# Simple vs Optimal Auctions: An Experimental Investigation

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September 15, 2018

## Abstract

In single object auctions when bidders are asymmetric, the Myersonian optimal auction is difficult to implement because of its complexity and possible discouragement effect on the bidders. In these cases, Hartline and Roughgarden (2009) proposes a "simple" auction that revenue approximates the optimal auction. This paper experimentally studies the performance of the simple auction vis-a-vis the optimal auction in terms of revenue generation.

**Keywords** Optimal Auction, Simple Auction, Asymmetric Bidders

**JEL Classification** D44, C90

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‡We would like to thank Bhaskar Dutta, Yoram Halevy, Debasis Mishra, Noam Nisan, Tim Salmon, and Dale Stahl for helpful comments and feedback. *This is a preliminary version. Do not cite.*

# 1 Introduction

An ongoing research agenda in the mechanism design literature, mostly for the economic theorists and the algorithmic game theory community, is the design of 'simple' auctions, where 'simplicity' of the auction format is taken as a design objective for its own sake. There might be several reasons for searching for simpler auction formats where complexity can thwart practical implementability. The objective of our study is to examine how close some 'simple' auctions can approximate revenue-optimal auctions, i.e. how much revenue we can trade-off for choosing a 'simple' auction instead of an optimal one.

In the **single-object** environment with bidders having independent valuations, Myerson (1981) provides the revenue-maximizing optimal auction format[1]. When bidder's valuations are drawn independently from *identical* distributions, the implementation of the optimal auction is surprisingly simple: *running a Vickery auction with a monopoly reserve price*, which is the most common auction format used by popular platforms like eBay.

However, if the bidders' valuations are drawn from *asymmetric* distributions, the optimal auction becomes computationally complex and very difficult to implement in reality. This involves calculations of 'virtual valuations' in the allocation rule as well as calculating a complex price formula. These can have serious considerations in the bidders' behaviors, and thus the seller's revenue in the following ways:

(a) *Complexity*: The allocation rule and the price formula are too complex for the bidders to comprehend and may require a considerable degree of cognitive ability. This can potentially affect their bidding behaviors.

(b) *Virtual Valuation*: The optimal auction rule prescribes that the object will be given to the bidder with the *highest virtual valuation*. For a given range of parameters of the valuation distributions, the highest virtual valuation bidder may not be the highest valuation bidder, and knowing this a-priori might change the bidding behavior: it may lead to more aggressive bidding or lead to a *discouragement effect* among the bidders, which might dampen the bidding incentive.

Thus in reality it is difficult to implement a Myerson auction if the auctioneer anticipates the bidders to be *ex-ante* heterogeneous. Rather a much *simpler* auction (Hartline and Roughgarden (2009), Hartline (2012)) format is more frequently used in this scenario by different auction platforms. Auctioneers prefer to use the same Vickery auction, but now with different *bidder-specific reserve prices.* Hartline and Roughgarden (2009) theoretically shows that this "*simple auction*" guarantees *at least 50%* of the expected revenue compared to the optimal auction's expected revenue. However, since the theoretical calculations ignore the above-mentioned behavioral issues which may affect the bidding strategies, in reality a Myerson auction actually might not perform as well as the theory predicts. Thus due to these behavioral issues, the simple auction might even better approximate an optimal auction than what the theory predicts.

[1] Similar question is discussed in Riley and Samuelson, Maskin and Riley (2000). A detailed treatment of the theory of auction design can be found in Krishna (2009), Klemperer (1999), and Klemperer (2018).

To this end, we propose to conduct laboratory experiments to compare the performances of these two auction formats in terms of revenue generation. In particular, we seek to address the following issues:

- Is the actual revenue from Myersonian optimal auction ($\overline{R_O}$) significantly different on average than the theoretical prediction ($ER_O$)? If so, can this difference be explained by the effect of complexity and discouragement?
- Is the actual revenue generated from conducting the 'simple auction' ($\overline{R_S}$) different on average than the theoretical simple auction ($ER_S$)?
- Is the difference between the average revenues from conducting an optimal auction vis-a-vis a simple auction significantly different than the theoretically predicted difference? Formally, is the following difference

$$||ER_O - ER_S| - |\overline{R_O} - \overline{R_S}||$$

statistically significant ? If so, can it be explained by the effect of complexity and discouragement?

- How does the result change with the degree of asymmetry?
- We also seek to estimate the experimental bidding functions under both the auctions.

## 1.1 Related Literature

This paper adds to the growing literature of simple auction. Especially to the practitioners of computer science and algorithmic game theory, implementability. of auction rules is a concern, hence there is a strand of literature that looks at different simpler auction formats and examines how well these auctions approximate the revenue maximizing auctions. Along these lines, different papers, for example, Hartline (2012), Alaei et. al. (2018), Hartline et. al. (2014), Fu et. al. (2013), Bhattacharya et. al. (2013), Hartline and Roughgarden (2009) consider different types of computationally less challenging "simple" auctions. They explore the revenue loss associated with the use of these simple auctions. In multi-unit auctioning environment Hart and Nisan (2017), Vetsikas et. al. (2012) also examine the performance of similar simpler auction rules. While these studies theoretically find the maximum revenue loss from conducting simple auctions, our study is the first one to experimentally test the properties of such a simple auction. We use the simple auction format as defined in Hartline and Roughgarden (2009) and Hartline (2012) and using a controlled laboratory experiment we want to explore if simple auctions can approximate the revenue generated by optimal auctions to a higher degree than what the theory predicts, owing to its simpler rules. This study thus complements the theoretical findings in this literature.

This study also adds to the literature that examines asymmetric auctions in controlled laboratory experiments. Asymmetric auctions have been studied extensively in the experimental literature.

Güth et. al. (2005) compare first price and second price auctions if bidders are asymmetric, Güth and Ivanova-Stenzel (2003) examines the case without assuming common belief, Pezanis-Christou, and Sadrieh (2003) examine the bidding function in asymmetric auctions, Georganas and Kagel (2011) study asymmetric auctions with resale possibility[2]. There are experiments studying the properties of the auction format followed by eBay, with anonymous reserve prices (Bajari and Hortacsu (2003), Garratt et. al. (2012)). However, to the best of our knowledge, we are the first to test the predictions from Myerson optimal auction and compare its performance to the simple auction in these environment.

# 2 Theoretical Model

## 2.1 Optimal Auction

We will restrict our attention to the single object auction with independent and private valuations. Formally, there are $n$ bidders bidding for an object. The seller does not value the object. The private valuation for the object for a bidder $i$ is given by $v_i$. Assume that $v_i$ is drawn from a distribution $F_i$. The associated density function $f_i$ has support contained in $\Theta_i \subseteq [0, v_{\max}]$. $F_i s$ are independent, but not necessarily identical. Without loss of generality, let us assume that bidders are ordered such that $F_i$ first order stochastically dominates $F_j$ $\forall i > j; i, j = 1, ..n$[3]. Assume that the distributions are "regular".

**Definition 1 (Regular Distribution)** *A distribution $F$ is called regular if the "virtual valuation"*

$$\varphi(v) = v - \frac{1 - F(v)}{f(v)} \tag{1}$$

*is a monotone strictly increasing function of $v$. That is,*

$$\varphi(v) > \varphi(v^0) \text{ whenever } v_{\max} \geq v^0 > v \geq 0.$$

We maintain the assumption that the auctioneer knows these distributions a-priori, but not the realizations of $v_1, v_2, ..., v_n$. The realizations are privately observed by the bidders.

We are focusing on sealed bid auctions, where the bidders submit bids: $b_i : \Theta_1 \times \Theta_2 \times .... \times \Theta_n \to \mathbb{R}^n$. An auction in this environment is a collection of an allocation rule $x(b) : \mathbb{R}^n \to \mathbb{R}^n$, and a payment rule $t(b) : \mathbb{R}^n \to \mathbb{R}^n$.

For a given auction format $(x(b), t(b))$, for a bid profile $b$,bidder $i$ has utility[4]

$$u_i(b) = v_i[x_i(b) - t_i(b)]$$

[2]For a complete review of the literature, refer to Kagel (2000)

[3]That is, $F_i \leq F_j$ $\forall i > j, i, j = 1..n$. In the symmetric case, $F_i = F_j \forall i \neq j$.

[4]We use the standard quasilinear utility function.

Seller's ex-ante expected revenue in this case:

$$ER(x(b),t(b)) = E_b\left[\sum_{i=1}^{n} t_i(b)\right]$$

We will restrict our attention to Dominant Strategy Incentive Compatible (henceforth DSIC) auctions.

**Definition 2 (DSIC)** *An auction $(x(b),t(b))$ is Dominant Strategy Incentive Compatible if each bidder has a dominant strategy to bid truthfully, i.e., the optimal bidding function is $b_i = v_i$ for every $b_{-i}$.*

Hence, the expected revenue can be rewritten as:

$$ER(x(v),t(v)) = E_v\left[\sum_{i=1}^{n} t_i(v)\right]$$

Myerson (1981) finds the optimal, i.e., revenue-maximizing DSIC auction rule in this environment.

**Optimal DSIC Auction (Myerson, 1981)** *The optimal DSIC auction is given by the payment rule:*

$$t_i(v) = \begin{cases} z_i(v_{-i}) & \text{if } x_i(v) = 1 \\ 0 & \text{otherwise} \end{cases}$$

*where*

$$z_i(v_{-i}) = \inf\{s_i|\varphi_i(s_i) \geq 0, \text{ and } \varphi_i(s_i) \geq \varphi_j(v_j)\forall j \neq i\}$$

*i.e., $z_i(v_{-i})$ is the lowest winning bid for $i$ against all $v_{-i}$,*

*and the allocation rule:*

$$x_i(v_{-i}, s_i) = \begin{cases} 1 & \text{if } s_i > z_i(v_{-i}) \\ 0 & \text{otherwise} \end{cases}$$

In other words, the optimal auction assigns the good to the bidder with the highest virtual valuation, if that virtual valuation clears the reserve price $\varphi_i^{-1}(0)$. The bidder pays the reserve price or the second highest bid, whichever is the higher. Only the winning bidder pays any positive amount. Call the maximum expected revenue from running an optimal auction: $ER_O$.

In the symmetric case when $F_i = F_j \forall i \neq j$, since $\varphi_i(v) = \varphi_j(v)\forall i \neq j$, the optimal auction simply takes the form of a Vickrey auction with the monopoly reserve price $\varphi^{-1}(0)$. Thus, under symmetry, the optimal auction is easily implementable.

However, if the bidders are ex-ante asymmetric, that is, the distributions are not identical, the optimal auction does not have an easily implementable form. It involves assigning the object to the individual with the highest virtual valuation and using bidder specific reserve prices. Also, in that case, the highest valuation bidder might not win the object. For example, if the valuation of bidder $i$ is drawn from the uniform distribution $U[\alpha_i, \beta_i]$, then

$$\begin{aligned} f_i(v_i) &= \frac{1}{\beta_i - \alpha_i}; \\ \varphi_i(v_i) &= v_i - \frac{1 - F_i(v_i)}{f_i(v_i)} = 2v_i - \beta_i \end{aligned}$$

and if $\beta_i < \beta_j$ it is possible that $2v_i - \beta_i > 2v_j - \beta_j$ even if $v_i < v_j$, so the highest valuation bidder may not always win. This auction discriminates against the bidders for whom the upper bounds on the value estimates are higher.

From the bidders' point of view, this allocation rule can be too complex to understand, and also may result in ex-ante discouragement if the distributions are such that the highest valuation bidder may not have the highest virtual valuation, hence may not win the auction.

## 2.2 Simple Auction

The optimal single-item DSIC auction with asymmetric bidders takes a complex form: someone other than the highest bidder might win, and the payment rule involves virtual bid, which can be complex for a bidder with no technical expertise. Fittingly, this optimal auction format generally does not resemble any auctions used in practice.

Instead of using the optimal auction, we can use simpler formats called "Simple Auctions" (Hartline and Roughgarden, 2009 Hartline and Roughgarden (2009)) in order to approximate the maximum revenue. They demonstrate how the revenue of a simple auction can approximate that of the optimal auction when we relax the assumption that the value distributions of the bidders are identical. Consider the same environment as detailed in the last section, with $F_i s$ first order stochastically ordered.

Let us consider the following **Simple Auction**:

i) Set the reserve price for bidder $i$, $r_i = \psi_i^{-1}(0)$.

ii) Allocate the good to the highest bidder for whom $\psi_i(b_i) \geq r_i$, if any. If there is a tie, it is broken randomly.

iii) The winning bidder pays the maximum of his reserve price and the second highest bid that meets the reserve price of the second highest bidder.

We have the following Proposition:

**Proposition 1 (Hartline and Roughgarden, 2009)** *Let the expected revenue of the optimal auction be $ER_O$ and the expected revenue of the simple auction be $ER_S$. Suppose the valuations of the bidders are drawn independently from distributions that satisfy the Monotone Hazard Rate condition. Then,*

$$ER_S \geq \frac{1}{2} ER_O.$$

Thus the simple auction is to run the Vickery auction, but with bidder-specific reserve prices. This simple auction guarantees at least half the revenue of the optimal auction. The simple auction also avoids complexity in the sense that under the simple auction it is the highest valuation bidder, not the highest virtual valuation bidder, who always wins the auction. The virtual values are only used by the auctioneer to set the bidder-specific reserve prices.

Call the maximum revenue possible under simple auction:$ER_S$.

The central question of this paper is to examine how well in reality this simple auction approximates the optimal auction. The theoretical upper bound does not consider the behavioral concerns that might exist, as we have explained. Hence, our hypothesis is that the revenue generated from a simple auction can approximate the revenue from an optimal auction significantly better than what theory predicts.

# 3 Experimental Design

To examine how well simple auction performs vis-a-vis the optimal auction, and if the behavioral hypotheses hold, we will use a series of laboratory experiments. In every auction there is a fictitous commodities for sale, the bidders observe the private monetary value[5] for this object before they bid. The valuation distributions are parameterized. We use three different sets of parameters in order to explore the bidding behavior of the subjects: in the benchmark case (Parameter set 1) the asymmetry does not have a bite; Parameter set 2 has a lower degree of asymmetry than Parameter set 3. For each set of parameters, we run the optimal and simple auctions as separate treatments. The treatments are described below:

*Treatment 1: Parameter set 1 (Benchmark Case):*

$$\begin{aligned} n &= 2 \\ v_1 &\sim U[150, 200] \\ v_2 &\sim U[100, 200] \end{aligned} \qquad \text{(Parameter set 1)}$$

Hence:

$$f_1(v) = \frac{1}{50}; f_2(v) = \frac{1}{100}$$
$$F_1(v) = \frac{v-150}{50}; F_2(v) = \frac{v-100}{100}$$

For any bid profile $(b_1, b_2)$, the virtual bid functions are:

$$\varphi_1(b) = 2b - 200 = \varphi_2(b)$$

[5] This can be thought of as the private reselling value of the object. Full instructions are included later.

So, even though $F_i$s are asymmetric, the virtual valuations are symmetric functions[6].

Here, the optimal auction prescribes:

$$\begin{aligned} x_1(b) &= 1, x_2(b) = 0 \text{ if } b_1 \geq b_2 \\ t_1(b) &= b_2, t_2(b) = 0 \end{aligned}$$

and similarly for the case when $b_2 > b_1$, i.e., $v_2 > v_1$.

In this environment, there is no possible discouragement effect, so in effect the simple and optimal auction both take the exact same form. We award the highest bidder the object, and he pays the second highest bid if it clears the reserve price.

$$ER_o = ER_S = 175$$

*Treatment 2: Optimal Auction for Parameter set 2:*

$$\begin{aligned} n &= 2 \\ v_1 &\sim U[100, 200] \\ v_2 &\sim U[100, 150] \end{aligned} \qquad \text{(Parameter set 2)}$$

So,

$$\begin{aligned} f_1(v) = \frac{1}{100;} f_2(v) = \frac{1}{50} \\ F_1(v) = \frac{v-100}{100}; F_2(v) = \frac{v-100}{50} \end{aligned}$$

Clearly, $F_1$ FOSDs $F_2$.

The virtual bids are:

$$\begin{aligned} \varphi_1(b) &= 2b - 200; \\ \varphi_2(b) &= 2b - 150 \end{aligned}$$

The optimal auction prescribes

$$\begin{aligned} x_1(b) &= 1, x_2(b) = 0 \text{ if } \varphi_1(b_1) \geq \varphi_2(b_2) \\ t_1(b) &= b_2, t_1(b) = 0 \end{aligned}$$

and

$$\begin{aligned} x_2(b) &= 1, x_1(b) = 0 \text{ if } \varphi_2(b_2) \geq \varphi_1(b_1) \\ t_2(b) &= b_1, t_1(b) = 0 \end{aligned}$$

[6] Notice that to simplify the auction rules even further, we have chosen the distributions so that the reserve price is never binding.

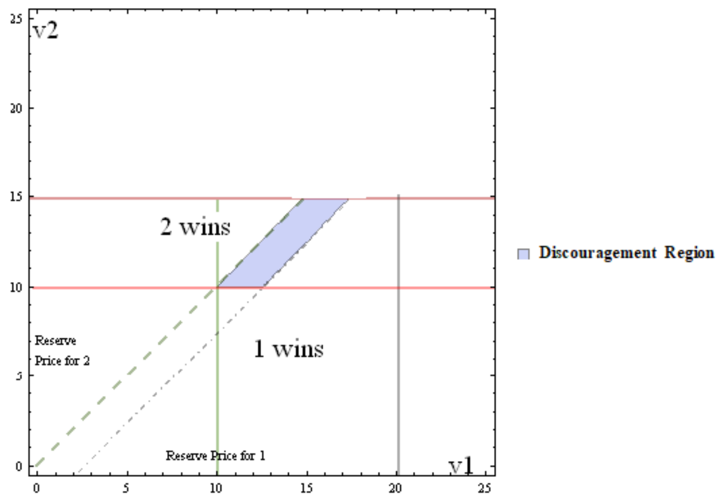


Figure 1: Discouragement Region for Parameter Set 2

So, for the range

$$b_2 + 25 > b_1 > b_2$$

bidder 1 has the highest bid (and highest valuation), but still does not win. This region is depicted in figure 1 and has an area of 62.5. Here,

$$ER_o = 129.16$$

We will run two subtreatments for the optimal auction using this set of parameters in order to see how strong the discouragement effect is.

*Treatment 2A:* In the first treatment, after the instructions and demonstrations, we do not explicitly point it out to the bidders that there is a possibility that the highest bidder may not be the highest virtual bidder, and hence may not win. It is possible that some of the subjects will not notice that feature during the demo, hence the discouragement effect may be weak.

*Treatment 2B:* In this subtreatment, which we can term as an "information treatment," from the examples that we will use as demo, we clearly illustrate how the highest bidder may not win. We anticipate that this awareness might evoke a strong discouragement effect.

*Treatment 3: Simple auction for Parameter set 2*

For the same set of parameters , in this treatment we run a simple auction. The simple auction in this environment prescribes

$$\begin{aligned} x_1(b) &= 1, x_2(b) = 0 \text{ if } b_1 \geq \max b_2 \\ t_1(b) &= b_2, t_2(b) = 0 \end{aligned}$$

and

$$\begin{aligned} x_1(b) &= 0, x_2(b) = 1 \text{ if } b_2 \geq b_1 \\ t_2(b) &= b_1, t_1(b) = 0 \end{aligned}$$

$$ER_S = 120.83$$

We observe that the theoretical difference between the expected revenues in Treatment 2 and 3 is:

$$ER_O - ER_S = 129.16 - 120.83 = 8.33$$

*Treatment 4:Optimal Auction for Parameter set 3:*

$$\begin{aligned} n &= 2 \\ v_1 &\sim U[100, 200] \\ v_2 &\sim U[100, 120] \end{aligned} \tag{Parameter set 3}$$

So,

$$f_1(v) = \frac{1}{100}; f_2(v) = \frac{1}{20}$$
$$F_1(v) = \frac{v - 100}{100}; F_2(v) = \frac{v - 100}{20}$$

The virtual bids are:

$$\begin{aligned} \varphi_1(b) &= 2b - 200; \\ \varphi_2(b) &= 2b - 120 \end{aligned}$$

Here, we have a strictly higher degree of asymmetry. The data from this treatment and the next one can be used to see if the performance of simple auction vis-a-vis complex auction significantly responds to the level of asymmetry.

The optimal auction in this environment prescribes

$$\begin{aligned} x_1(b) &= 1, x_2(b) = 0 \text{ if } b_1 \geq b_2 + 40 \\ t_1(b) &= b_2, t_1(b) = 0 \end{aligned}$$

and

$$\begin{aligned} x_2(b) &= 1, x_1(b) = 0 \text{ if } b_2 \geq b_1 - 40 \\ t_2(b) &= b_1, t_1(b) = 0 \end{aligned}$$

So, for the range

$$b_2 + 40 > b_1 > b_2$$

bidder 1 has the highest bid (and highest valuation), but still does not win. We can calculate the expected revenue:

$$ER_o = 146.66$$

*Treatment 5: Simple Auction for Parameter set 3:*

For the same set of parameters, we run simple auction in this treatment.

The simple auction in this environment prescribes

$$\begin{aligned} x_1(b) &= 1, x_2(b) = 0 \text{ if } b_1 \geq b_2 \\ t_1(b) &= b_2, t_1(b) = 0 \end{aligned}$$

and

$$\begin{aligned} x_2(b) &= 1, x_1(b) = 0 \text{ if } b_2 \geq b_1 \\ t_2(b) &= b_1, t_1(b) = 0 \end{aligned}$$

Expected revenue:

$$ER_S = 109.33$$

We can see that the theoretical expected revenues differ more in case of higher degree of asymmetry:

$$ER_O - ER_S = 146.66 - 109.33 = 37.33$$

We will implement these treatments using the Between Subjects Design. We intend to test the following set of hypotheses.

### 3.1 Hypotheses

1. *Revenue Comparisons: Theory vs Experiment:*

   (a) *Optimal Auction:* The average revenue earned from running optimal auction ($\overline{R_O}$) in Treatment 2 and 4 are significantly different than the theoretically predicted $ER_o$ in these two treatments. In particular, the difference $|ER_O - \overline{R_O}|$ is significantly greater in $T2$,and $T4$ compared to $T1$, the benchmark case.

   (b) *Simple Auction:* The average revenue from running simple auction $\overline{R_S}$ in $T3, T5$ are significantly different than the theoretically predicted $ER_S$ in these two treatments.

2. *Revenue Comparison Between Optimal and Simple Auctions:* The difference between predicted expected revenue from Optimal and Simple auctions is significantly different than the observed difference between average revenues, i.e. $||ER_O - ER_S| - |\overline{R_O} - \overline{R_S}||$ is significant. We will compare the revenue for each of the parameter sets Parameter set 2 and Parameter set 3. *This is the central hypothesis that we aim to test.*

3. *Effect of Discouragement:* There is significant difference in bidding behavior and expected revenue when the subjects are aware of the fact that highest bidder may not win in optimal auction. Comparing $T2$ and $T2A$ we can test this hypothesis.

4. *Bidding Function under Optimal Auction:* Under optimal auction, truthful bidding is observed.

5. *Bidding Function under Simple Auction:* Under simple auction, truthful bidding is observed.

6. *Effect of Degree of Asymmetry:* The differences $|ER_O - \overline{R_O}|$, $|ER_S - \overline{R_S}|$, and $||ER_O - ER_S| - |\overline{R_O} - \overline{R_S}||$ is significantly different under parameter set Parameter set 3 than parameter set Parameter set 2.

7. *Effect of Risk Aversion under Optimal and Simple Auction:* There is no significant effect of subject's risk attitude on the bidding behavior.

## 3.2 Design of the Study

To test these hypotheses, we will use the *Between Subjects* design, where in each experimental session the subjects will face only one treatment. The experiments will be conducted in Ashoka Experimental Laboratory. The computer interface will be designed by zTree. After several pilot sessions, here will be 4 full sessions, each with 24 bidders.

In each session, after the subjects are seated, the instructions will be read out (also handed out in printed version). After that, to gain a better understanding, the subjects will face two on-screen examples, each with a pair of valuations for the subject and his/her opponent. Using the on-screen calculator, the subject can try different bidding strategies and understand the problem better. In one of the examples, the valuation pair is chosen such that the highest valuation bidder is not the highest virtual valuation bidder. In the Information treatment $T2B$, after the subjects have worked with these examples, we explain them, pointing out that in one of the examples, there is a possibility that the highest bidder might not win the auction. In other treatments, we do not explicitly inform the subjects about this, instead the subjects go straight to the auction rounds. In each session, after 3 practice rounds, there will be 25 rounds of auction with the parametric environment associated with the specific treatment. Bidders are randomly assigned as weak or strong bidder at the beginning, and this type stays the same throughout. In each round, bidders are randomly and anonymously matched to form a pair with one strong and one weak bidder. Each session the winning bidder gets his/ her payoff in Experimental Currency Units (ECU).

After the auction rounds, we will run a *cognitive ability test* containing two different modules, one taken from Wechsler Adult Intelligence Scale (WAIS), and another basic quantitative literacy test, in order to check if the complexity of optimal auction matters.

The first module, taken from the 11 modules of WAIS test, is aimed at measuring the speed and processing time of an individual[7]. This is a symbol-digit correspondence test, similar to a submodule in the nonverbal section of the WAIS, where the subjects are asked to match as many numbers and symbols as possible in a given time according to a given correspondence. In particular, the subjects are presented with a screen that has 9 unfamiliar symbols, each paired with one of the digits $1-9$. On that screen, a symbol out of these 9 symbols appears, and the subject has to type the correct corresponding number into the box. Once a number is entered, a new screen with another symbol appears. Subjects have 90 seconds to find as many correspondences between symbols and numbers as they can, using the correct number for each symbol. Thus, speed and accuracy in applying the given correspondence under time pressure determine how well an individual does on the test.

The second module is a quantitative literacy or numerical test that is designed in order to gauge how comfortable the subject is with arithmetic calculations (similar to the intelligence test in Weschler (2008)). Here, there will be 4 simple problems involving the basic operations of arithmetic, viz. addition, subtraction, multiplication, and division. Each subject will have 180 seconds to solve as many problems as they can. The speed and accuracy in solving these problems will indicate how quickly the subject can grasp the idea of virtual bid.

At the end there will be a standard BDM (Becker-DeGroot-Marschak) mechanism[8] in order to elicit risk preference so that we can control for that. Here, the subject will be given 10 choices, each between a given lottery that pays 100 with probability 1/2 and 0 otherwise, and a certain monetary payoff, starting at 0 up to 100 with an increment of 10. The amount where the subject switches from a certain payoff to the lottery will give us his/her certainty equivalent. At the end of the BDM mechanism, one of the choices is picked randomly and the subject is paid according to that choice. To implement the lottery we will use a physical device (a six-sided dice).

Finally, subjects fill out a questionnaire to give feedback.

For payment purposes, 5 rounds out of the 25 auction rounds are chosen randomly, apart from the payment obtained from the BDM. The total ECUs earned in those 5 rounds will be converted into cash payments by the ratio: 1 ECU= 1 INR. To cover for any potential loss, subjects will be endowed with 300 INR at the beginning of the experiment.

The experimental sessions will be conducted by November, 2018.

[7]This module is same as the one used in Dohmen et. al. (2010).

[8]For details, refer to Kagel and Roth (1997).

# 4 Discussion and Future Work

In a related series of experiments, we also seek to compare the revenue generated from optimal auction with that generated from conducting an eBay-like auction with a single anonymous reserve price even when the bidders are *ex-ante* asymmetric, and see how closely this auction format approximates the optimal auction. This will give us an insight if we can even give away the bidder-specific discriminatory reserve prices. This would also substantiate the fact that eBay sometimes uses anonymous reserve price even under the scenario of asymmetric bidders. Another future line of research will explore the properties of a simple auction in multi-unit environment.

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# Instructions

Thank you for participating in this experiment on economic decision making. Please pay attention to this instruction and also the accompanying slides. If you follow these instructions carefully and make careful decisions you might earn a considerable amount of money which will be paid to you in cash and in private at the end of the experiment.

The experiment will consist of two parts and last about one and a half hours. The amount of money you make will depend on the decisions you and all other participants make during the experiment.

Your computer will assign you an ID number, and at the end of the session you will be given an envelope with that ID number on it containing your monetary earnings. The person handing you your envelope will not know how much money is in the envelope. Thus, absolute anonymity and privacy will be maintained.

Please remain silent during the experiment. If you have any questions, or need assistance of any kind, raise your hand; one of the experiment administrators will come to you and you may whisper your question to him. Please do not talk, laugh, or exclaim out loud. We expect and appreciate your adherence to these rules.

During the experiment you will take part in several auctions. In every auction a fictitous commodity is for sale, which you can resell to the experimenters. Your resale value for this good, called your valuation, lies within a value range. You are one of the two bidders. There are two types of bidders: Type 1, whose valuation lies in the range $[100, 200]$, and Type 2, whose valuation lies in the range $[100, 150]$[9]. In each auction there are two bidders, one of Type 1 and the other Type 2. At the beginning, you will be randomly assigned as Type 1 or Type 2 and you will be privately notified about your type. Each bidder keeps his own type throughout the session. If you are a Type 1 bidder, in each auction, your private valuation is independently drawn from the interval $[100, 200]$, with every integer number between 100 and 200 being equally likely. Similarly, if you are a Type 2 bidder, in each auction, your private valuation is independently drawn from the interval $[10, 20]$, with every integer number between 100 and 150 being equally likely. Notice that both bidders in each auction knows the valuation range for his opponent for sure, but not the exact valuation. In each auction, a Type 1 bidder is randomly and anonymously matched with a Type 2 bidder.

After being matched and observing own valuation which will be displayed on your computer screen, you have to place an integer bid in the range of 100 to 200 .Using this bid, your virtual bid will be calculated according to the formula:

$$virtual\ bid = 2(bid) - 200 \tag{2}$$

For example, if you bid 180, your virtual bid will be $180 * 2 - 200 = 160$. Once both the bidders submit their bids, the bidder with the highest virtual bid will win the good in that auction, and will

[9] This is the instruction for Treatment 2A, so we implement Parameter set 2.

pay the bid placed by the other bidder. In that auction, the winner will earn a payoff= valuation - payment. The loser will earn a zero payoff from this auction. For example, if your valuation is 190, you bid 180 and your opponent bids 160, then you will win this auction, pay 160 , and will earn a payoff of $190 - 160 = 30$, your opponent will earn a payoff of 0. Similarly, if your valuation was 150, you bid 180 and opponent bids 160, you will win and pay 160, earning a payoff of $150 - 160 = -10$. These payoffs are in experimental currency units ECU and will later be converted into INR using the ratio: 1 ECU = 1 INR. Your payoffs from each auction round will be stored by the computer. You will be paying 25 auction rounds, each time being randomly and anonymously matched with a bidder of the other type. Out of these 25 auction rounds, at the end, randomly 5 auction rounds will be selected and your payoffs from those auctions will be summed, converted into INR and paid in cash to you.

Before we begin, please go through the two examples displayed on your screen.

We will now begin interaction with the computers. If you have any questions before we begin the experiment, please RAISE YOUR HAND and a moderator will be with you shortly.

We will now begin the experiment. Please pay attention to your monitor and click the mouse when prompted to do so. Please click on the Continue button on each screen after you have read the information and/or made the choice.

(After examples, 3 practice rounds and then 25 rounds of auction.)

Now, on your computer screen 9 symbols will be displayed, each corresponding to a digit $1 - 9$. Next, you have to match the correct digit with the symbol displayed to you. Please do as many as possible within 90 seconds of time.

(WAIS module)

Now on your screen 4 simple math problems will appear, each involving basic arithmetic operations. Please solve as many as possible within 180 seconds.

(numerical test)

Next, you will be presented a table on screen. In that table, there are 10 rows, each asking you to make a choice between a lottery that will pay you 100 INR or $0INR$ with equal probability, and a sure amount. Please click on the button in each row to indicate your choice for that row. After all of you have submitted their choices for all 10 rows, one row will be randomly picked. If your choice in that row was the lottery, we will roll a dice in front of you. If the front face turns up any number $1 - 3$, you will get 100 INR, otherwise you will get nothing. If your choice for that particular row was the sure amount (say $x$), then you will get $x$ INR for sure. So, please turn to your monitors now and make the choices carefully.

(later)

Please complete the questionnaire displayed on your screen. To preserve your privacy, type xxx when asked for name in order to maintain privacy and anonymity; do not write your own name. While you give us your valuable feedback, we will be putting your winning amounts in the respective envelopes. Please fill out the receipt with your winning amount as well. Thanks for participating in this experiment!