretical prediction that they would be the same. Moreover, we will compare the revenues generated at each auction, since in the case of a behavioral difference we no longer expect revenue equivalence to hold. Indeed, we will show that there were large differences in subjects' earnings between different treatments.

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. We discuss some related work in Section 5 and the conclusions follow.

2 The Setup

In order to compare the behavior of subjects between indirect and direct mechanisms, we construct direct mechanisms which are TOE to the first-price sealed-bid auction, say Direct(α) mechanisms. In a Direct(α) mechanism, potential buyers are asked to submit a sealed value instead of a sealed-bid. The submitted values are then opened by a mediator who multiplies them by α to find out the calculated bids of the buyers. The potential buyer with the highest calculated bid gets the good and pays her/his calculated bid.

We will now derive the equilibrium bid function of the first-price sealed-bid auction. Then, we will argue why the first-price sealed-bid auction and a Direct(α) mechanism should generate equivalent outcomes.

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 $u^{"} \leq 0$.[2]

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

[2]Homogeneity assumption simplifies the illustration of the model, however, our results are independent of it, as shown in Section 4.3.

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

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

where $\beta(0) = 0$.

If agents have Constant Relative Risk Aversion (CRRA) utility functions with risk aversion coefficient equal to $1 - r$, 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.[3]

Note that the first-price sealed-bid auction is an indirect mechanism where each bidder's message space $M = [0, 100]$ and the outcome function g specifies who wins the auction and how much he/she needs to pay. For simplicity we will refer to the first-price sealed-bid auction as "Indirect".

2.2 Direct(α) Mechanism

Here 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 $S : V \to V$. 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 $1 - r$, (4) will simplify to

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

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

and the unique equilibrium strategy is:

$$S(v_i) = \frac{N-1}{\alpha(N-1+r)} v_i. \tag{6}$$

In equilibrium, the submitted value function, given by equation (6), 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 forms 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).[4]

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 which is then converted into cash at the end of the session. Conversion rates of the treatments differed in order to balance the average earnings among them.[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	Points/Dollar conversion rate
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	35

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

[4] In Section 4.3, we also show that the same result holds for heterogenous bidders.

[5] We had run a pilot experiment before the real experiments. We witnessed that a direct mechanism generates more revenue than the indirect mechanism. Later on, we will also argue that different conversion rates does not change any of our results.

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[6] 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 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.[7]

The main aim of this paper is to see if there is any behavioral difference between direct and indirect mechanisms. Therefore, we designed the experiment in such a way that the direct mechanism is not complicated. If the corresponding direct mechanism is complicated, it is not fair to say that the difference is behavioral. The reason for the difference 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) as well.

4 Results

4.1 Indirect Mechanism versus Direct(0.95)

We start by explaining the data of Indirect. The reasons of choosing Direct(0.95) will be clarified later within this section. Throughout our analysis, in order to account for repeated observations for a given individual, we will correct variance-covariance matrix.[8]

[6] We are grateful to Benjamin Chiao, who provided the program for our use.

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

[8] We eliminate the first five rounds from the data. Therefore, our estimation uses 225 observations. Later on, we will also provide the reader with tables which summarize all the regression analysis that we

We regressed bids on values and we found that the coefficient of the estimated bid function of the Indirect is 0.95.[9] We did not observe a significant coefficient for the quadratic term when we applied a nonlinear estimation and, therefore, our data suggests a linear bid function. Indeed, a homogeneous CRRA model explains the behavior well in the Indirect at the aggregate level for some risk aversion coefficient $1 - r$, which will also be derived from the data within this section.

If individuals have CRRA utility functions with risk aversion coefficient equal to $1-r$, equation (3) implies linear bidding behavior. Therefore, data suggests that subjects have CRRA utilities, and, they are bidding 0.95 times the value. An incentive compatible direct mechanism corresponding to the standard first-price auction will then be the Direct(0.95) where potential buyers are asked to report their values knowing that the reported values are going to be multiplied with 0.95 to calculate the bids. This implies that we should see truth telling (on average) in the Direct(0.95) and therefore an outcome-equivalence between indirect and direct mechanisms.

Figure 1 shows the deviations from truth telling. It is easy to see that the average behavior is not truth telling since the histograms are skewed to the right. We see that, in the Direct(0.95), out of 225 observations, 17% of the time subjects revealed their true values. However, subjects often had a tendency to give lower values than their actual values. We also repeat the same analysis by restricting ourselves to the values higher than 50. There are two main advantages of eliminating the data points corresponding to the low values. First, it is important to know if individuals revealed their true values when they had high values since the winning values are usually high values.[10] Second, by eliminating the data points where subjects were least motivated, we will be able to perform a better analysis. When we do that, we see that truth revelation decreases significantly (i.e., less than 10% of the time subjects reveal their true values).

We will now compare the mechanisms behaviorally by using a simple transformation of the raw data. Remember that in equilibrium, the submitted value function, given by equation (6), multiplied with α should be equal to the bid function, given by (3). Therefore, we convert submitted values into calculated bids in order to test the theoretical prediction that the bid functions should be the same.[11]

Although the Indirect and the Direct(0.95) are TOE, our data suggests that there is a behavioral difference between mechanisms.[12] Indeed, we found that the coefficient of the estimated bid function is 0.9[13], i.e., in the Direct(0.95) subjects are shaving 5% more. We

have performed for the mechanisms.

[9] The constant in the regression equation is equal to -0.66. However, it is not significant at the 5% level.

[10] Probability of winning with a value of 50 is 0.06. Indeed, there were only 5 winning values less than or equal to 50 out of 135 winning values in total (summing up the data of Indirect, Direct(0.95), Direct(0.9)).

[11] Since there is no reason to believe that people are coming from different populations, we can assume the risk aversion coefficient to be the same between subjects of different treatments. Also, note that, not only CRRA utility functions but any utility functions would give us outcome-equivalance.

[12] 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.

[13] The constant in the regression equation is equal to 0.77 and is significant at the 10% level.

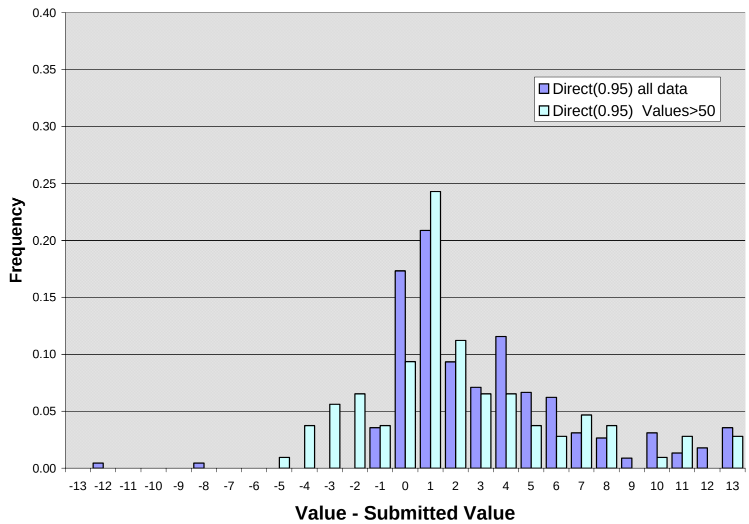

Figure 1: Percentages of deviations from truth telling in Direct(0.95) for values greater than 50 (white) and for all data (gray)

have used dummy variable approach in testing for the equivalence of the two regressions and found that the estimated bid functions are significantly different.[14] Our finding did not change when we repeated the same analysis by correcting the variance-covariance matrix to account for correlation across observations for a given individual. We observed that, bid functions are still significantly different (at 5% level).

In fact, when we compare the subjects' earnings[15], we see that in the Direct(0.95) subjects have earned 19.67 points on average compared to the Indirect where subjects earned only 13.73 points on average. The difference between the earnings is 43%. Indeed, the expected increase in earnings from shaving 5% to 10% is approximately 42% if we restrict ourselves with values greater than 50.

At this point, another question that might come up is whether the players are really playing a Nash equilibrium which seems to be the basic assumption so far. That is, how can we be sure that the players are not playing according to some ad hoc rule of thumb as has been suggested in the literature (for example, Chen and Plott (1988)). It is true that we cannot rule out a theory of linear rules of thumb just by looking at the data in

[14] Dummy variable approach tests for equality between sets of coefficients in two linear regressions. 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 Indirect, 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). See Gujarati (1995) for a reference, where advantages of the dummy variable technique over the Chow test is also discussed.

[15] Throughout we consider earnings as the points collected by the subjects.

the Indirect. The data is also consistent with individuals shaving 5% of their value as a rule of thumb. However, if this is really the case, we should have observed the same behavior in the Direct(0.95). Since in the Direct(0.95) they are actually shaving 10% of their value, our data cannot be explained by a simple ad hoc reasoning.

Can the observed behavioral difference be due to how risky the subjects considered the mechanisms to be? We derived the risk aversion coefficients consistent with the data. In the Indirect, we see that the risk aversion coefficient is 0.72 with standard deviation 0.019; whereas in the Direct(0.95), the risk aversion coefficient is 0.65 with standard deviation 0.022. 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.

Another relevant question is, if we chose another α, would we continue to observe the differences between the mechanisms? Moreover, are the direct mechanisms behaviorally equivalent? We chose $\alpha = 0.9$ to answer our questions.[16]

4.2 Direct(0.9)

The data of the Direct(0.9) is surprisingly different from both the Indirect and the Direct(0.95).[17] Table 2, below, summarizes the estimated bid functions, in order to make the comparisons easier.[18]

Linear Regressions[a]				
		with constant		without constant
		constant	Value	Value
Indirect		-0.657 (0.515)	**0.945**** **(0.012)**	**0.935**** **(0.007)**
Direct (α)	$\alpha = 0.95$	**0.765*** **(0.370)**	**0.900**** **(0.011)**	**0.912**** **(0.009)**
	$\alpha = 0.90$	**0.880*** **(0.420)**	**0.856**** **(0.012)**	**0.869**** **(0.009)**

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

Table 2: Summary of regression results

The coefficient of the estimated bid function is 0.86; subjects are shaving 14% of their

[16] One may wonder whether the incentive compatible mechanism assuming risk neutrality would give truth telling. We also run an experiment with Direct(0.8). It generates the same bid function as Direct(0.95) and we observed truth telling for less than 10% of the cases.

[17] We repeat the dummy variable approach. Pair-wise comparisions of the regressions give us significant differences (at 5% significance level) among the mechanisms (with and without the corrections of the variance-covariance matrix).

[18] Table 2 presents an important observation that the standard errors in the regressions are same among the treatments, which strengtens our hypothesis that the individuals are consistently behaving differently among the mechanisms.

values. As one can guess, subjects' behavior was even less risk averse in the Direct(0.9). Indeed, we found that the risk aversion coefficient associated with this mechanism is 0.4 with standard deviation 0.022! This is a huge difference when compared with the one estimated for the Indirect and there is still a big difference when compared with the estimated coefficient of the Direct(0.95). 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. The average subjects' earning was 30.81 points (i.e., subjects' revenue more than doubles if the Direct(0.9) is used instead of the Indirect.).

We have seen that homogenous CRRA model cannot consistently explain the observed behavior in the mechanisms since we have derived different risk aversion coefficients for each treatment. Next section will allow for heterogenous agents.

4.3 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.[19]

In Appendix C, we show that, for any α, Direct(α) mechanism is still TOE to Indirect for each bidder even when we allow for the possibility of heterogeneous agents. Therefore, for each individual i, the bid function of the Indirect and the calculated bid functions of the direct mechanisms would be the same. This implies that, even under heterogeneity, data sets of the Indirect and direct mechanisms should be coming from the same population.

We followed the same empirical analysis used in Cox and Oxaca (1995) to calculate 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 and the Direct(0.9), and, at the 10% significance level, for the Indirect and the Direct(0.95). As a result, CRRAM model cannot consistently explain the observed data.

[19] Although CRRAM model improves the fit at the individual level, it does not necessarily improve the fit for the aggregate data. (see Goeree, Holt and Palfrey (2002))

A Pair-Wise Comparison of Risk Aversion Coefficients[a]		
	Direct (0.95)	**Direct (0.90)**
Indirect	1.359 (0.087)	4.044 (0.0001)
Direct (0.95)		3.248 (0.0006)

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

Table 4: Nonparametric Regressions

4.4 Is it due to framing?

We have also checked if there is any behavioral discrepancy between the Indirect and the Direct(1). Notice that the only difference between these two mechanisms is that in the Direct(1) subjects were 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.

However, we did not observe a significant discrepancy between these mechanisms.[20] 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.[21] Clearly, the difference between the direct mechanisms cannot be explained by the wording that we have used either, since they only differ by coefficient α.

Although our data cannot be explained by framing, it may still be true that α causes biases in the decisions made by individuals if α is acting as a reference point (initial parameter). In the psychology literature, cognitive reference points have been defined as any stimuli to which other stimuli are related (Rosch 1975). Individuals decisions can be affected by a reference point even if it offers no relevant information from a theoretical point of view.

5 Related Literature

The closest literature to what we are doing includes the following:

Laffont and Martimort (1997) point out that the Revelation Principle presumes costless communication and non-cooperative behavior by agents. They, however, argue that considering collusion as an exception is not realistic. Therefore, one cannot rely on the

[20] The similarity between these two mechanisms can also be seen in Figure 3 in Appendix B. For the econometric analysis that follows, we will be eliminating subject 2 as an outlier.

[21] Moreover, testing the Direct(1) helps us to show that there is no significant effect of different conversion rates between direct and indirect treatments on the behavior of the subjects.

Revelation Principle, which does not take into account the informational constraints when collusion is allowed.

Parkes (2003) considers a setting where agents do not have complete information over their preferences since preference elicitation is costly, and therefore the Revelation Principle is not applicable. Parkes introduces a new variant of the Revelation Principle and shows that, with costly preference elicitation, indirect mechanisms, such as proxied ascending-price auctions, achieve better allocative efficiency than direct mechanisms, such as second price auctions. Our paper differs from his, since we show that even with the complete information[22] the direct and the indirect mechanisms are behaviorally different.

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 (forthcoming).

However, these papers do not question the behavioral aspects of the direct and indirect mechanisms which we believe are the most important issues to be considered while designing a mechanism. One should recognize the behavioral differences between two equivalent mechanisms and decide upon the design of the optimal mechanism taking these effects into consideration.

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 behavior raises the revenues for the seller in the indirect mechanism and therefore revenue equivalence between the mechanisms does not hold. We also observe behavioral differences within direct mechanisms. There are significant differences between the bid functions and therefore the revenues generated.

These findings raises questions on the applicability of the Revelation Principle. Therefore, while searching for the optimal mechanism, it may not be valid to restrict attention to the direct mechanisms alone.

[22] We followed the induced value method in our design. At the beginning of each round, subjects were told their value as opposed to being given an interval of possible values.

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 Control Treatment

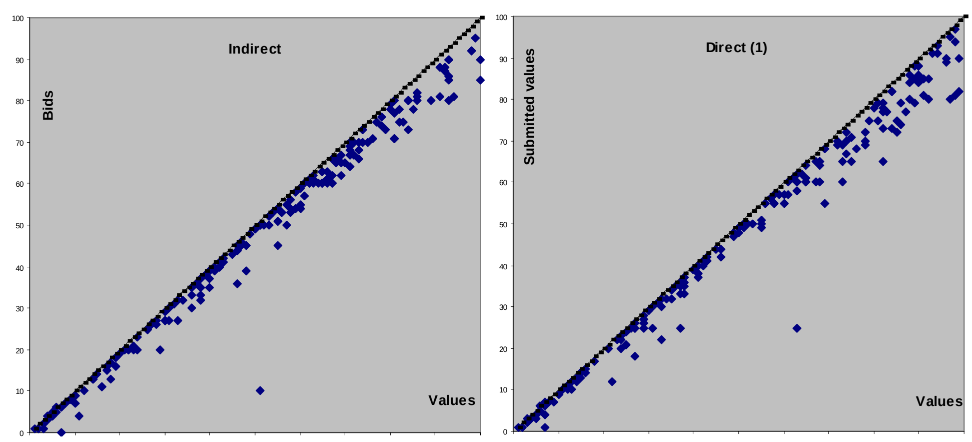

Figure 3: Indirect versus Direct(1)

C 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

$$G(b) = [\int_r H(\pi(b, r))d\Phi(r)]^{n-1} \tag{7}$$

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

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

$$G(b_i)u(v_i - b_i, r_i) \tag{8}$$

The first order condition with respect to b_i is

$$G'(b_i)u(v_i - b_i, r_i) - G(b_i)u_1(v_i - b_i, r_i) = 0 \tag{9}$$

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.

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

This implies

$$\frac{d(G(b_i)u(\pi(b_i, r_i) - b_i, r_i))}{db_i} = G(b_i)u_1(\pi(b_i, r_i) - b_i, r_i)\pi_1(b_i, r_i) \tag{11}$$

Integrating (11) yields

$$G(b_i)u(\pi(b_i, r_i) - b_i, r_i) = \int_0^{b_i} G(y)u_1(\pi(y, r_i) - y, r_i)\pi_1(y, r_i) \tag{12}$$

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 (12) 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 (8).

We will now show that, for any α, Direct(α) mechanism is still TOE to Indirect 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

$$K(s) = [\int_r H(p(s,r))d\Phi(r)]^{n-1} \tag{13}$$

And, the expected utility of reporting a value s_i equals

$$K(s_i)u(v_i - \alpha s_i, r_i) \tag{14}$$

The first order condition is

$$K'(s_i)u(v_i - \alpha s_i, r_i) - \alpha K(s_i)u_1(v_i - \alpha s_i, r_i) = 0 \tag{15}$$

Now, it is easy to see $s(v_i, r_i) = \frac{b(v_i,r_i)}{\alpha}$ satisfies equation (15). 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 and the calculated bid functions of the direct mechanisms are the same.

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