# Shake It Up Baby: Scheduling with Package Auctions*

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**Abstract**

In many disciplines success depends on access to scarce resources, such as unique instruments. In large scale scientific collaborations, technologies have broadened access to scarce scientific and engineering resources. While broader access is often applauded, little attention has been focused on the problem of efficient and equitable resource allocation in the face of increased demand created through collaboratory use. This paper applies concepts from mechanism design to compare different resource allocation schemes (RAD, Vickrey, and knapsack) in the laboratory. Experimental results show that knapsack achieves a more equitable distribution of resources than RAD or Vickrey, but that RAD and Vickrey are both more efficient than knapsack. The findings highlight the need for systematic exploration of allocation mechanisms within collaboratories, where simple optimization (e.g., knapsack) is likely to produce a sub-optimal match of resources to needs.

**Keywords**: package auctions, scheduling, experimental economics

**JEL Classifications**: C91, D44

# 1 Introduction

The National Science Foundation (NSF) and other federal agencies are making significant investments in expanding the ability of geographically distributed groups of scientists to conduct research via the Internet (e.g. Atkins et al. 2003). One means to enhance the work of dispersed teams is the “collaboratory.” First proposed in the late eighties, a collaboratory is a center without walls, in which researchers can perform their research without regard to physical location interacting with colleagues, accessing instrumentation, sharing data and computational resources, and accessing information in digital libraries (Wulf 1993). The collaboratory idea is a descendent of earlier notions, such as Vannevar Bush’s 1945 proposal for the “memex;” Douglas Engelbart’s 1968 demonstration of graphical user-interfaces for computer-supported meetings; and the creation in 1969 of the ARPAnet. There are currently several hundred collaboratories in use within multiple scientific communities, including space physics, medicine, software engineering, and neuroscience (Finholt 2002).

The George E. Brown, Jr. Network for Earthquake Engineering Simulation (NEES) is a ten-year NSF program focused on accelerating and improving earthquake engineering research through the use of a collaboratory (it.nees.org). The NEES collaboratory connects earthquake engineering researchers to sixteen state-of-the-art laboratory facilities distributed around the United States. These facilities were built with the explicit intent of combining their capabilities through the Internet. For example, users of the NEES collaboratory are able to collect data across instrument modalities spanning key earthquake engineering sub-disciplines. In this approach a test of a bridge pier system might include performance data on: a) the soil the pier sits on (e.g., from physical geotechnical simulations run using specimens in a centrifuge); b) the pier structure (e.g., from physical structural simulations run using specimens on a shake table); and c) the bridge deck (e.g., from numerical simulations). Through NEESit the results of collaboratory studies will be accessible through shared data repositories, remote participants will be able to observe experiments, and under highly controlled circumstances remote participants will be able to control experiments in real-time.

A critical element of the NEES vision, and of collaboratories generally, is that Internet-mediated methods for conducting and observing research should diminish the advantages of physical collocation. Specifically, proximity to unique instruments has frequently created differential access, both to the instruments and to the community of scientists who use the instruments (Hagstrom 1965, Traweek 1992). In NEES, a critical goal of making the sixteen new sites accessible over the Internet is to broaden use of the facilities, particularly among researchers at institutions that lack earthquake engineering research equipment. To ensure that broader use occurs, NSF stipulated the creation of a non-profit corporation, NEES Inc. (nees.org), as an additional element of the NEES program intended to operate the NEES collaboratory over the period 2004 through 2014.

NEES Inc. has responsibility for governing the use of NEES facilities, as well as for allocating maintenance and operation funds. A central concern of NEES operations is to ensure shared use of the sixteen new laboratories. Specifically, a special committee of the NEES Inc. board of directors has oversight of shared use policies and mediates disputes arising from conflicts in shared use. Unfortunately, beyond the requirement that NEES accomodates shared use, NSF has not offered specific guidelines about how to achieve this goal. At an abstract level, the problem confronting NEES Inc. is a mechanism design problem. That is, NEES Inc. controls instrument time designated for shared use at the sixteen NEES laboratories (i.e., use by researchers in the broader earthquake engineering community, not just those collocated with the NEES equipment). This instrument time, presumably, has value for researchers, such that demand for instrument time will exceed supply. For example, in astronomy there is intense competition for telescope time (Etherton et al. 2004, Olson and Porter 1994).

Understanding how to achieve efficient and equitable allocation of scarce resources is a key focus of research on mechanism design. For instance, allocation solutions in other domains (e.g., the sale of frequency spectrum by the Federal Communications Commission) involve various forms of auctions. There are two reasons why it is important to explore similar approaches for resource allocation in collaboratories. First, in the absence of mechanisms it seems likely that collaboratory users will default to allocation through a scheduling czar or by insiders (e.g., instrument owners). This approach runs the risk that facilities will be under-utilized and that allocation decisions may be subject to bias (e.g., political influences). Second, absent any specific allocation mechanisms, collaboratory users may arrive at naive pricing schemes for resources, such as flat unit costs versus costs that reflect actual demand (and hence value). For example, the unit cost assumption breaks down when a user places a premium on allocation of contiguous operating intervals (i.e., ten hours together versus ten one hour segments dispersed over several days).

Collaboratory operators, such as NEES Inc., will be the immediate beneficiaries of an effort to design and demonstrate mechanisms for allocation of instrument time within collaboratories. However, more generally, research into the problem of efficient and equitable resource allocation within large-scale collaborations is important. For instance, if the NEES collaboratory is a precursor to the organization of infrastructure across a wide variety of scientific and engineering communities then the problems confronted by NEES are likely to emerge in these other settings. That is, if sharing of instruments is to become the norm, then there must be a corresponding set of mechanisms to support this sharing. It seems unlikely that simple altruism, particularly in highly competitive scientific and engineering fields, will yield satisfactory solutions. Instead, the time is right to conduct research that will produce a toolbox of candidate mechanisms, with proven characteristics, so that when communities confront breakdowns or bottlenecks in the use of instruments, or any shared resource, these difficulties can be overcome quickly or avoided completely.

In this paper, we construct a laboratory environment, within which we evaluate the performance of three allocation mechanisms. Although our choice of environment and parameters is guided by a specific application, the allocation of equipment time for NEES,[1] our results provide insights relevant to other scheduling and allocation problems as well. Compared to past research on scheduling, our paper differs in both the allocation mechanisms used and the characteristics of the environment. For example, Olson and Porter (1994) compare four mechanisms in the laboratory, motivated by the Jet Propulsion Laboratorys problem of assigning time slots on its Deep Space Network of large antennas, where each agent is assigned at most one slot.[2] When agents can demand multiple slots with complementarities, the scheduling problem is considerably more complex. Such an envi-

[1]Hence, we borrow the Isley Brothers' album title, "Shake it up baby," for the application of this research to the earthquake research community.

[2]See Wellman et al. (2001) for a theoretical analysis of multiple ascending single-good auctions for the scheduling problem.

ronment is created in Ledyard et al. (1996), where they compare variants of the Adaptive User Selection Mechanism (AUSM) with a committee process. Like Ledyard et al. (1996), we also allow multiple slots and package bidding. Furthermore, we test a new ascending package auction mechanism, the Resource Allocation Design (RAD), which is created by merging the better features of the AUSM and the FCC Simultaneous Multiple Round auction designs and is shown to perform better than either parent (Kwasnica et al. 2005). We compare the performance of RAD, Vickrey and a knapsack mechanism which is a best-case representation of existing scheduling mechanisms in collaboratories.

The rest of the paper is divided into five sections. In Section 2, we identify three allocation mechanisms and describe their features. In Section 3, we describe our experimental design. Based on the theoretical properties of the mechanisms and the laboratory environment, we present our hypotheses in Section 4. Section 5 presents our results and in the final section we discuss the results.

## 2 Allocation Mechanisms

In this section we outline the technical details of three allocation mechanisms. We assume that a critical feature of the instrument time allocation problem is that contiguous time slots are more valuable than the sum of separate slots. For example, in the case of the NEES collaboratory, the difficulty of experiment set-up and teardown dictates a preference for consecutive time intervals to minimize installation effort. Therefore, package auctions might be an important mechanism in achieving efficient allocation of equipment time. We consider two package auction mechanisms, Vickrey and RAD, compared with an ordinal ranking mechanism, knapsack, selected as a best-case representation of how allocation is currently accomplished. The Vickrey auction (Vickrey 1961, Clarke 1971, Groves 1973) is an important standard for nearly all mechanism design work, and for auctions in particular. Therefore, we use it as a benchmark to assess the performance of our ascending bid auction and the knapsack mechanism. Among ascending bid auctions which allow package bidding, we choose RAD as a candidate for implementation in collaboratories, as, to our best knowledge, it has not been surpassed by any other ascending auctions in terms of efficiency in experimental investigations (Kwasnica et al. 2005, Brunner et al. 2006). To introduce our allocation mechanisms, we first set up a simple framework that allows us to explain the auctions clearly.

In this framework, let $N = \{1, \ldots, n\}$ be a finite set of bidders. Let $K = \{1, \ldots, k\}$ represent the set of objects to be sold, and $X = \{0, 1\}^k$ represent the set of combinations of objects. Let $\mathcal{B}_i$ be a set of *bids* of bidder $i$. Each bid is a pair, $b = (x, p)$, where $x \in X$ corresponds to the packages desired and $p \in \mathbb{R}_+$ is the bid price. Let $v_i : X \to \mathbb{R}_+$ be bidder $i$'s *valuation function* that assigns a value to a package. For iterative auctions, let $t = 1, 2, 3, \ldots$ represent the iterations or rounds. Finally, $\delta = (\delta_1, \ldots, \delta_b)$ is an indicator vector, where $\delta_j \in \{0, 1\}$ indicates whether bid $(x_j, p_j)$ is *winning* or *losing*, and where $b$ is the total number of bids. As the winner determination problem is part of every package auction design, we formally define this problem for our experiment.

**Definition (Package auction winner determination problem).** The package auction winner determination problem is to maximize the sum of all bids, indicating each bid as *winning* or *losing*, under the constraint that each item can be sold to at most one bidder:

$$\max_{\delta} \sum_{j=1}^{b} \delta_j p_j \quad \text{subject to} \quad \sum_{j \in \{j : \delta_j = 1\}} x_j \leq (1, 1, \ldots, 1). \tag{1}$$

One of the most important goals in multi-object auctions is for all bidders to bid truthfully. We now define a truthful bid: a bid $(\mathbf{x}, p) \in \mathcal{B}_i$ is a *truthful bid*, if $v_i(\mathbf{x}) = p$. The allocation associated with the solution to the winner determination problem maximizes the aggregate surplus, when every bidder bids for all packages and the bids are all truthful.

## 2.1 The Vickrey Auction

The Vickrey auction with package bidding is dominant strategy incentive compatible, i.e., bidding one's true valuation is always optimal regardless of others' strategies. Furthermore, it implements the efficient outcome.

1. At the beginning of each auction, bidders select the packages they would like to bid on, and the amount they would like to bid for each package.

2. Once all bidders have submitted their bids, the auctioneer will solve the winner determination problem, (1), by choosing the combination of submitted bids that yields the highest sum of bids.

3. To compute prices, the auctioneer then, one at a time, chooses each winning bidder as a pivotal bidder. The auctioneer solves the winner determination problem again, but ignores the bids of the pivotal bidder. Once this new allocation has been determined, the auctioneer compares the sum of bids generated by this allocation with those generated when no bids are excluded. The difference is the rebate for the pivotal bidder.

4. At the end of the auction, a winning bidder's price is the difference between her bid and her rebate.

Example: Suppose $n = 3$, $k = 3$, and the minimum package is one month. At the end of an auction, the following bids have been submitted:

Bidder A: {month 1, month 2, month 3} = 200, {month 1} = 80

Bidder B: **{month 1} = 100**, {month 1, month 2}=120

Bidder C: **{month 2, month 3} = 150**, {month 3} = 80

The winning bids (in boldface) are B's bid on {month 1} and C's bid on {month 2, month 3}, as they generate the highest revenue 250.

To compute B's price, we ignore his bids. The winning bids then become A's bid on {month 1} and C's bid on {month 2, month 3}:

Bidder A: {month 1, month 2, month 3} = 200, **{month 1} = 80**

~~Bidder B: {month 1} = 100, {month 1, month 2}=120~~

Bidder C: **{month 2, month 3} = 150**, {month 3} = 80.

The revenue from those winning bids is $80 + 150 = 230$. Thus, the additional revenue that B generates is $250 - 230 = 20$. Therefore, B pays $100 - 20 = 80$.

Similarly, to compute C's price, we ignore her bids. Then the winning bid is A's bid on {month 1, month 2, month 3}:

Bidder A: **{month 1, month 2, month 3} = 200**, {month 1} = 80

Bidder B: {month 1} = 100, {month 1, month 2}=120

~~Bidder C: {month 2, month 3} = 150, {month 3} = 80~~

The revenue would be 200. Therefore, the additional revenue that C generates is $250 - 200 = 50$. Thus, C's final price is $150 - 50 = 100$.

Despite its attractive theoretical properties, the Vickrey auction has some disadvantages. In the package auction context, there are three main concerns.[3] First, the Vickrey auction might be vulnerable to collusion. For example, bidders have the incentive to use shill bidders through which they could manipulate the allocation and prices in their favor. Second, it might suffer from the monotonicity problem,[4] i.e., adding bidders might reduce equilibrium revenues. Third, previous laboratory experiments show that, in the single object case, the dominant strategy in second-price auctions is not transparent. Many experimental subjects consistently overbid in second-price auctions and do not seem to learn from prior experience (Kagel 1995).

When the Vickrey auction is extended to allow package bidding, however, its performance has been quite different in the lab. Previous laboratory experiments indicate that, in environments with a small number of packages, the Vickrey auction can achieve high allocation efficiency in multi-object auctions with package bidding (Isaac and James 2000), and that it outperforms a complex ascending bid auction in terms of efficiency and revenue (Chen and Takeuchi 2005). It is an open question whether it can retain its performance in more complex environments.[5] This study addresses this issue by expanding the number of packages to a more realistic level.

[3]Note the first two problems do not appear when all goods are substitutes for all bidders.

[4]See Milgrom (2004) Chapter 8 for examples.

[5]For a comprehensive analysis of the Vickrey auction, including its practical limitations, see Ausubel and Milgrom (2006).

## 2.2 Resource Allocation Design (RAD)

The RAD mechanism is an iterative ascending bid package auction proposed by Kwasnica et al. (2005). The RAD mechanism borrows features from the AUSM mechanism (Banks et al. 1989) and the Milgrom FCC Design (Milgrom 2004). From the former, RAD borrows the use of package bidding, while from the latter, it borrows its iterative feature, the eligibility rule, and the price improvement rule. Furthermore, RAD calculates the prices on the individual items that underlie the packages. We first explain some terminologies.

The *eligibility rule* puts an upper limit on the number of items a bidder can bid on in a round as a function of one's past bidding behavior. A bidder's eligibility is the maximum number of items she is allowed to bid on in round $t$, which is exactly the number of items on which she had active bids in round $t-1$. In the experiment, in the first round, she can bid on any and all packages. In each subsequent round, she is allowed to bid on as many packages which jointly contains as many items as she has placed bids on in the previous round. The effect of the eligibility rule can be briefly summarized as a "use it or lose it" rule.

The *price improvement rule* specifies a minimum price for each package based on the bids that were submitted in the previous round and a price improvement factor. The price improvement rule, in conjunction with the eligibility rule, helps to drive an auction to a close. In what follows, we describe the algorithm.

1. Rounds and bid structure: RAD is a simultaneous, multi-round auction in which bidders may submit bids on packages in each round. Each bidder can bid on packages that are feasible given her eligibility constraint.

2. Acceptable bids: In the first round, an acceptable bid must be equal to or exceed the minimum opening bid for each package. After each subsequent round, prices are calculated for each package on the basis of bids received in the previous round. Bids must be equal to or exceed the prices for each package.

3. The auctioneer first solves the winner determination problem, (1), by maximizing revenue subject to feasibility. Bids selected this way are called provisional winning bids.

The auctioneer then calculates market clearing prices for each of the packages, $\Pi^t$. "The pricing rule calculates prices that reflect (as closely as possible) the marginal sales revenue of each package based on bids received" (Brunner et al. 2006). Prices for packages are given by the sum of the prices for each item in the package. More specifically, let $W^t$ be the set of provisional winning bids at round $t$, and $L^t = B^t \setminus W^t$ be the set of losing bids at $t$. To compute prices $\Pi^{t+1}$, we solve the following problem:

$$\min_{\Pi^t, Z, g} Z$$

Subject to

$$\sum_{k \in K} \Pi^t_k x_{jk} = p_j, \text{ for all } b_j = (p_j, x_j) \in W^t$$

$$\sum_{k \in K} \Pi^t_k x_{jk} + g_j \geq p_j, \text{ for all } b_j = (p_j, x_j) \in L^t$$

$$0 \leq g_j \leq Z, \text{ for all } b_j \in L^t$$

$$\Pi^t \geq 0.$$

4. Provisional winning bids are automatically resubmitted.

5. End of round feedback: At the end of each round, bidders receive information on all provisionally winning bids.

6. Closing rule: The auction closes if the provisional winning bids remain the same for two consecutive rounds. In this case, provisionally winning bids become the winning bids, used to calculate auction earnings.

   If the closing rule has not been met, the auction proceeds to another round and the minimum bid prices increases by a factor above the market clearing prices. In the experiment, the factor is set to 10%.

In the experimental literature on auctions, single unit iterative ascending auctions, such as the English auction, tend to outperform their sealed bid counterpart in terms of efficiency. Therefore, in the package bidding context, we expect that RAD will generate higher efficiency than Vickrey.

### 2.3 Knapsack with Ordinal Ranking

In many scientific communities, allocation of instrument time can be determined by a scheduling czar, a committee (Olson and Porter 1994) or some formal or informal optimization procedure which uses the ordinal ranking information from potential instrument users. The knapsack mechanism is an idealized representation of the latter. In this mechanism, everyone submits ordinal rankings of packages, from the top choice (# 1) to the last choice (# $k$ for k packages). The top choice is awarded $k$ points, second choice $k-1$ points, ..., and so on. The computer will allocate goods in such a way that maximizes the total number of points.

This class of knapsack mechanisms with ordinal ranking has two problems. First, truth-telling is not a dominant strategy. One can easily construct examples to show that truthful ranking of all packages based on one's valuations for the packages might not be optimal. Second, bidders cannot express the intensity of their preferences. Therefore, we expect that the knapsack mechanism will generate lower efficiency than Vickrey and RAD. Because of the prevalence of knapsack-like mechanisms in scheduling, we use it as a useful benchmark of typical allocation approaches in order to evaluate the two auction mechanisms.

## 3 Experimental Design

Our experimental design reflects both theoretical and technical considerations. Specifically, we are interested in two important questions. First, how do the Vickrey, RAD and Knapsack mechanisms compare in performance? Second, how do subjects respond to the incentives in each mechanism? In this section we describe our economic environment and experimental procedures.

### 3.1 Economic Environment

The environment is designed to capture the essential aspects of a scientific or engineering collaboratory, using the NEES collaboratory as a model. As the number of approved projects for NEES range from 9 to 20 each year, we have 9 researchers in each experimental session. There are two dimensions of heterogeneity, the size of the project and time preference. We operationalize these two dimensions as researcher types. The ‘big’ researchers have larger grants and projects, which take longer to complete than ‘small’ researchers. In the time preference dimension, we have three types, those who prefer early slots, late slots, and those who are indifferent.

Based on actual NEES operation horizons, we assume the facility is available for 24 months. We set one month as a minimum unit. Let $\underline{\mathrm{m}}$ be the required minimum number of months to run a project, with $\underline{\mathrm{m}} = 3$ for big researchers and $\underline{\mathrm{m}} = 2$ for small researchers. Each additional month to $\underline{\mathrm{m}}$ gives a researcher value $\beta_i$, but she has no value for any additional time beyond $\bar{m}$. The discount factor, $\delta_i$, denotes a researcher's time preference, while $lag$ denotes the months between the ideal beginning month and the actual beginning month, $m_{\text{begin}}$. A researcher with access to the facility from $m_{\text{begin}}$ to $m_{\text{end}}$ has the following utility function,

$$v_i(m_{\text{begin}}, m_{\text{end}}) = \begin{cases} 0 & \text{if } m_{\text{end}} - m_{\text{begin}} < \underline{\mathrm{m}}, \\ \delta_i^{lag}\left(v_i + \beta_i(m_{\text{end}} - m_{\text{begin}} - \underline{\mathrm{m}})\right), & \text{if } \underline{\mathrm{m}} \le m_{\text{end}} - m_{\text{begin}} \le \bar{m}, \\ \delta_i^{lag}\left(v_i + \beta_i(\bar{m} - \underline{\mathrm{m}})\right), & \text{if } m_{\text{end}} - m_{\text{begin}} > \bar{m} \end{cases} \tag{2}$$

where

$$lag = \begin{cases} m_{\text{begin}} & \text{for researchers who prefer early months,} \\ m_{\text{begin}} - 23 & \text{for researchers who prefer late months,} \\ 0 & \text{for researchers who are indifferent.} \end{cases} \tag{3}$$

While the discount factor, $\delta_i$, is set to 0.9, 1.0 and 1.2 for those who prefer early, indifferent and late months respectively, parameters $v_i$ and $\beta_i$ are i.i.d. draws from the following uniform distributions at the beginning of each auction:

$$\beta_i \sim U[10, 20], \tag{4}$$

$$v_i \sim U[20, 100] \quad \text{for small researchers,} \tag{5}$$

$$v_i \sim U[20, 150] \quad \text{for big researchers.} \tag{6}$$

A small project bidder has values for packages that last for 2 to 4 months. A big project bidder has values for packages that last for 3 to 5 months.[6] As a result, a small project bidder can bid on packages that start on month 1 to month 23, while big project bidders can bid on packages starting from month 1 to month 22. Note a big project bidder bids on 63 packages, while a small project bidder bids on 66 packages.

In sum, the values of the packages are determined by the value of the base package, bidder discount factor, and the value of an additional month, $\beta$. The value of the base package in turn is determined by the bidder's type.

| Bidder ID | Project Type | Time Preference | ($\delta_i$) | Package Size |
|---|---|---|---|---|
| 1 | Big | Prefer late | (1.2) | 3 to 5 months |
| 2 | Big | Indifferent | (1.0) | 3 to 5 months |
| 3 | Big | Prefer early | (0.9) | 3 to 5 months |
| 4 | Small | Prefer late | (1.2) | 2 to 4 months |
| 5 | Small | Indifferent | (1.0) | 2 to 4 months |
| 6 | Small | Indifferent | (1.0) | 2 to 4 months |
| 7 | Small | Prefer early | (0.9) | 2 to 4 months |
| 8 | Small | Prefer early | (0.9) | 2 to 4 months |
| 9 | Small | Prefer early | (0.9) | 2 to 4 months |
| Total Demand | | | | 21 to 39 months |

Table 1: Design Parameters: Bidder Preferences

Table 1 summarizes the main features of bidder preferences. Each experimental session has nine bidders, where three has big projects and six small projects. The three big bidders each has different discount factors, while among the six small project bidders, one has a discount factor of 1.2, two have 1.0, and three have 0.9. Early months are more competitive than late ones, reflecting the stylized fact that in most scientific communities early experiment, and hence, potential discoveries, are more valuable. The total demand for months is between 21 and 39 months, while the total supply is 24 months.

[6]Again, these parameters are chosen based on the NEES environment, where allocations of six months or longer to a single project are politically infeasible.

### 3.2 Experimental Procedures

Each experimental session required exactly nine participants. The participants were recruited from the University of Michigan, including both the graduate and undergraduate population, with majors in science, math, or engineering, as we are interested in application of the results in collaboratories. Once the participants arrived they reviewed and signed an informed consent form. At the beginning of each session, each participant was given printed instructions. Before the instructions were read aloud by one of the experimenters, the participants drew from a deck of index cards for a player ID that determined their project type (big or small) and their discount factor (1.2, 1, or 0.9). The instructions were then read aloud. Participants were encouraged to ask questions during and after the experiment. The instruction period averaged around 30 minutes. Then participants took a quiz designed to test their understanding of the mechanism. At the end of the quiz, the experimenters collected, graded, and returned the quiz to each of the participants. The experimenters then reviewed the answers with the participants. The participants were given 10 minutes to finish the quiz in the RAD treatment, and 7 minutes in the Vickrey or the knapsack treatments.

There were no practice auctions in any of the experimental conditions. In the Vickrey and knapsack treatments, participants had seven minutes per auction to input their bids, while in the RAD treatment, they had four minutes for the first round and two minutes for all subsequent rounds in each auction. There were a total of eight auctions in each of the Vickrey and knapsack sessions, and three to five auctions in each of the RAD sessions.[7]

At the conclusion of auctions, participants tallied their cumulative earnings, filled out a short demographic survey, and wrote down the strategies that they used. We use the induced value method (Smith 1982). Participants were paid based on their experimental profits.

Table 2 presents features of the experimental sessions, including mechanisms, number of experimental sessions, the number of participants in each condition and the exchange rates.

[7]Recall that RAD is an iterative auction, therefore, the number of rounds in each auction is endogenous and varies from auction to auction. For the same reason, the exchange rate for RAD is lower than the Vickrey or knapsack treatments.

| Mechanism | # sessions | # participants | Exchange Rate |
|---|---|---|---|
| Vickrey | 5 | 45 | 12 |
| RAD | 5 | 45 | 4 |
| Knapsack | 5 | 45 | 20 |

Table 2: Features of Experimental Sessions

Overall, 15 independent computerized sessions were conducted in the RCGD lab at the University of Michigan from July 2005 to April 2006. No participant was used in more than one session, yielding a total of 135 participants across all treatments. Each session lasted approximately two and a half hours. In addition to their auction earnings, participants could earn money based on their quiz answers. A participant with fully correct answers could earn up to $5. The average earning (including quiz award and a $10 showup fee) was $34.44, and the standard deviation was $16.21. Data are available from the authors upon request. Experimental instructions are posted on `http://www.si.umich.edu/~yanchen/`.

# 4 Hypotheses

Based on the theoretical predictions and our experimental design, we identify the following hypotheses. Hypotheses 1 and 2 are based on the dominant strategy of the Vickrey auction.

**Hypothesis 1.** *In Vickrey auctions, bidders will bid on all packages.*

**Hypothesis 2.** *In Vickrey auctions, bidders will bid truthfully.*

Unlike the Vickrey auction, the theoretical properties of knapsack has not been fully characterized. Even though truth-telling is not a dominant strategy, we speculate that it can be a focal point.

**Hypothesis 3.** *In the knapsack mechanism, bidders will rank all packages.*

**Hypothesis 4.** *In the knapsack mechanism, bidders will rank packages truthfully.*

Similarly, the theoretical properties of RAD are not yet completely characterized. We formulate the following hypotheses based on the known properties of RAD.

**Hypothesis 5.** *In RAD auctions, bidders will not bid above value.*

**Hypothesis 6.** *In RAD auctions, bidders will use all their eligibility for packages priced below their value.*

We now formulate hypotheses which compare the aggregate performance of the three allocation mechanisms. We will look at efficiency and equity. Unlike traditional applications of auctions such as procurement auctions, in the context of scheduling, auctioneer revenue is not an important measure. Furthermore, the knapsack mechanism does not generate any revenue for the auctioneer.

**Hypothesis 7.** *Vickrey and RAD will generate the same level of efficiency.*

Theoretically, Vickrey should generate the highest efficiency, while efficiency under RAD will be at most as high as Vickrey. Therefore, the alternative hypothesis is that Vickrey will generate higher efficiency than RAD. Since knapsack does not elicit the intensity of preferences, we expect that the allocation efficiency under knapsack will be lower than either auction mechanisms.

**Hypothesis 8.** *Vickrey and RAD will generate higher efficiency than knapsack.*

In the scheduling context, equity might also be an important outcome measure, which we will elaborate in Section 5. However, as we are not aware of any theoretical equity comparisons across the mechanisms, we leave it as an empirical question.

# 5 Results

In this section, we first examine individual bidder behavior in each allocation mechanism. We then compare the aggregate performance of the mechanisms in terms of efficiency and equity.

## 5.1 Individual Behavior in Vickrey

Our Vickrey auction experiment consists of five independent sessions, each of which has nine subjects. Therefore, we have a total of 45 subjects. In each experimental session, a subject participates in 8 auctions. In each auction, a subject can bid on any of the 63 (or 66) packages.

A bidder's strategy in a package Vickrey auction has two dimensions, whether to bid on a package and how much to bid on a package if one decides to bid on it. A bidder's strategy on either dimension affects her profit. Recall it is a weakly dominant strategy for each bidder to bid on all packages, and to bid their true value on each package.

| | Active Bids% | Bid/Value |
|---|---|---|
| Auction 1 | 0.291 | 0.551 |
| Auction 2 | 0.434 | 0.574 |
| Auction 3 | 0.441 | 0.582 |
| Auction 4 | 0.480 | 0.708 |
| Auction 5 | 0.499 | 0.726 |
| Auction 6 | 0.537 | 0.734 |
| Auction 7 | 0.565 | 0.742 |
| Auction 8 | 0.587 | 1.038 |

Table 3: Bidding Under Vickrey

Table 3 presents the proportion of active bids and the bid/value ratio under the Vickrey auction, averaged across all sessions. Bidders in a Vickrey auction, on average, bid on 47.94% of the packages, and bid 70.69% of their true value. However, both the proportion of active bids and the Bid/Value ratio are increasing over time, indicating that bidders are learning the weakly dominant strategy.

To investigate which factors induce a higher proportion of active bids, we use a probit model with robust clustering at the session level. Table 4 presents results from four specifications. The dependent variable is PlaceBid, a dummy variable, which equals one if a bidder places a bid on a package and zero otherwise. Independent variables include Value of a package, AuctionNumber, which captures the effect of learning, PreferEarly, a dummy variable which equals one if a bidder prefers early months, and zero otherwise, PreferLate, a dummy variable which equals one if a bidder prefers late months, and zero otherwise,

| | Dependent Variable: PlaceBid | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Value | 0.004 | 0.004 | 0.005 | 0.006 |
| | (0.001)*** | (0.001)*** | (0.001)*** | (0.001)*** |
| AuctionNumber | | 0.039 | 0.039 | 0.039 |
| | | (0.003)*** | (0.003)*** | (0.003)*** |
| PreferEarly | | | 0.197 | 0.209 |
| | | | (0.107)* | (0.100)** |
| PreferLate | | | 0.149 | 0.19 |
| | | | (0.173) | (0.153) |
| BigPlayer | | | | -0.101 |
| | | | | (0.072) |
| Observations | 23400 | 23400 | 23400 | 23400 |

*Notes:*

1. Robust standard errors in parentheses are adjusted for clustering at the session level.
2. Significant at: * 10% level; ** 5% level; *** 1% level.

Table 4: The Likelihood of Bidding on a Package in Vickrey Auctions

and BigPlayer, a dummy variable which equals one if the bidder is a big player, and zero otherwise. While specification (1) is our basic model, (2) adds the effects of learning, (3) adds the effects of time preferences, and (4) investigates the effects of project size (Big vs. Small).

**Result 1 (Whether to Bid on a Package).** While the proportion of active bids is significantly less than 1, bidders are significantly more likely to bid on packages with higher values. The proportion of active bids increases significantly over time. Controlling for the value of packages, bidders who prefer early months are significantly more likely to bid on packages.

**Support.** As bidders interact with each other within a session, we analyze the bidding probability based on the mean proportions of active bids for each of the 5 sessions, which are $(0.676, 0.287, 0.413, 0.526, 0.495)$ respectively. The sign test rejects the null hypothesis that the proportion of active bids is equal to one ($p = 0.043$). Table 4 presents results from probit specifications. The coefficients are probability derivatives. The Value of a package increases the likelihood of bidding on a package by 0.4% ($p < 0.01$). The likelihood of bidding also increases in the AuctionNumber by 3.9% ($p < 0.01$), indicating significant learning effect. Controlling for Value and AuctionNumber, PreferEarly increases the likelihood of bidding on a package by 20.9% ($p < 0.05$). ∎

By Result 1, we reject Hypothesis 1. Recall that 4 bidders prefer early months while only 2 bidders prefer late months. Thus, the significant coefficient on PreferEarly indicates the effect of the competition among the bidders who prefer early months.

We now explore the second dimension of bidding strategy, how much to bid on a package. To investigate how much participants bid on a package in a Vickrey auction, we use a structural approach based on Hypothesis 2. To test this hypothesis, we classify Vickrey bidders into three categories: underbidder, truthful bidder and overbidder. Specifically, we run the following simple OLS regression on active bids for each bidder with robust clustering at the auction level.

$$\text{Bid}_{pt} = \beta \text{Value}_{pt} + \epsilon_{pt}, \tag{7}$$

where the subscript $p$ denote package and $t$ denotes the number of auctions. We then test the null hypothesis: $\hat{\beta} = 1$. Based on the result, we classify each bidder into one of three categories. A bidder is classified as an *underbidder*, if we can reject the hypothesis of truthful bidding at the 5% level and the coefficient is below 1. She is classified as a *truthful bidder*, if we cannot reject the hypothesis of truthful bidding at the 5% level. Lastly, she is classified as an *overbidder*, if we can reject the hypothesis at the 5% level and the coefficient is above 1. We summarize the analysis of bidding behavior in the Vickrey auction in the following result.

**Result 2 (Bid Price in Vickrey).** Bidders in a Vickrey auction, on average, bid 76.1% of their true value. Of our participants, 73.3% can be classified as underbidders, 20.0% as truthful bidders and 6.7% as overbidders.

**Support.** The OLS estimate of $\hat{\beta}$ in Equation (7) is 0.646, with the robust standard errors clustered at the session level equal to 0.071. A two-sided Wald test rejects the null hypothesis of bids being equal to values ($p = 0.008$). The classification of bidders comes from regressions at the individual level. The average $R^2$ of individual regressions is 0.895, with a standard deviation of 0.116. ∎

By Result 2, we reject Hypothesis 2 for 80% of the bidders. Our finding that most bidders either underbid or bid their true value in Vickrey auctions is consistent with Isaac and James (2000) and Chen and Takeuchi (2005). This is surprising, as most previous laboratory studies of single-unit Vickrey auctions find that bidders tend to overbid in such environments (Kagel 1995). As the package Vickrey auction is more complex than the single-unit version, subjects might start cautiously by bidding below value.

Figure 1 presents the scatter plot of raw bids under Vickrey for small (left column) and big (right column) project bidders. We notice early months are much more competitive, and therefore, most of the bids over value (above the 45 degree line) are from researchers who prefer early months.

We use a probit model to examine the likelihood of overbidding. Table 5 presents results from two specifications. The dependent variable is OverBid, a dummy variable, which equals one if a bid on a package is greater than the value and zero otherwise. Independent variables include Value of a package, PreferEarly, PreferLate, Indifferent, and Startmonth,

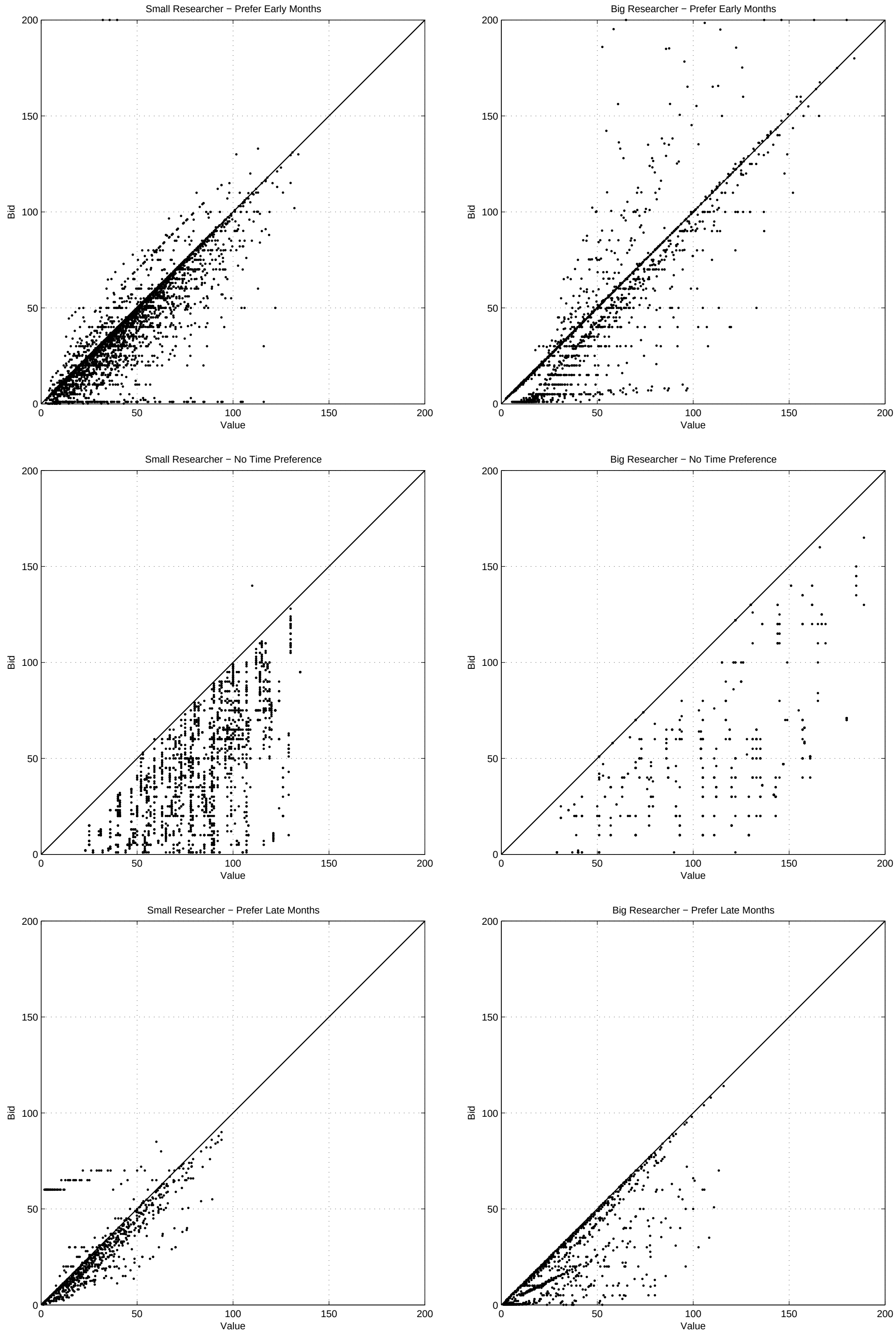


Figure 1: Bidding Behavior in Vickrey Auctions

| | Dependent Variable: OverBid | |
|---|---|---|
| | (1) | (2) |
| Value | 0.0001 | -0.0002 |
| | (0.0002) | (0.000) |
| PreferEarly | 0.240 | 0.227 |
| | (0.099)*** | (0.095)*** |
| PreferLate | 0.321 | 0.151 |
| | (0.156)*** | (0.126)* |
| PreferEarly*Startmonth | | -0.003 |
| | | (0.002)*** |
| PreferLate*Startmonth | | 0.000 |
| | | (0.001) |
| Indifferent*Startmonth | | -0.001 |
| | | (0.000)*** |
| Observations | 11217 | 11217 |

Robust standard errors in parentheses are adjusted for clustering

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5: The Likelihood of Overbidding in Vickrey Auctions

the beginning month of a package. Specification (1) indicates that bidders who prefer early or late months are more likely to overbid compared with indifferent bidders. Specification (2) reveals the characteristics of packages bidders are likely to overbid. While the interaction between PreferEarly and Startmonth is negative and significant, the interaction between PreferLate and Startmonth is not significant, with the estimated coefficient being zero. The likelihood of overbidding is decreasing in Startmonth for bidders who prefer early months, while not for bidders who prefer late months. This result also highlights the effect of the competition among bidders.

## 5.2 Individual Behavior in Knapsack

Our Knapsack experiment consists of five independent sessions, each of which has nine subjects. Therefore, we have a total of 45 subjects. In each experimental session, a subject participates in 8 allocations. In each allocation, a subject can rank any of the 63 (or 66) packages between 1 and 63 (or 66).

Like in a Vickrey auction, a participant's strategy in a knapsack allocation has two dimensions, whether to rank a package and how much to rank a package if one decides to rank it. A participant's strategy on either dimension affects her profit. Recall that truth-telling is not a dominant strategy in our knapsack mechanism. However, truthful revelation might be a focal point.

We define an analogous Bid/Value ratio for the knapsack mechanism as follows. For the submitted ranking $r$ for a package $x$, we find the corresponding package, $x^r$, which yields the same ranking $r$ if it is submitted truthfully. We then calculate the ratio of the value of $x^r$ to the value of $x$, $v_i(x^r)/v_i(x)$. We use this ratio as the Bid/Value ratio under the knapsack mechanism. For submitted ranks, we regress the value of $x^r$ on the value of the package $x$ with no constant, and then classify the bidders with the same criteria as in the Vickrey auction.

Table 6 presents the proportion of active ranking and the Bid/Value ratio under the knapsack mechanism, averaged across all sessions. Bidders in a Knapsack allocation, on average, rank 57.8% of the packages, with a Bid/Value ratio of 115.8%.

To investigate which factors induce a higher proportion of active bids, we use a probit

| | Active Bids% | Bid/Value |
|---|---|---|
| Auction 1 | 0.510 | 1.304 |
| Auction 2 | 0.591 | 1.241 |
| Auction 3 | 0.580 | 1.207 |
| Auction 4 | 0.597 | 1.111 |
| Auction 5 | 0.599 | 1.106 |
| Auction 6 | 0.585 | 1.110 |
| Auction 7 | 0.579 | 1.104 |
| Auction 8 | 0.585 | 1.105 |

Table 6: Ranking Under Knapsack

model with robust clustering at the session level. Table 7 presents results from four specifications. The dependent variable is PlaceRank, a dummy variable, which equals one if a participant ranks a package and zero otherwise. Independent variables include Value of a package, AllocationNumber, which captures the effect of learning, PreferEarly, a dummy variable which equals one if a participant prefers early months, and zero otherwise, PreferLate, a dummy variable which equals one if a participant prefers late months, and zero otherwise, and BigPlayer, a dummy variable which equals one if the participant is a big player, and zero otherwise. Again, while specification (1) is our basic model, specification (2) adds the effects of learning, (3) adds the effects of time preferences, and (4) investigates the effects of player type (Big vs. Small).

**Result 3 (Whether to Rank a Package).** While the proportion of active ranking is significantly less than 1, bidders are significantly more likely to rank packages with higher values. The proportion of active ranking does not increase over time. Controlling the value of packages, bidder time preferences have no significant effect on the likelihood of ranking packages.

**Support.** As bidders interact with each other within a session, we analyze the ranking probability based on the mean proportion of active bids for each of the 5 sessions, which are $(0.491, 0.608, 0.762, 0.437, 0.594)$ respectively. The sign test rejects the null of the proportion

| | Dependent Variable: PlaceRank | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Value | 0.004 | 0.005 | 0.006 | 0.006 |
| | (0.001)*** | (0.001)*** | (0.001)*** | (0.001)*** |
| AllocationNumber | | 0.007 | 0.008 | 0.008 |
| | | (0.007) | (0.008) | (0.008) |
| PreferEarly | | | 0.159 | 0.155 |
| | | | (0.099) | (0.100) |
| PreferLate | | | 0.154 | 0.143 |
| | | | (0.108) | (0.146) |
| BigPlayer | | | | 0.030 |
| | | | | (0.160) |
| Observations | 23400 | 23400 | 23400 | 23400 |

*Notes:*

1. Robust standard errors in parentheses are adjusted for clustering at the session level.
2. Significant at: * 10% level; ** 5% level; *** 1% level.

Table 7: The Likelihood of Ranking Packages in Knapsack Allocations

of active ranking equal to one ($p = 0.041$, one-sided). Table 4 presents results from probit specifications. The coefficients are probability derivatives. The Value of a package increases the likelihood of bidding on a package by 0.45% ($p < 0.001$). The likelihood of bidding does not significantly increase in the AllocationNumber ($p = 0.294$), indicating no learning throughout the allocations. Neither time preference nor project size has a significant effect on the likelihood of ranking a package ($p > 0.10$). ∎

By Result 3, we reject Hypothesis 3. We now explore the second dimension of ranking strategy, how much to rank a package. We first look at a scatter plot presentation of raw bids in knapsack allocations.

Figure 2 presents the scatter plot of the raw bids under the knapsack mechanism for small and big project bidders. The horizontal axis represents the true value of a ranked package, $v_i(x)$, while the vertical axis represents the value of package for the reported rank, $v_i(x^r)$. Note that the panels for bidders who are indifferent look sparse since they have only three values for all packages per auction. In contrast to the Vickrey auction, time preference does not seem to be a significant factor in the amount of over-rank (above the 45 degree line).

Using a similar approach to classify the participants as in the Vickrey auction, we find the following result.

**Result 4 (Ranking in Knapsack).** Of the participants in knapsack allocations, 20.0% can be classified as underbidders, 64.4% as truthful bidders and 15.6% as overbidders.

**Support.** The OLS estimate of $\hat{\beta}$ in Equation (7) is 1.005, with the robust standard errors clustered at the session level equal to 0.004. A two-sided Wald test rejects the null hypothesis of bids being equal to values ($p < 0.001$). Bidder classification comes from regressions at the individual level. The average $R^2$ of individual regressions is 0.945, with a standard deviation of 0.081. ∎

Given the lack of a theoretical benchmark for the knapsack mechanism, we take the empirical distribution of values as given and use simulations to generate benchmarks for comparisons. In particular, we look at two categories of simulations. In the first category, which we will refer to as the "benchmark" simulations, we rank the packages on behalf

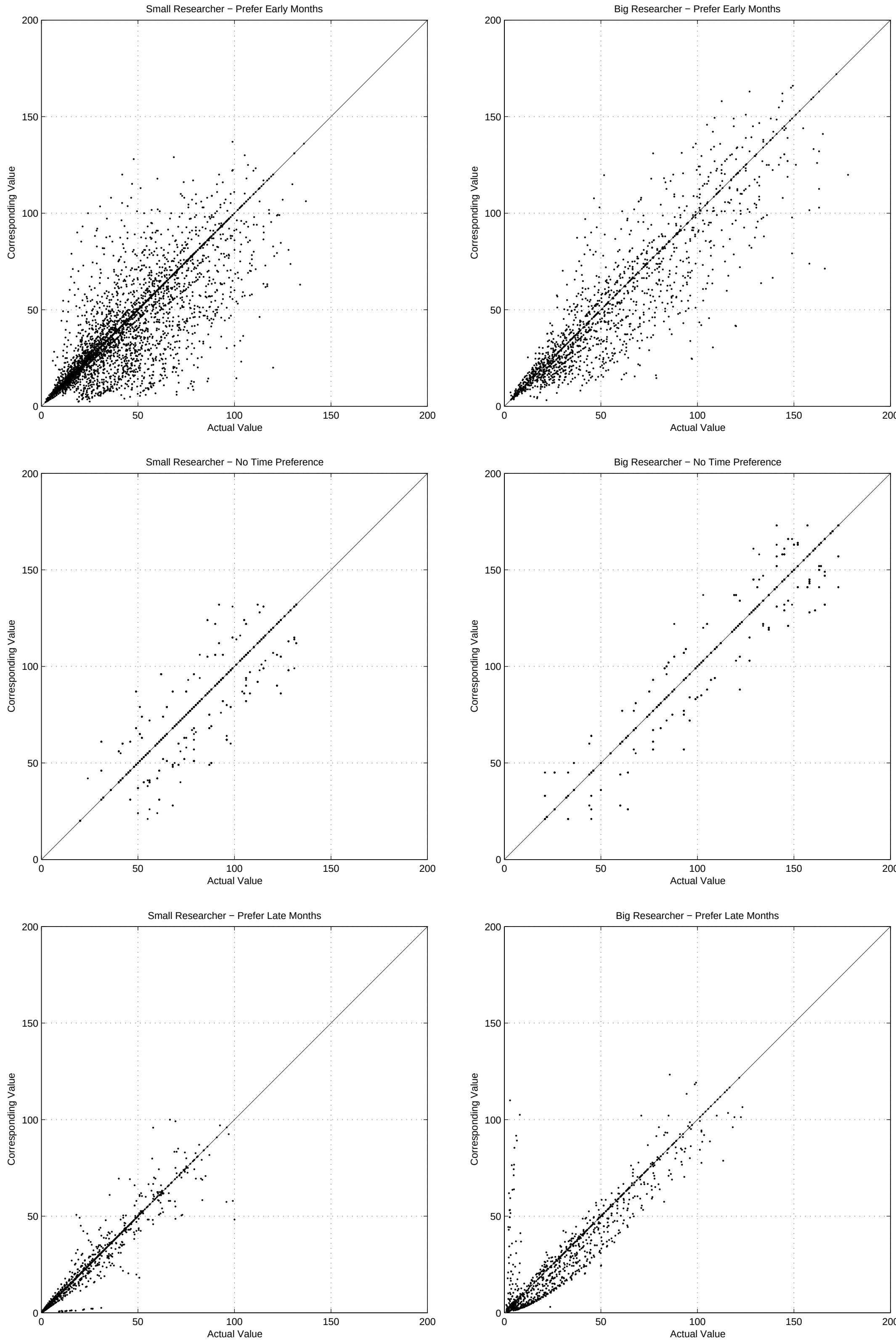


Figure 2: Ranking Behavior in the Knapsack Mechanism

of the bidders to evaluate the surplus generated under different ranking strategies. There are four sets of simulations under this category, determined by two dimensions. The first dimension is the number of packages that we rank: do we rank all the packages or a random number of packages? The second dimension is whether we rank the packages truthfully or randomly. The four cases then are: (a) rank all the packages truthfully, (b) rank random number of packages truthfully, (c) rank all the packages randomly, and finally, (d) rank random number of packages randomly.

We now only describe the algorithm for (d), as the methods for the other three categories can be inferred accordingly. Recall that we have 5 independent sessions of knapsack, each with 8 allocations, yielding a total of 40 allocations. In running the simulations, we submit ranking on behalf of the bidders. For each of the 40 allocations, and for each of the nine bidders in a given allocation, we randomly pick the number of packages the bidder would rank on from a discrete uniform distribution on the integer values with a support of 0 to 63 for a big bidder and 0 to 66 for a small bidder. For example, for a big bidder, suppose we draw 45 packages to rank. We then randomly pick 45 of the 63 packages, each of which has an equal probability of being ranked as the #1 package. Of the remaining 44 packages, each has an equal probability of being ranked as the #2 package, and so on. We repeat this process until all 45 packages have been ranked. While there is only one way to (a) rank all the packages truthfully , for each of the other three cases, (b), (c) and (d), we run 25 iterations and compute the average of the total surplus.

Figure 3 presents the average total surplus for each of the four benchmark simulations, as well as the actual achieved total surplus in the experiments. The upper horizontal line is the total surplus of the optimal allocation, while the lower horizontal line is the total surplus from a random allocation process. It is striking that the actual achieved surplus in the experiment is close to that of ranking all packages truthfully.

**Result 5 (Truthful Ranking of All Packages Leads to Highest Surplus).** With the empirical distribution of values for the 40 allocations, under the knapsack mechanism, simulation (a) ranking all bids truthfully yields the highest surplus, followed by, in decreasing order, the actual achieved surplus, (b) ranking random number of bids truthfully, (d) ranking random number of bids randomly, and (c) ranking all bids randomly, respectively.

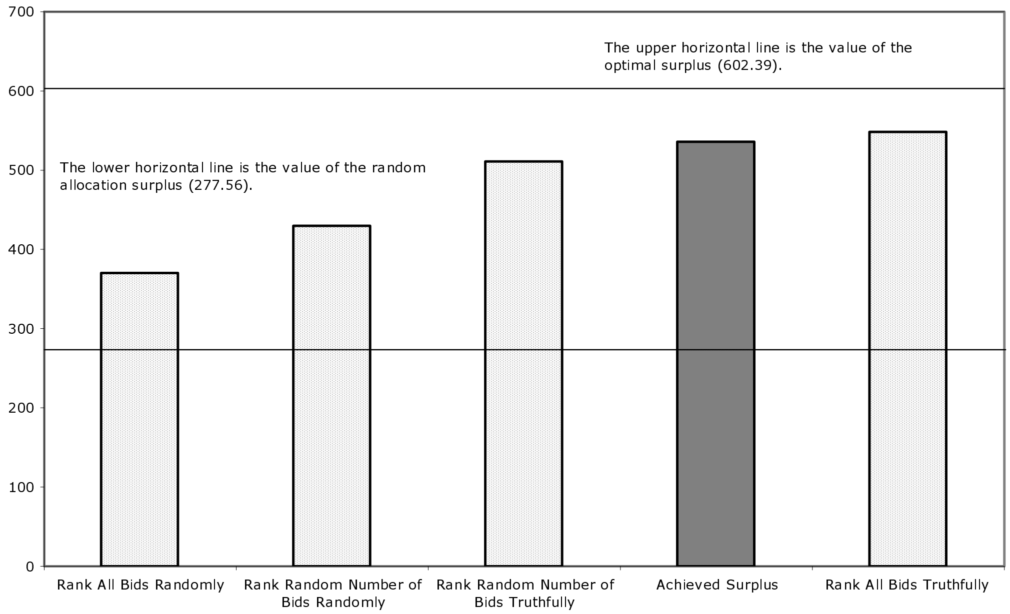


Figure 3: Average Total Surplus from Benchmark Simulations

**Support.** Sign tests reject the null of equal surplus for each pairwise comparisons of aggregate surplus of the four simulations and the achieved surplus ($p < 0.001$). ∎

To investigate whether participant strategies are best responses to the empirical distributions of strategies, we manipulate the rankings submitted by the bidders in two ways. First, we look at their truncation decisions and examine whether we can increase bidder profit by ranking more packages for them. For each allocation, holding the rankings of the other bidders constant, we choose one bidder at a time, and complete her rankings truthfully for her. We find that, out of 360 ranking vectors, simulated completion of 8 vectors (2.22%) increases bidder profit, in 16 cases (4.44%), it decreases, and in 336 out of 360 cases (93.33%) bidder profit remains the same.

**Result 6 (Strategic Truncation).** When rankings of packages are completed truthfully for each bidder, one at a time, average bidder profit remains the same as the actual observed profit.

**Support.** For each session, we compute the average simulated profits by completing the ranking truthfully for a given bidder. We then compare the average simulated profits with actual session-level average profits. Two-sided permutation test fails to reject the null of equal profits ($p = 0.4174$). ∎

To find out whether bidder profit might increase if each of them were to rank packages truthfully, we choose a bidder, one at a time, and re-rank all her bids truthfully, while keeping others' ranking constant. We find that, in 60 out of 351 cases (17.09%), bidder profit increases, in 38 out of 351 cases (10.83%), it decreases, while in 253 out of 351 cases (72.08%), bidder profit remains the same.[8]

**Result 7 (Strategic Ranking).** When bidder rankings of packages are truthfully, one bidder at a time, average bidder profit remains the same.

**Support.** For each session, we compute the average simulated profits by ranking all packages truthfully for each bidder, one at a time. We then compare the average simulated profits with actual session-level average profits. Two-sided permutation test fails to reject the null of equal profits ($p = 0.3824$). ∎

Together, Results 6 and 7 indicate that, on average, bidder profit would not increase significantly, had they been more truthful. Another interpretation is that bidder ranking strategies are close to best responses to the empirical distribution of strategies.

### 5.3 Bidding Behavior in RAD

In the RAD mechanism, since bidding above value exposes the bidder to the risk of getting negative profit, we expect bids to be below value. We now define the bid/value ratio under RAD as follows.

$$\text{Bid/Value Ratio}(x_j) = \frac{\text{Submit Price}(x_j) - \text{Market Price}(x_j)}{\text{Value}(x_j) - \text{Market Price}(x_j)} = \frac{p_i(x_j) - \Pi_j x_j}{v_i(x_j) - \Pi_j x_j} \tag{8}$$

**Result 8 (Bids in RAD).** The mean Bid/Value ratio is significantly less than 1.

[8] The simulation only has 351 observations, as we could not complete one of the simulated sessions within 48 hours.

**Support.** Among 8651 bids placed by all bidders, only 53 (0.6%) are above their values. The mean Bid/Value ratio is 0.541 and the 95% confidence intervals (clustered at the session level) is [0.435, 0.647]. One-sided Wald test rejects the null hypothesis of the bid/value ratio being one at the 0.03% level. ∎

By Result 8, we fail to reject Hypothesis 5. We now explore the response of bidding behavior to the eligibility constraint.

For a given set of submitted bids from a bidder, there are packages that the bidder does not bid on. Hypothesis 6 implies that those remaining packages must be either or both of the following: i) their temporary profits are negative (i.e., unprofitable), and/or ii) any additional bid on them will violate the eligibility constraint (i.e., ineligible). We find, however, that significant amount of packages do not fall into these categories. They are profitable and eligible, which implies that bidders fail to bid on profitable packages even though they can.

**Result 9 (Eligibility).** Bidders submit significantly fewer bids than their eligibility, leaving profitable packages on the table.

**Support.** In 5 sessions, there are 19 auctions and 124 rounds. Thus, the total number of rounds is 1116. In 884 rounds, we observe that bidders left profitable package(s) on the table. For each of those 884 rounds, we compare the used eligibility and the given eligibility. The mean values are 10.46 and 13.54, respectively. The t-test shows the difference is significant at the 0.01% level.

By Result 9, we reject Hypothesis 6. Together, Results 8 and 9 indicate that while most bidders place bids below their value, which is a transparent feature of ascending auctions, they did not effectively use the eligibility rule, which is a relatively difficult concept.

### 5.4 Aggregate Performance

In this section, we will report the aggregate performance of the three allocation mechanisms in terms of efficiency and equity.

Two measures have been used to compute the efficiency for an auction outcome. Let $x_i$ be the package that is actually allocated to participant $i$, and $x_i^*$ be the package that would be allocated in the optimal allocation, whereby the sum of bidder values are maximized. A simple efficiency measure takes the ratio of total surplus from the actual and the optimal allocations. In contrast, a normalized efficiency measure uses the difference between the actual (optimal) surplus and the average surplus resulting from 10,000 random allocations,[9] $x_i^{rand}$. Specifically,

$$\text{Efficiency} = \frac{\sum_i v_i(x_i) - \sum_i v_i(x_i^{rand})}{\sum_i v_i(x_i^*) - \sum_i v_i(x_i^{rand})}. \tag{9}$$

As both measures have been used in the literature, we conduct our efficiency analysis using both and find similar results. In what follows, we report the normalized efficiency measure.

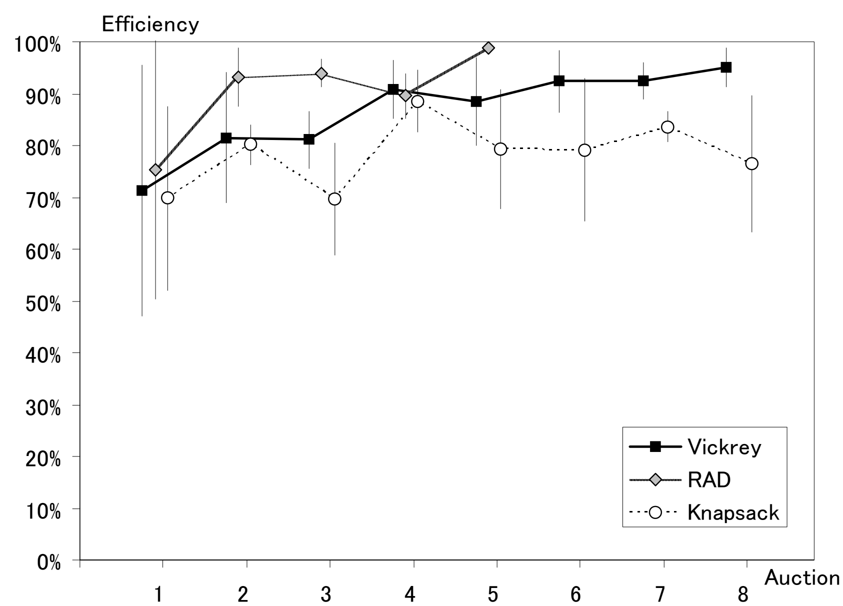


Figure 4: Efficiency comparison across mechanisms

Figure 4 presents the average time series efficiency and standard deviation (error bars) of the three mechanisms. Consistent with individual learning under the Vickrey auction, the average efficiency under Vickrey increases over time and is higher than knapsack. RAD

[9]In implementing the random allocation, we randomly generate 10,000 queues using uniform distribution of participants in queue positions. For each queue, the first participant is given a package randomly chosen from all the packages. The second participant is given a package randomly chosen from the remaining packages, and so on.

also generates higher efficiency than knapsack. Note that RAD only has 3-5 auctions in each session, while both Vickrey and knapsack have eight auctions.[10] While RAD generates higher efficiency in the early auctions, Vickrey catches up by auction #4.

**Result 10 (Efficiency).** Vickrey and RAD each generate significantly higher efficiency than knapsack. The efficiency comparison between RAD and Vickrey is insignificant.

**Support.** We computed the session average, average of the last two auctions in each session. For session average efficiency comparisons, we had the following results, where the p-value for each one-sided permutation test is written under the inequality sign.

$$\text{Knapsack} \underset{\mathbf{0.03}}{<} \text{Vickrey} \underset{0.38}{<} \text{RAD},$$
$$\text{Knapsack} \underset{\mathbf{0.03}}{<} \text{RAD}.$$

Taking into account the effects of learning, we looked at the average efficiency of the last two auctions in each session, and found the following result:

$$\text{Knapsack} \underset{\mathbf{0.01}}{<} \text{Vickrey} \underset{0.72}{<} \text{RAD},$$
$$\text{Knapsack} \underset{\mathbf{0.01}}{<} \text{RAD}.$$

∎

By Result 10, we fail to reject Hypotheses 7 or 8.

While the efficiency index measures whether time slots are allocated to the bidders who value them the most, we used the Gini coefficient to measure the distributional equity among participants. Given the set of allocations, $(x_1, x_2, ..., x_n)$, the Gini coefficient based on the values of allocated packages is defined as follows,

$$\text{Gini Coefficient} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} \|v_i(x_i) - v_j(x_j)\|}{2n\sum_{k=1}^{n} v_k(x_k)}.$$

[10] To avoid laying the error bars on top of each other, there is a slight shift for each mechanism, which has no numerical significance.

Note that a higher Gini Coefficient corresponds to greater inequality. In the extreme cases, it is 0 if every participant gets the same value from the assigned packages (perfect equality), while it is approximately 1 if one participant receives some months while other participants receive nothing (perfect inequality). Alternatively, one can compute the Gini coefficient based on participant profits. Again, we compute our Gini coefficients using both values and profits, and report the former in the text and the latter in a footnote. Since the knapsack mechanism does not involve payments while the two auction mechanisms do, the Gini coefficients based on value are more comparable across mechanisms, even though the results are qualitatively the same.

In the auction literature, it is unusual to use equity as an outcome measure. However, in equipment time scheduling problems, we argue that equity is an important measure. One of the policy goals of the National Science Foundation is to increase the utilization of its facilities by broadening participation. Therefore, NSF should care about the equitable use of facilities. The Gini coefficient is widely used to measure income inequality in a country and has been used by CSCW researchers to measure equality of participation in group discussions (e.g. Weisband et al. 1995).

Figure 5 presents the average time series Gini coefficients (based on value) and the standard deviation (error bars) for each of the three mechanisms. One striking feature is that knapsack was roughly the lower envelope of the observations, indicating more equitable distribution of time slots than the other two mechanisms.

**Result 11 (Equity).** The knapsack mechanism is significantly more equitable than either the Vickrey or RAD mechanism. The equity comparison of Vickrey and RAD is insignificant.

**Support.** Permutation tests of session average and last two auction average across mechanisms have the following results:[11]

[11] If we use profits instead of values to caculate the Gini coefficients, all inequalities hold at $p < 0.01$. Note that when we calculate the Gini coefficient based on profits, we normalize all profits by substracting the largest negative profit, so all profits are non-negative.

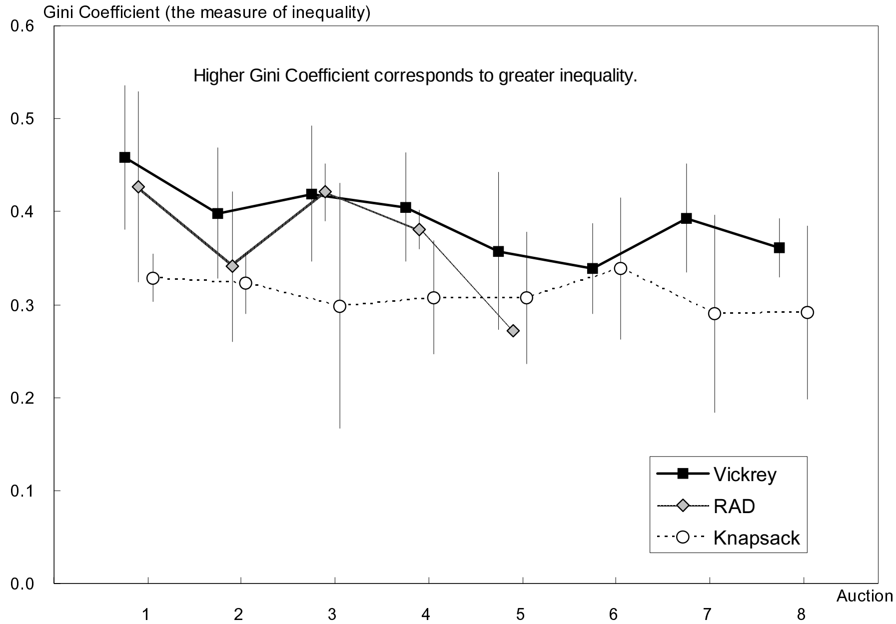


Figure 5: Equity comparison across mechanisms

$$\text{Knapsack} \underset{\mathbf{0.01}}{<} \text{Vickrey} \underset{0.55}{<} \text{RAD},$$

$$\text{Knapsack} \underset{\mathbf{0.01}}{<} \text{RAD}.$$

Taking into account the effects of learning, we examine the average Gini coefficients of the last two auctions in each session, and find the following result: [12]

$$\text{Knapsack} \underset{0.03}{<} \text{Vickrey} \underset{0.27}{<} \text{RAD},$$

$$\text{Knapsack} \underset{0.02}{<} \text{RAD}.$$

∎

Therefore, there is an efficiency and equity tradeoff among the three mechanisms. While the two auction mechanisms are significantly more efficient than the ordinal ranking knapsack mechanism, the latter is more equitable than either of the auction mechanisms. This

[12]Again, if we use profits instead of values, all inequalities hold at $p < 0.01$ except for Vickrey < RAD at $p = 0.03$.

is because, unlike in auctions, bidders cannot express the intensity of preferences under the knapsack mechanism, which in turn leads to a worse match of needs and allocations (efficiency), and yet a more equitable allocation.

## 6 Discussions

This paper reports an experimental investigation of three scheduling mechanisms for a relatively complex environment designed to mimic key aspects of actual collaboratories, such as the NEES collaboratory. We captured variation in the resources of collaboratory users (i.e., big vs. small projects) and in the time preferences of users (i.e., early, middle, or late in a 24-month period). Experimental participants were then assigned randomly to project types and asked to bit for instrument time using one of three mechanisms – two that were auction-based (Vickrey and RAD) and one based on ordinal ranking (knapsack).

Results showed that knapsack was more equitable than either Vickrey or RAD. However, both Vickrey and RAD were more efficient than knapsack. Intuitively, by using ordinal ranking, the knapsack mechanism does not allow bidders to express the intensity of their preferences. In the hypothetical collaboratory, this favored small project bidders and made it easier for them to obtain slots. Therefore, the knapsack allocation was more equitable, to the extent that everyone got something. Knapsack was not good at giving slots to those who valued them the most, however, where both of the auction mechanisms were better at giving the right people the right slots, at the expense of equity. Therefore, a choice among these mechanisms roughly boils down to a tradeoff between efficiency and equity, and which has more weight in the designer's objectives.

There are a number of limitations to this study, such as the usual caveats about the external validity of laboratory experiments used to simulate real world phenomena. However, there is extensive evidence that experimental participants do accurately represent economic behavior within the domain of auctions and other mechanisms. Similarly, while the hypothetical collaboratory can't model all the nuance of an actual collaboratory, it is possible to stylize key aspects of collaboratory use relevant to specific problems (e.g., allocation of scarce instrument time) and to operationize these aspects as parameters within an experimental design. Perhaps most important, it was not our purpose to use experimental methods to capture the full fidelity of collaboratory use. Rather, the experimental approach gave us a sufficiently realistic arena to examine particular aspects of collaboratory use with an eye toward future work that might focus on allocation in actual collaboratories.

We see four critical next steps in terms of advancing beyond this paper. First, we believe the results will have greater validity when participants are members of authentic scientific and engineering communities. That is, instead of using undergraduates and graduate students, we would like to use practicing scientists and engineers – in the expectation that these participants will identify more strongly with the instrument allocation task and therefore have greater investment in bidding outcomes (i.e., valuations will be more truthful and accurate). Second, we would like to conduct surveys of scientific and engineering communities that depend on scarce resources (e.g., astronomy) to better identify current mechanisms used to allocate instrument time. In this paper, for instance, we adopted knapsack as a proxy for typical allocation mechanisms based on evidence that some variant of knapsack is used to allocate time on the Chandra X-ray observatory. Assuming we find other mechanisms in use, we would like to include these as comparisons in future experiments. Finally, our larger ambition is to use the body of experimental results to inform adoption of specific allocation mechanisms within scientific and engineering communities, like NEES, and then study the consequences of the use of the allocation mechanism. Ideally we would like to find multiple communities to conduct quasi-experiments contrasting varying mechanisms. Finally, in the experiment, we assume that participants can use real money to bid on instrument time, while in reality, we are not yet aware of such practice. One possibility is that NSF might consider allocating bidding points or a bidding budget to participants, however, the allocation of bidding points will in itself be an interesting if politically contentious problem. The significant efficiency gain from an ordinal ranking mechanism to an auction mechanism warrants attention to explore the feasibility of using money or bidding points in real facility or instrument scheduling problems. Furthermore, almost all NEES sites are expected to be used for research outside of NSF and most do. When there is private demand for public resources, private interests, such as oil exploration companies or construction firms, might be asked to use currency to bid. In this situation, our research points to package auctions, such as RAD, as an efficient equipment time allocation mechanism.

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