Experimental Testbeds for ECOSEL: A Market Framework for Private Provision of Forest Ecosystem Services

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Private Provision of Forest Ecosystem Services

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Abstract

We attempt to design a market framework (which we call ECOSEL) for private provision of forest ecosystem services. ECOSEL is a non-regulatory framework that uses a voluntary public good provision mechanism (in a form of an auction) in conjunction with a multi-objective optimization algorithm to create a market for forest ecosystem services. It is expected to be attractive to the demand side of the ecosystem service market since only Pareto-efficient bundles of services are offered for auction, and it is expected to be attractive to the supply side as well by creating a source of non-timber income for forest landowners. ECOSEL is capable of flexible response to demand for other relevant dimensions of forest-related environmental amenities such as biodiversity, viewshed or recreational services. Following Roth's (2002) advice on behavior of economists as "market engineers", we use both experimental economics to improve the design of the ecosystem services market. Concurrently, we provide experimental evidence on the efficiency and revenue-generating properties of a multi-good subscription game of incomplete information.

Introduction

Many forest benefits are public goods characterized by various degrees of *non-excludability* and *non-rivalry*. It is usually impractical (or morally unjustifiable) to exclude one from enjoying a scenery or an old-growth forest patch even if the individual did not pay for the privilege. Ecosystem services such as carbon sequestration or nutrient cycling can serve as examples of pure public goods. As is well-known in public economics, conventional markets typically under-provide these goods. In the forest ecosystem service context, the consequences of these under-provisions can be severe as forest landowners or other decision makers will likely choose the most profitable land use or management alternative available to them. Real estate development or conversion to non-forest uses compromise or eliminating forest ecosystem services. In the United States alone, hundreds of thousands of hectares of non-federal forestland are lost each year due to urban sprawl (Alig et al. 2003) – a process partly induced by our inability to reward landowners for forest preservation and associated ecosystem service provision. Intensive timber production can also lead to decreased provision of ecosystem services. Command-and-control responses to these market failures, such as the State of Washington's Forest Practices Rules provide little to no incentive for landowners to enhance ecosystem services from their land. On the extensive margin, strict regulation provides an incentive for forest landowners to convert their land to a non-forest use, with very negative consequences for ecosystem services. On the intensive margin, command-and-control measures provide no incentive to provide the ecosystem services beyond the legally mandated minimum. A functional market for ecosystem services would allow forest-dependent communities to diversify their revenue sources reducing reliance on volatile timber markets, and could allow the timber industry to better align their forest management to reflect the values of the public concerned with environmental issues.

Voluntary alternatives to regulatory approaches for creating desired ecosystem services include certification schemes and auctions. Certification providers such as the Forest Stewardship Council (FSC) promote ecosystem services by labeling forest products that are produced in sustainably managed forests. Extensive monitoring mechanisms are in place to ensure that on-the-ground management, as well as the entire supply chain, is in compliance with the certification standards. The mechanism captures a unique market segment of players who are willing to pay extra dollars for sustainably produced forest products. Auctions have also been applied to determine the market prices of other ecosystem-related products such as carbon emissions credits (Buckley et al. 2006) or the location of sewage treatment plants (Minehart and

Neeman 2002). Reverse auctions, where the auctioneer is the buyer and the bidders are the sellers have been used to distribute public funds for the production of ecosystem services (Greenhalgh et al. 2007). In a reverse auction, the government encourages landowners to bid on services they can provide on a competitive basis. Landowners submit proposals as to how they will provide key ecosystems services, such as reduced phosphorus pollution, sedimentation, or increased wildlife habitat, targeted by a conservation program. Stoneham at al. (2002) describes the BushTender program's use of reverse auctions to maintain biodiversity in Victoria, Australia. A similar reverse auction approach has been used near military bases where adjacent landowners bid to provide habitat for endangered species (McKee and Berrens 2001).

The concept

We propose ECOSEL as an alternative, non-regulatory approach that is different from existing mechanisms. The rationale behind ECOSEL is the following. A landowner can manage his or her land in a variety of ways within the constraints of the applicable laws and regulations. Some management alternatives lead to more, while others lead to less environmental services for the public. For example, a forest landowner might decide to clear-cut his forest and convert it to a non-forest use. This would likely compromise the ability of the land to provide forest habitat for wildlife, sequester carbon or potentially clean water for downstream users. Alternatively, the same landowner could preserve the forest cover and retain many ecosystem functions. This option, however, would result in opportunity costs for the landowner due to forgone timber or development revenues, or both. The goal of ECOSEL is to provide a decentralized mechanism to pay compensation to the landowner for the *minimum costs* that are associated with the desired changes in management. ECOSEL achieves this by combining forest ecosystem service optimization component with an auction component.

The ecosystem service optimization component:

Typically, there are a large number of compromise management alternatives available for the landowner between polar solutions such as complete development versus preservation. Some of these compromises are *Pareto-efficient* with respect to the environmental outputs that they would lead to, and with respect to the associated implementation cost. In this context, a management alternative is Pareto-efficient if none of the associated environmental outputs or the associated cost can be improved (i.e., increased for environmental outputs, or decreased for costs) without compromising another output. The notion of Pareto-optimality is critical because it helps finding management options that lead to different bundles of forest ecosystem services in the most (opportunity) cost-efficient way possible. ECOSEL identifies these cost-efficient options for a given forestland, time period, and a predefined set of ecosystem outputs. While the number of Pareto-efficient management plans can be high, it is ultimately a finite number as most of the landowner's decisions are discrete choices. We use multiobjective optimization to explicitly capture the tradeoffs between ecosystem services and implementation costs.

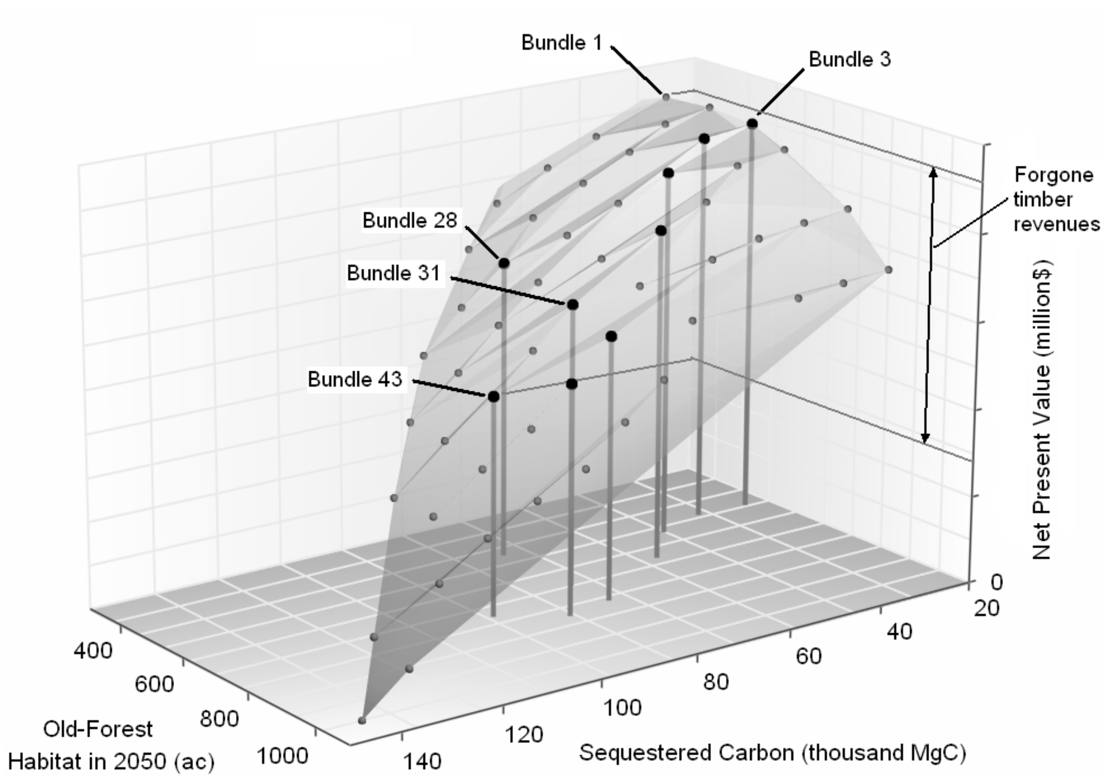

Figure 1. Pareto-optimal forest management plans for Pack Forest, Washington. Each point on the 3-dimensional surface represents a management plan, or equivalently, an ecosystem services bundle. Only five of the bundles are labeled and the net timber revenues on the vertical axis are hidden in compliance with Pack Forest policies.

The outcome of the optimization process is a production possibilities frontier (e.g., Figure 1) for the relevant ecosystem service outputs, from which total and marginal ecosystem service production costs can be derived. This key feature of the tool is far from trivial: a significant obstacle to functioning ecosystem markets is often a lack of understanding of the underlying natural production processes, and a lack of easily identifiable least-cost ecosystem production options. Indeed, the notion of "costs" and "tradeoffs" is only relevant when minimum costs of producing a particular combination of ecosystem services are identified. The ECOSEL optimization component entails the use of detailed data on the physical characteristics of the forest, as well as simulation and GIS modeling to generate the Pareto-efficient set of tradeoffs between ecosystem services and costs. As a practical matter, ECOSEL seeks to provide potential sellers with a tool to develop the supply function for their unique forest condition and the unique combination of ecosystem service outputs. This may significantly increase the interest in the program among forest landowners, many of whom lack the capacity to develop such supply surfaces themselves.

The market (auction) component:

Once a set of Pareto-efficient management plans is identified, an auction takes place where dollar bids are solicited for each selected plan. The opportunity costs found through optimization serve as the bases for the reserve prices to be used in the auction. The management plan for which the combined value of bids exceeds the corresponding reserve price by the largest margin (i.e., a profit-maximizing plan) at the end of the auction is implemented by the landowner. The landowner is obliged to implement the winning plan, which in turn leads to the bundle of services that were desired by the bidders. Should the bids fall short of the lowest reserve price, all bids are returned to the participants and the auction concludes without any forest management commitments put in place. Legal contracts are in place to ensure that the plan is implemented in due course and no unjustifiable deviations occur.

Thus, the auction component of ECOSEL can be thought of as a multi-good voluntary public goods contribution game with a predefined provision point and refundable contributions (a.k.a., *subscription game*, Admati and Perry, 1991). Economic theory suggests that a mechanism like ECOSEL may be able to provide an efficient level of ecosystem services while earning a profit for the landowner (e.g., Bagnoli and Lipman 1989; Menezes et al. 2001; Barbieri and Malueg 2008). While many voluntary mechanisms for public goods provision have been proposed (e.g., Ledyard 1995), the subscription game has the following attractive features leading to us choosing it as the basis of ECOSEL: 1) it is very simple, especially in comparison to other public good provision mechanisms, and can be easily understood by market participants; 2) it is easily extended to the context of multiple bundles of multiple ecosystem services; 3) it has attractive theoretical (Bagnoli and Lipman, 1989; Barbieri and Malueg, 2008) and experimental properties (e.g., Bagnoli and McKee, 1991).

A simple characterization of the proposed auction mechanism can be given by letting I denote the set of bundles of ecosystem services that are available in the auction, and by letting K denote the set of players who are bidding for these services. Assume that each Player $k \in K$ has a certain value (or indirect utility), v_i^k associated with each Bundle $i \in I$. Finally, let b_i^k denote the final bid that Player k places on Bundle i and let r_i denote the reserve price for Bundle i. The following characterize the ECOSEL game.

(1) *Social Surplus*: If the provision game – which is open to all potential buyers – is successful and one of the management plans, say Bundle i wins, *social welfare* will increase by social surplus SS_i, which is the sum of the resulting net benefits to the bidders and the resulting net benefits to the provider (Eq. 1):

$$SS_i = \sum_{k \in K} \left(v_i^k - b_i^k \right) + \sum_{k \in K} b_i^k - r_i = \sum_{k \in K} v_i^k - r_i \qquad (1)$$

As it is evidenced by Equation (1), social surplus will only depend on the values that the players assign to the winning scenario and on the associated reserve price. Figure 2 provides a more intuitive exposition of this result: The amount by which the total of bids exceeds the reserve price only affects the bidders' and the provider's respective shares in the benefits. The sum of the two shares, which is the social surplus, remains constant as long as the total value of the bids exceeds the reserve price. If the bids do not exceed the reserve price, then the social surplus is zero. Thus, we describe the efficiency of the provision mechanism not only in terms of the surplus generated for the consumers, but also in terms of overall economic efficiency. Existence of seller surplus does not undermine the efficiency of the mechanism, as it only serves to redistribute the social surplus from the bidders (consumers) to the seller (forest landowner).

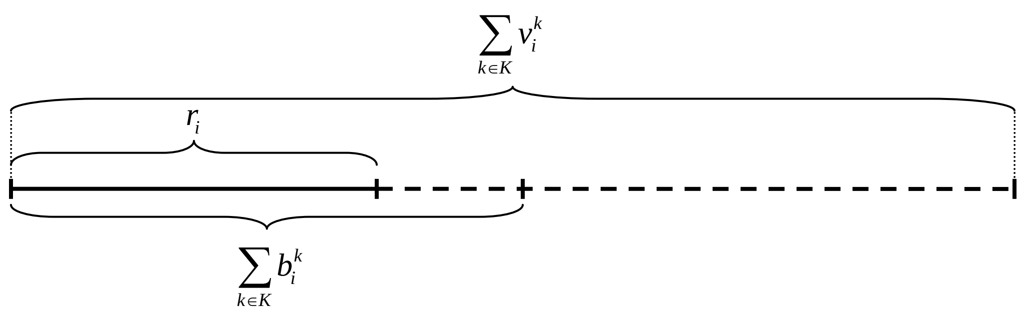

Figure 2. Social surplus generated by the ECOSEL subscription game depends only on the combined value that the players assign to the winning bundle of services and the associated reserve price.

(2) *Theoretical Welfare Maximum*: The Theoretical Welfare Maximum is reached at Bundle *i* if, of all the bundles of ecosystem services that are available in the auction, it is Bundle *i* that is collectively valued the highest by the players relative to the associated reserve price (Eq. 2):

$$\sum_{k \in K} v_i^k - r_i = \underset{j \in I}{Max} \sum_{k \in K} v_j^k - r_j \quad (2)$$

(3) *Winning Conditions*: There are two necessary conditions for Bundle *i* to win. First, the total value of bids on Bundle *i* must exceed the reserve price (Inequality 3). Second, the amount

of this excess must be greater than the excesses at any of the other bundles (Eq. 4). These two conditions together are a sufficient to determine if a particular bundle is winning in the auction.

$$\sum_{k \in K} b_i^k - r_i \geq 0 \tag{3}$$

$$\sum_{k \in K} b_i^k - r_i = \underset{j \in I}{Max} \sum_{k \in K} b_j^k - r_j \tag{4}$$

4) *Efficiency*: An outcome of the ECOSEL subscription game is efficient if (2), (3) and (4) all hold, i.e., if the winning management scenario maximizes social surplus. If only inequality (3) holds, the management plan that leads to Bundle *i* is welfare-improving, but both (3) and (4) must hold for the plan to be economically optimal.

An illustration

This section, which is based on Tóth et al. (2008), illustrates the ECOSEL optimization component using the University of Washington's 4,300 ac Pack Forest as an example. Pack Forest is a self-sustaining operation with revenue coming from timber production. The dual mission of the forest is to demonstrate sustainable forest stewardship and to generate revenues to support students and other programs at the College of Forest Resources, University of Washington. Since Pack Forest is located near the Tacoma metropolitan area, the real estate value of the land is estimated to be significantly higher than its timber value. This puts the property at risk of conversion to development, which would compromise one of its core missions. To reduce conversion risk, the administration is interested in increasing revenues from ecosystem services rather than by intensifying timber production. The case study simulates the choices and constraints that thousands of private forest landowners face in the region.

We identify spatiotemporally explicit forest management plans for Pack Forest over 45 years (2005-2050) that would lead to Pareto-optimal combinations of carbon sequestration, old-forest habitat production and timber revenues. For simplicity, carbon sequestration was defined based on the net change of carbon content in standing timber between 2005 and 2050 given a particular management plan. “Old-forest” habitat was defined as the total area of forest stands that would be older than 115 years at the end of the planning horizon if a given management plan was implemented.

The following three-objective mathematical programming model was used to generate the management plans. The model was solved using specialized, discrete, multi-objective optimization techniques introduced and tested in Tóth et al. (2006) and Tóth and McDill (2009). The details are given in the Appendix.

The Pareto-efficient solutions found for the three-objective model are shown in Figure 1. Each point represents a management plan in terms of projected carbon sequestration, old-forest habitat production and timber revenues that would be achieved if the plans were implemented. The 3-dimensional production possibilities frontier (a.k.a., *efficient* or *tradeoff frontier*) on Figure 1 illustrates the tradeoffs that are associated with the production of the three outputs. Of the many bundles found, the Director of Pack Forest selected five (Bundle 1, 3, 28, 31, 43) for hypothetical bidding. While Bundle 1 represents the management alternative that would maximize net timber revenues for the landowner, the other four plans would lead to more of one or both of the non-timber outputs at gradually increasing opportunity costs (vertical axis). The reserve prices of the bundles were calculated based on forgone timber revenues and forgone development rights. While the forgone timber revenues were obtained directly from the solutions of the mathematical program, the value of development rights was arbitrarily set to a symbolic value.

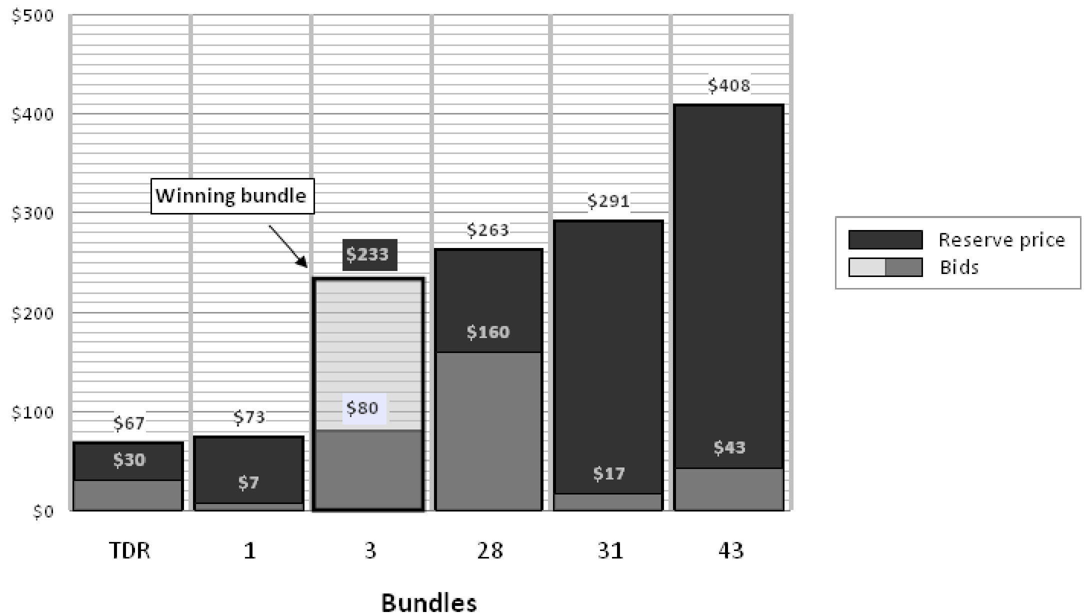

Figure 3. The final snapshot of the bidding chart used to symbolically sell old-forest habitat and carbon sequestration services from Pack Forest, Washington. The black bars are the reserve prices and the light/dark grey bars represent the aggregate value of the bids that were placed on the bundles (dark grey=those below the reserve price; light grey=those above the reserve price).

To simulate how a real auction at Pack Forest, three preliminary auctions were organized. The 75 participants of the first auction included forest landowners, timber industry, academia, state officials and representatives of environmental and conservation organizations. Each participant was given an endowment of $10 that he or she could either keep or use in the auction. The five bundles shown on Figure 1 plus a Transfer of Development Rights (TDR) option were used for the experiment. The reserve prices were adjusted to the total dollar amount that was given to the participants. The TDR option was assigned the lowest reserve price as it would allow maximum managerial flexibility for the landowner as long as no development occurs

(Figure 2). The other options would not only preclude development but they would also require that the landowner follows a particular management plan. As a reward for successful bidding, and to emulate the public goods nature of the real outcome, the auctioneers pledged to double the winning bids and donate money to forest conservation causes, to purchase carbon offsets, or donate to an academic organization. The donations to these three entities were proportional to the ecosystem services outputs that would result from the winning scenario (that is, a management plan which generates relatively more carbon sequestration, if selected, entailed a promised donation to be mostly used for purchasing carbon offsets). If the TDR bundle won, donation to an academic institution would be made to mirror the public goods associated with forest preservation other than habitat preservation or carbon sequestration. The bidding took place in three rounds where the current totals of the bids were displayed on a large screen in a chart similar to the one on Figure 3. The final result of the first mock auction is shown in Figure 3. Bundle 3 was the winning scenario, generating $153 for the hypothetical seller. 65% of the dollar endowment was used in the. A similar mock auction played with a small class of University of Washington undergraduates resulted in Bundle 43 winning. The third preliminary auction involved 14 bidders who represented a variety of environmental organizations interested in forest ecosystem services. This time, the purchasing power of the players was adjusted to their stated annual conservation budgets. This information was acquired from the bidders anonymously prior to the mock auction. The dollar amounts to be allocated to the players for use in the experiment were proportional to the stated budgets. As a result, those players who represented organizations with large conservation budgets were given much larger funds than those who reported smaller budgets. A random monetary endowment was provided to those who did not volunteer a conservation budget or volunteered a small amount. Two sessions, each comprising several rounds of bidding, were arranged. Communication among bidders was not allowed in the first but it was allowed in the second session. The players were not informed about the second session prior to the auction.

The "non-communication" session resulted in the TDR bundle winning, the "communication" session resulted in Bundle 3 winning. Forty two percent of the endowment was used in the "non-communication" auction, and 52% was used in the "communication" auction.

While preliminary "mock" auctions with potential ecosystem service buyers are interesting in possibly providing a glimpse of the distribution of ecosystem service preferences among the potential buyers, they suffer from several shortcomings which we try to address in our laboratory work.[1] First, since we did not induce the utilities that the bidders place on ecosystem services, we have no way of judging an outcome as to its efficiency. This is quite problematic as we aim to design a mechanism which has good efficiency properties. Second, the degree of dominance and experimental control was low. Participants, who are professionally involved in forestry issues, seemed to be distracted by minute details of forest management and thus may not have viewed the bundles the way we intended for them to view it (lack of dominance). The first mock auction suffered from a lack of experimental control as it was conducted at the conclusion of a professional meeting and the participants were tired. Finally, we do not yet have enough systematic replications of each auction setup in order to draw conclusions from the experimental trials with actual ecosystem service bundles. For these reasons, we turn to the laboratory in the hope of learning more about the performance of the ECOSEL auction component.

Laboratory Experiments

The auction component of ECOSEL can be thought of as a multiple-good, discrete public good subscription game with incomplete information. While the theoretical properties of a

[1] Individual-level analysis of bids is being conducted concurrently, but is outside of the scope of this paper.

complete-information subscription game has been studied (e.g., Bagnoli and Lipman, 1989; Admati and Perry, 1991; Marx and Matthews, 2000), and encouraging welfare properties have been established, games of incomplete information have proven to be much less tractable. Even static, two-player problems generate a profusion of equilibria and more exact characterizations require strong simplifying assumptions (Alboth et al., 2001; Barbieri and Malueg, 2007, 2008; Laussel and Palfrey, 2003; Menezes et al., 2001). The general consensus in the theoretical literature seems to be that, under incomplete information, the subscription game is not efficient (i.e., there is a positive probability that a good is not provided in cases when it is efficient) (Menezes et al., 2001; Laussel and Palfrey, 2003; Barbieri and Malueg, 2007). However, Menezes et al. (2001) establish that a subscription game (where contributions are refunded if a threshold is not met) is superior to a contribution game (where no refunds are made). Also, Barbieri and Malueg (2008) show that a subscription game can act as a profit-maximizing selling mechanism over all incentive-compatible selling mechanisms. However, we are not aware of any theoretical or experimental study of an incomplete information subscription game with multiple goods[2].

Experimental research on the performance of public good subscription games started with Bagnoli and McKee (1991) setting out to test Bagnoli and Lipman's (1989) theoretical findings of good efficiency properties of such games. While Bagnoli and McKee (1991) found strong evidence that the subscription game results in efficient public good provisions, their results were challenged by Mysker et al. (1996). Uncertainty regarding subject pool effects (Cadsby and Maynes, 1996), incomplete information about valuations (Marks and Croson, 1999), the number

[2] Providing a mathematical characterization for the ECOSEL mechanism would be a significant contribution to the theory given the potential wide applicability of the provision mechanism. We hope to build a theoretical foundation that would give rise to insights regarding some classes of equilibria and revenue-generating properties of the game.

of subjects in the contributor's pool (Rondeau et al., 2000), and the effect of challenge and matching gifts both in the field and the laboratory settings (Rondeau and List, 2008) make generalizations regarding the efficiency of the production of ecosystem provisions difficult. The preponderance of evidence suggests we should include certain design features: a presence of discrete thresholds in contributions (Isaac et al., 1989; Suleiman and Rapoport, 1992; Dawes et al., 1986), or a full refund in case the contributions don't exceed the threshold (Isaac et al., 1989; Rapoport and Eshed-Levy, 1989; Cadsby and Maynes, 1999; Marks and Croson, 1998), however other features of the mechanism are not as clear, and demand further investigation. We seek to find an auction design which has the highest probability of achieving an efficient outcome (since we are using an induced value framework, this is observable in the laboratory), with the secondary (non-mutually exclusive) goal of maximizing seller revenue.

Design and nuisance variables

We explore the properties of our subscription game under the following conditions: 1) subject preference heterogeneity, with subject preferences being private information; 2) varying number of subjects in each auction and varying subject endowments; 3) random subject matching in each auction. These are essentially "nuisance" variables, and, although we could choose to fix either or all of them at a particular level, the choice was made to let it vary. The motivation mainly lies in the practical realm: in any realistic ecosystem service auction setting, buyer pools, their preferences and endowments are outside of the auctioneer's control.

The following were chosen to be the design variables, as neither economic theory nor experimental economics literature provide sufficient guidance for our context (i.e., multiple, mutually-exclusive units, incomplete information setting). First, the number of bundles of ecosystem services presented for the auction might affect the auction performance: a small number of bundles might provide insufficient flexibility so that each subject is unsatisfied with the choices offered, while a large number of bundles may prove to be too difficult for the subjects to analyze and this might result in scattered bids preventing convergence towards a potentially successful outcome (as in Bagnoli et al., 1992). [3]Second, it is not clear if threshold costs (reserve prices) should be disclosed to the bidders, or they should be kept hidden and the players would be notified only if a particular reserve price has been met. Although with repeated contribution rounds and disclosure of whether the bid totals exceeded the threshold, a coordinated group of bidders would have no difficulty closely bracketing the true reserve price, such coordination is not guaranteed ex ante. Finally, we wish to explore the impact of subject communication on auction efficiency and seller revenue: on one hand, subject communication may act to erode seller profits as bidders coordinate to just exceed reserve prices (thereby undermining the incentives for seller participation in ecosystem markets), while on the other hand, subject communication might help to focus the buyers and increase the provision of ecosystem services.

Hypotheses

Thus, we expect that the 3 treatments will have the following impact on auction efficiency and seller revenue:

<u>Number of bundles presented:</u>

H1E: While in reality, we might consider that not all bidders might find the offered set of ecosystem service bundles to be ideal, in the experimental setting, every buyer's

[3] An interesting extension would be explore endogenous bundle selection by the subjects in a two-stage process, where the initial set of bundles undergoes a selection process, and a reduced number is ultimately offered up for auction. Second, the buyers may strategically withhold their contributions if they anticipate that a better auction might be forthcoming in the future, and that the auctioneers might be offering an inferior auction first. We propose to empirically investigate such behavior by manipulating the subjects' information sets regarding the auction sequence.

preferences over bundles are fully described. Thus, we expect coordination problems to be present, and, therefore, we *hypothesize that the higher the number of bundles offered, the greater the coordination problem, and, in turn, the lower the contributions to the efficient bundle, and the lower the economic efficiency of the auction.*

H1R: Using the same reasoning, we expect that *higher number of bundles leads to lower seller revenues.*

<u>Threshold cost (reserve price) disclosure</u>

H2E: We expect coordination problems to be stronger in the case that threshold costs are not disclosed, as some bidding rounds might be "used up" on threshold cost discovery, as opposed to tacit or explicit bidder cooperation. Thus, *we expect the auctions without threshold cost disclosure have lower contributions toward the efficient bundle and lower economic efficiency of the auction.*

H2R: However, uncertainty over the bundle cost may lead to over-contributions in the cases where a bundle actually wins. *Conditional on a project winning, we expect seller revenue to be higher in auctions where threshold costs were not disclosed.*

<u>Subject communication:</u>

H3E: Although we do not expect subject communication to significantly affect free-riding, we do expect it to reduce the extent of the coordination problem. Thus, *we expect that auctions with subject communication allowed have higher contributions toward the efficient bundle and have higher economic efficiency.*

H3R: Subject communication should reduce the share of the overall surplus being lost to the seller. *We expect subject communication treatment to lead to lower seller revenues.*

Experimental design and procedures

The three binary treatment variables (number of bundles (high/low), threshold cost disclosure (yes/no), communication on bidding strategies allowed (yes,no)) implies 8 auction types to be tested in a full factorial design. We use the following orthogonal fractional factorial design in 4 auction types: T1 (No communication, 3 bundles offered, threshold costs disclosed), T2 (No communication, 5 bundles offered, threshold costs not disclosed), T3 (Communication allowed, 3 bundles, threshold costs not disclosed), and T4 (Communication allowed, 5 bundles, threshold costs disclosed). Each auction was replicated 4 times with a different subject pool.

Subjects were recruited among University of Washington undergraduates across a variety of disciplines. In order to preserve dominance, no mention of "public goods" or "ecosystem services" was on the recruitment flyer or during the experimental session until the post-auction debriefing questions. Our design (see Appendix) planned on 60 subjects participating. Out of 65 subjects recruited, 11 did not arrive, leaving our total subject pool at 54. Five classrooms were reserved for the study. Subjects arrived in the larger classroom (those arriving on time were paid a $5 on-time bonus), and were given an introductory presentation with the examples (see Appendix). A brief self-test and a sociodemographic survey were completed. Each subject received an envelope containing instructions, the sociodemographic questionnaire, and 4 envelopes guiding them to the appropriate auction classroom. A Latin squares design was used to assign a sequence of 4 auctions to 4 rooms, and each subject received a randomly assigned auction sequence and the corresponding room assignments.

Each subject was endowed with either 10 or 20 Experimental Monetary Units (EMUs) for each auction, with the exchange rate of 1 EMU being equal to 25 cents.[4] Each subject had a 0.5

[4] At the end of the experiment, the exchange rate was recalibrated to 1 EMU = 40 cents to bring the average subject per hour earnings in line with the State of Washington minimum wage rate ($8.55/hour).

probability of receiving either 10 or 20 EMUs as endowment for each of the auctions. EMUs did not carry over from auction to auction. Each auction had 5 bidding (contribution) rounds, and subjects were informed of the total bids and whether any bundle was winning after each round. All subjects were informed that Round 5 was the last round which determined the auction outcome. The entire experimental session lasted 3.5 hours.

Subject utilities and payoffs

In reality, we expect potential ecosystem service bidders to hold heterogeneous preferences over ecosystem service X (tons of carbon sequestered), and Y (old-forest habitat area). We induce heterogeneous preferences over X and Y via the following payoff function :

$$v_k^i = \begin{cases} \alpha_k X_i + \beta_k Y_i + w_k - b_k^i \ if \ \sum_{k=1}^{K} b_k^i - r_i \geq \max_j \left(\sum_{k=1, j \in I \setminus i}^{K} b_k^j - r_j \right) \geq 0, \ and \\ w_k \ otherwise \end{cases}$$

where k indexes subjects, $i, j \in I$ index bundles offered at auction, w_k is the subject's endowment, b_k^i is the subject's bid on winning bundle $i,$ and $\alpha_k, \beta_k \geq 0$ represent the subject's induced preferences over bundle i's "carbon sequestered", X_i, and "old-forest habitat area", Y_i. The subject only pays her bid if the bundle she bids for actually wins (full refund is given), and the seller (experimenter) gets to keep any excess of subjects' bids over the reserve prices r_i (no rebates are given). While there exists some experimental evidence (REFS) that the presence of various forms of rebates might enhance the contributions to a threshold public good, we chose not to pursue the rebate treatment (partially motivated by the fact that in order for the ecosystem auction to be attractive to sellers, a chance of positive seller profit would have to be offered, and that chance is taken away by a presence of full rebates). The X_i and Y_i numbers for each bundle were a scaling of the actual carbon sequestration potential and old-forest habitat area of the bundles developed for Pack Forest (see above). The preference parameters were drawn from $\{0,1,2\}$, with the restriction that no subject were to get both $\alpha_k = 0$ and $\beta_k = 0$.

The following Table summarizes the bundles presented to the subjects, the assumed consequences for "carbon sequestration" and "old-forest habitat", and their threshold costs as share of the (design) group endowment. The relative costs of all bundles represented the relative opportunity costs of changing management at Pack Forest.

Table 1. Bundles presented to participants.

Bundle	X_i, for auctions with bundles A, B, C: T1 and T3	Y_i, for auctions with bundles A, B, C: T1 and T3	r_i, % of group endowment	X_i ,for auctions with bundles A, B, C, D, E: T2 and T4	Y_i ,for auctions with bundles A, B, C, D, E: T2 and T4	r_i, % of group endowment
A	2.5	5.3	0.1	2.8	3.2	0.09
B	7.7	5.0	0.33	2.5	5.3	0.1
C	9.7	7.5	0.5	7.7	5.0	0.33
D	-	-	-	7.7	7.0	0.36
E	-	-	-	9.7	7.5	0.5

Due to the linear nature of payoffs and costs, every subject's most preferred bundle was either bundle C (in auctions T1 and T3) or bundle E (in auctions T2 and T4), and, consequently, those bundles represent the socially optimal bundles. However, although bundles' net social benefits grow as we go down the column in the table above (i.e., a move from A to B to C, etc. passes the Kaldor-Hicks compensation test), such moves are not unanimously preferred by all the subjects (thus they do not represent a Pareto-improvement).

Results

Table below presents some of the overall results. 16 total auctions were run as part of the main experiment, and the remaining 11 participant packets were used to run 4 more auctions in a class taught by one of the authors[5]. In 20 total auctions, the public good was provided 50% of the time. In the original 16 trials, the public good was provided 9 times (56.25% of the time). Thus, the mechanism is not fully efficient. Average relative efficiency (measured as the ratio of obtained net benefits to the maximum possible net benefits) was 0.42 across all trials. Fully efficient bundle (or "project", as it was described to the participants) was attained in 3 auctions, however, in those auctions where a threshold was reached, only 1 out of 10 auctions generated relative efficiency of less than 2/3 (and was still over 60%). Each of the auctions ending in a provision of a public good generated a positive profit for the seller, with an average of 3.1 EMUs (or an average profit margin of 3%). In this sense, the performance of the mechanism in terms of generating a profit for the seller of a public good is encouraging.

Hypothesis testing: relative efficiency

We first turn to testing the impact of the treatment variables on the relative efficiency of the auction mechanism. Relative efficiency of the auction was regressed on the treatment dummies and on the dummy variable, "rd4win", which indicates whether the auction had a bundle winning after the next-to-last bidding round, Round 4. The Table below presents the estimates from an OLS model and a double-limit Tobit model (since one could think of "latent" relative efficiency which is censored by 0 from below and by 1 from above).

[5] Subsequent analysis deals with the 16 auction trials. Results from the pool of 20 trials are available upon request. The authors feel that experimental control in the classroom experiment may have been compromised somewhat as some students indicated that they did not really anticipate receiving cash after a regularly scheduled class meeting. The class experiments, however, were timed to be of pedagogical value and place right after the discussion of public goods and before a game theory unit.

Table 2. Impacts on auction-level relative efficiency.

	OLS				Double-limit Tobit (Lower bound=0, Upper bound=1)			
	Estimate	S.E.	t-value	p-value	Estimate	S.E.	t-value	p-value
Comm.	0.1367	0.2031	0.6700	0.5138	0.1861	0.3856	0.4800	0.6295
3 Bundles	0.0140	0.1759	0.0800	0.9379	-0.3260	0.3723	-0.8800	0.3811
Disclosure	0.3167	0.1759	1.8000	0.0969	0.3864	0.3522	1.1000	0.2726
Rd4win	0.5649	0.2031	2.7800	0.0166	0.9002	0.3987	2.2600	0.0240
σ	-	-	-	-	0.7045	0.2294	3.0700	0.0021
Adj. R^2	0.6005			Log-likelihood	-13.6752			
N	16				16			

The data available does not allow for sharp predictions regarding the effects of subject communication or the number of bundles presented on the relative efficiency of the auction. However, the hypothesis that disclosing the threshold costs may aid in coordination and thus increase overall auction efficiency does find some limited support. Also, the fact that the presence of a Round 4 winner is significant and positively affects relative efficiency in both models suggests that once multiple public goods are introduced, overcoming coordination problems becomes an important component in the successful provision of a public good. More

Table 3. Summary of laboratory results

Trial	Endowment, EMUs	Efficient Total Benefit (TB)	Efficient Threshold Cost (TC)	TB/TC Ratio	Actual TB-TC	Actual Relative Efficiency	Threshold, % of endowment	Seller Profit	Profit Margin	Rd5. Closest contribution	Rd5. Closest Threshold	Shortfall	Shortfall, % of endowment
T1R1	320	476	185	2.6	0	0	0.58	0	0%	36	37	1	0%
T1R2	110	187	65	2.9	76	0.62	0.59	2	3%	15	13	-2	-2%
T1R3	100	208	100	2.1	0	0	1.00	0	0%	62	66	4	4%
T1R4	160	195	85	2.3	77	0.7	0.53	2	2%	19	17	-2	-1%
T2R1	230	275	130	2.1	0	0	0.57	0	0%	13	23	10	4%
T2R2	190	246	120	2.1	0	0	0.63	0	0%	80	120	40	21%
T2R3	160	218	90	2.4	118	0.92	0.56	10	11%	75	65	-10	-6%
T2R4	240	323	135	2.4	127	0.68	0.56	2	1%	29	27	-2	-1%
T3R1	150	202	90	2.2	0	0	0.60	0	0%	17	18	1	1%
T3R2	180	252	110	2.3	104	0.73	0.61	4	4%	26	22	-4	-2%
T3R3	220	305	115	2.7	190	1	0.52	11	10%	126	115	-11	-5%
T3R4	200	270	140	1.9	0	0	0.70	0	0%	110	140	30	15%
T4R1	110	181	75	2.4	100	0.94	0.68	13	17%	67	54	-13	-12%
T4R2	230	343	150	2.3	0	0	0.65	0	0%	100	108	8	3%
T4R3	200	354	115	3.1	239	1	0.58	2	2%	117	115	-2	-1%
T4R4	150	224	85	2.6	139	1	0.57	4	5%	91	85	-6	-4%
T1RAnd	180	187	90	2.1	0	0	0.50	0	0%	15	18	3	2%
T2RAnd	200	165	100	1.7	52	0.8	0.50	12	12%	32	20	-12	-6%
T3RAnd	160	206	80	2.6	0	0	0.50	0	0%	11	16	5	3%
T4RAnd	140	198	70	2.8	0	0	0.50	0	0%	49	50	1	1%
Mean	181.50	250.75	106.50	2.37	61.10	0.42	0.60	3.10	3%	54.50	56.45	1.95	1%
Standard Dev.	52.24	77.22	30.31	0.35	73.68	0.44	0.11	4.53	5%	38.75	42.60	13.06	7%

data is likely needed to say something more definitive about the impact of communication and number of bundles on relative auction efficiency.

Hypothesis testing: seller profit

Current data appears insufficient to support our conjectures on the impact of auction design on seller profit. For instance, hypothesis *H2R* speculates that, conditional on a bundle winning, the seller profits from auctions where threshold costs were not disclosed are higher than seller profits from auctions where a public good was provided but threshold costs were disclosed. While the average of seller profits in non-disclosure treatments was indeed higher than in disclosure treatments, the difference was not statistically significant.

Contributions toward the efficient bundle

One thing to note from Table 3 is that in many auction trials, the public good provision failed by a very small fraction of the total group endowment. In this regard it is interesting to ask: do Round 5 contributions toward the efficient bundle differ systematically across our treatments? Indeed, if any treatment can positively affect the total contributions, then any future auction designed utilizing such treatment is going to be more likely to succeed.[6] Furthermore, as the following Figure demonstrates, in a quite a few cases, the efficient bundle was successful at accumulating contributions in non-binding contribution rounds, only to fall short in the final round. Are any treatments more successful in demonstrating at least some convergence of bids to the threshold level?

[6] Note that the "Shortfall" column in the Table above does not just present the shortfall of contributions necessary to win the efficient public good, but instead shows the smallest shortfall in contributions across all available bundles. Analysis of contributions to inefficient bundles can proceed in the same fashion.

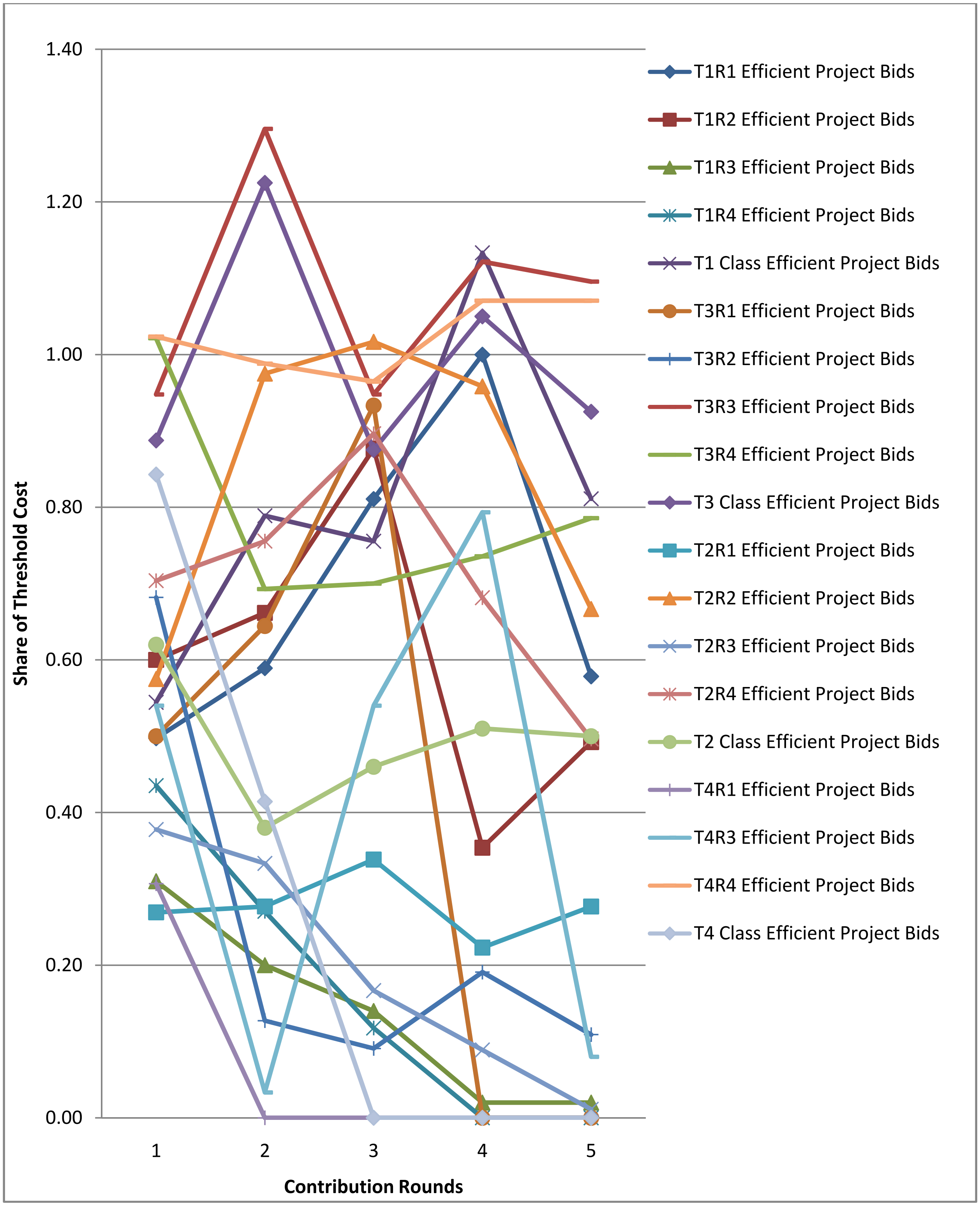

Figure 4. Contributions to the efficient bundle (project), by auction type.

The average contributions to the efficient bundle are significantly higher in the auctions with communication allowed ($p=0.02$) than in the auctions without communication between participants (participants were explicitly instructed not to discuss their endowments or their actual payoffs, which was to remain private information). Other treatments, however, did not affect average contributions to the efficient bundle.

However, an examination of the bidding dynamics between auctions with a small number of bundles and a large number of bundles does suggest that a smaller number of bundles might lead to more ready identification of the efficient bundle by the participants. Figures 5 and 6 below show the bidding behavior in these auctions over the bidding rounds.

Preliminary Conclusions

The experimental testing of the auction component of ECOSEL serves a dual purpose: first, it will inform the design of an actual ecosystem auction. The real-world implications of running an auction with legally binding commitments both on the part of the buyers and the seller (e.g., forest manager) are important and experimental test-beds are providing us with information needed to avoid costly mistakes or failure to get the actual auction off the ground. Second, data obtained from current and future experiments will allow us to empirically test the impacts of important design variables on the performance of a multi-good public good subscription game of incomplete information. The ability of bidders to coordinate their contributions toward the efficient bundle appears to be an important determinant of auction efficiency, while communication significantly raises the average contributions to the efficient bundle. More data appears to be needed for reaching any conclusions regarding the effect of other design variables.

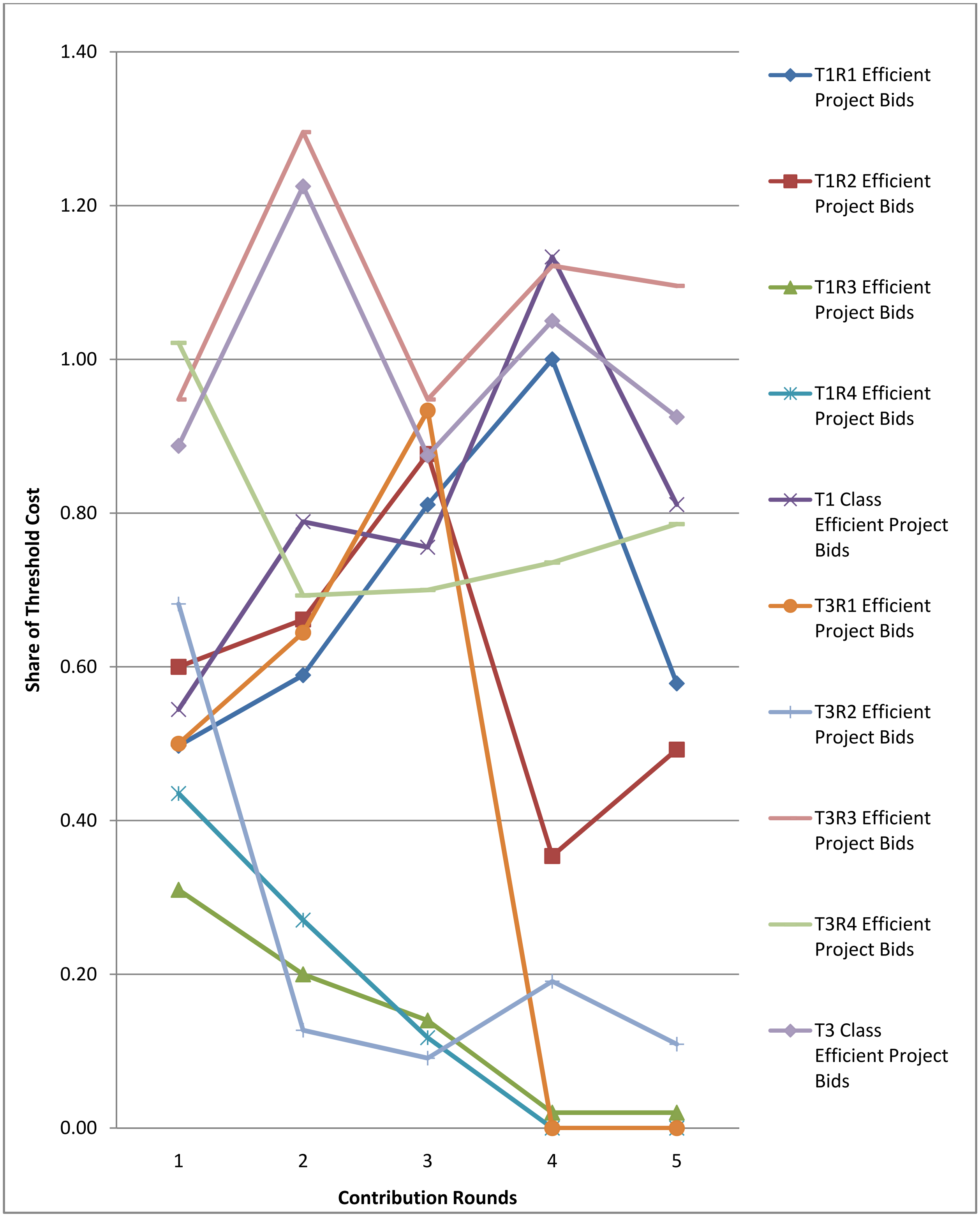

Figure 5. Contributions to the efficient bundle (project), auctions with 3 bundles presented.

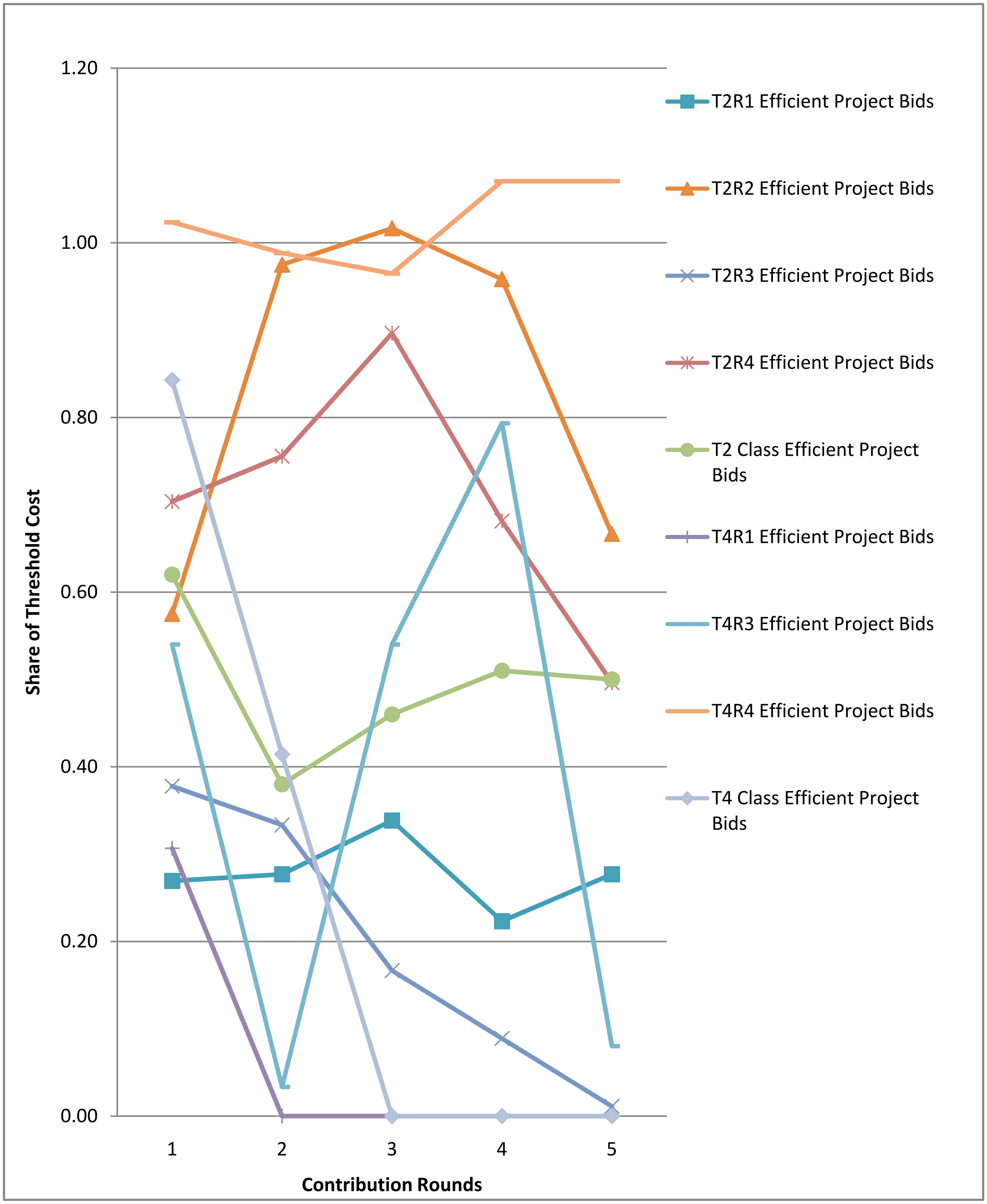

Figure 6. Contributions to the efficient bundle (project), auctions with 5 bundles presented.

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APPENDIX

- **The model formulation**

$$Max \sum_{m \in M} c_{mt} x_{mt} \qquad (1)$$

$$Max \sum_{m \in M} \sum_{t \in T} s_{mt} x_{mt} \qquad (2)$$

$$Max \sum_{m \in M} \sum_{t \in J_m} A_m x_{mt} \qquad (3)$$

subject to:

$$\sum_{t \in T} x_{mt} \le 1 \qquad \text{for } \forall m \in M \qquad (4)$$

$$\sum_{m \in M} v_{mt} \cdot A_m \cdot x_{mt} - H_t = 0 \qquad \text{for } \forall t \in T \setminus \{0\} \qquad (5)$$

$$b_{lt} H_t - H_{t+1} \le 0 \qquad \text{for } \forall t \in T \setminus \{0, \max_T t\} \qquad (6)$$

$$-b_{ht} H_t + H_{t+1} \le 0 \qquad \text{for } \forall t \in T \setminus \{0, \max_T t\} \qquad (7)$$

$$\sum_{m \in C} x_{mt} \le |C| - 1 \qquad \text{for all } C \in \mathcal{C} \text{ and } \forall t \in T \setminus \{0\} \qquad (8)$$

$$\sum_{m \in M} \left[A_m \sum_{t \in T} (Age_{mt}^T - \overline{Age}^T) x_{mt} \right] \ge 0 \qquad (9)$$

$$x_{mt} \in \{0,1\} \qquad \text{for } \forall m \in M \text{, and } \forall t \in T \qquad (10)$$

where the decision variable is:

x_{mt} = a binary decision variable whose value is 1 if management unit *m* is to be harvested in period *t*. In other words, x_{mt} represent a harvesting prescription for management unit *m*. When *t* = 0, the value of the binary variable is 1 if management unit *m* is not harvested at all during the planning horizon (i.e., x_{m0} is the "do-nothing" alternative for management unit *m*). Note: in some cases, the index *j* is used to denote the harvest period. In these cases x_{mj} is the same as x_{mt} if $j = t$;

the auxiliary/accounting variables are:

H_t = the total volume of sawtimber in mbf harvested in period *t*; and

the parameters are:

M = the set of management units in the forest ($|M| = 186$ for Pack Forest);

T = the set of planning periods in the planning horizon ($|T| = 9$ for Pack, assuming 5-year long periods and a 45-year long planning horizon);

A_m = the area of management unit *m* in acres;

c_{mt} = the discounted net revenue per hectare if management unit *m* is harvested in period *t*, plus the discounted residual forest value based on the projected state of the stand at the end of the planning horizon;

s_{mt} = the amount of carbon sequestered in management unit *m* over the entire planning horizon if unit *m* is cut in period *t*;

v_{mt} = the volume of sawtimber in mbf/acre harvested from management unit *m* in period *t*;

b_{lt} = a lower bound on decreases in the harvest level between periods *t* and *t+1*;

b_{ht} = an upper bound on increases in the harvest level between periods *t* and *t+1*;

C = one *cover*, or groups of contiguous management units, whose combined area is just above the maximum harvest opening size;

□ = the set of all covers;

J_m = the set of all prescriptions under which management unit *m* meets the minimum age requirement for old-forest habitat at the end of the planning horizon (in 2050);

Age_{mt}^{T} = the age of unit *m* at the end of the planning horizon if it is cut in period *t*; and

$\overline{Age}^{T}$ = the target average age of the forest at the end of the planning horizon.

Some set theoretical notation:

$|M|$ = number of elements in set *M*; and

$\forall t \in T \setminus \{0, \max_T t\}$ = all members of set *T* except the largest member and zero.

Equation 1 maximizes the discounted net revenues from the forest over the planning horizon, plus the discounted residual value of the forest. This is the traditional, commodity production option. Equation 2 maximizes the net carbon sequestered in the forest over the entire planning horizon. Coefficient set s_{mt} is calculated using the Pack Forest's Landscape Management System and is based on the net change in carbon content of standing timber over the 45 year planning horizon. Equation 3 maximizes the combined area of stands that older than 115 yrs at the end of the planning horizon. Constraint set 4 ensures that each management unit in the forest can only be harvested at most once during the planning horizon. Since none of the stands in Pack Forest are managed on a rotation shorter than 50 years, which is longer than the 45 year planning horizon, this restriction is reasonable.

Constraint sets 5-7 ensure that the total harvest volume flow will not fluctuate too much from one period to the next. Bounds b_{lt} and b_{ht} determine the percentage by which the harvest volume can go below or above the level in the previous period.

Inequalities 8 are the green-up constraints that ensure that the size of contiguous clearcuts never exceeds a certain limit. The maximum harvest opening size is 120 acres defined by the Forest Practices Rules of the state of Washington. We used a 100 acre limit in this experiment further restricting the extent of clearcuts. The formulation of these constraints requires either the complete enumeration of covers (contiguous sets of units whose combined area just exceeds the maximum opening size) using McDill et al.'s (2002) Path Algorithm, or only a partial enumeration using Tóth at el.'s (In Review) dynamic ARM concept. ARM refers to the Area Restriction Model, a term coined by Murray (1999) for harvest scheduling.

Constraint 13 ensures that the area-weighted average age of the forest at the end of the planning horizon will be at least $\overline{Age}^{T}$. Different average ending ages can be defined for each forest type or species. Along with the harvest flow and the green-up constraints, these restrictions prevent the forest from overharvesting. Constraints 10 identify x_{mt} as binary.

Instructions

Thank you for agreeing to take part in this experiment conducted by University of Washington researchers. This project provides an opportunity to earn a considerable amount of money, but only if you are careful to follow directions, make good decisions, and pay attention to the decisions that others are making. Therefore, it is important for you (and for our research!) that you take your time to understand the instructions. These instructions are your private information. Please do not communicate with the other participants unless expressly encouraged to do so. If you have any questions, please ask us.

Throughout the experiment we will use Experimental Monetary Units (EMUs) rather than U.S. dollars. At the end of the experiment your EMU earnings will be converted to U.S. dollars at an exchange rate of 1 EMU = 0.25 U.S. dollars (25 cents).

You have picked an envelope containing a randomly assigned sequence of experiments that you will participate in. A computer randomly generated that sequence, and it is important that you follow your own instructions for the duration of the experiment. We have 4 different classrooms where experiments are conducted simultaneously. Your envelope contains your individual sequence of classrooms. Please move to the classroom indicated when we ask you.

Your task

The experiment consists of you participating in a series of mock auctions. Each auction will last for 5 bidding rounds. At the beginning of each auction, you will be given a randomly assigned amount of EMUs. We will refer to that amount as your "endowment". Your EMUs do not carry over between auctions: that is, you cannot use the EMUs you used in one room in another room. You are assigned EMUs in each experiment and it is important to remember that each auction is a new research trial. However, your EMUs accumulate, and at the end of the experiment you will be paid (total EMUs accumulated/4) dollars. Therefore you should seek to maximize your EMUs in each auction.

In each auction, you and other participants in your room will be presented with a number of 'projects'. You may contribute (bid) any fraction of your endowment to any of the presented projects. Each project has a threshold cost associated with it. If the sum of participants' bids exceeds the project threshold cost, the project will "win" and you will earn the amount of EMUs indicated on your instructions sheet. Your earnings is the "value" you place on the project. Only one project can "win". If contributions to more than one project exceed the threshold cost, for the project for which contribution exceed the cost by the largest amount, wins. Contributions in excess of the threshold cost are kept by the experimenter.

You can bid for multiple projects, but the sum of your bids cannot exceed your endowment. If a project does not "win", you do not have to actually pay your bid. However, if the project you bid for "wins", you MUST surrender the EMUs you bid on that project. If no project accumulates enough bids to cover its cost, you get to keep your endowment, but you earn no additional money.

After each round of bidding, you will be informed of 1) the total bids for each project and 2) whether any project is "winning". If, after the last round of bidding, a project "wins", you must put the EMUs you bid on the winning project in the envelope and hand it to us.

Example and Control Questions

In order for you to better understand the auction, let's go through a simple example. The values below are NOT the values you will see in actual auctions, and are for illustrative purposes only. Let's walk through the bidding rounds of a sample auction:

Projects, costs, and earnings

Project	Threshold Cost, EMUs	Your earnings if project wins, EMUs
A	100	5
B	200	12
C	300	15

Suppose your endowment is 10 EMUs. Now, the bidding starts, and we orient you to the auction:

Round 1

Project	Threshold Cost, EMUs	Your earnings if project wins, EMUs	Your bid, EMUs	Total group bid, EMUs	Project winning?
A	100	5	2	150	Yes
B	200	12	3	210	No
C	300	15	5	250	No

Both projects A and B have sufficient bids to cover their threshold costs, but total bids for A exceeds the cost by 50 EMUs, while total bids for B exceed the cost by only 10 EMUs, so, after Round 1, A is "winning".

Round 2

Project	Threshold Cost, EMUs	Your earnings if project wins, EMUs	Your bid, EMUs	Total group bid, EMUs	Project winning?
A	100	5	0	130	No
B	200	12	5	240	Yes
C	300	15	5	250	No

Both project A and B have sufficient bids to cover their threshold costs, but total bids for B exceed the cost by 40 EMUs, while the total bids for A exceed the cost by only 30 EMUs, so, after Round 2, B is "winning".

Round 3

Project	Threshold Cost, EMUs	Your earnings if project wins, EMUs	Your bid, EMUs	Total group bid, EMUs	Project winning?
A	100	5	0	110	No
B	200	12	3	220	Yes
C	300	15	6	280	No

Round 4

Project	Threshold Cost, EMUs	Your earnings if project wins, EMUs	Your bid, EMUs	Total group bid, EMUs	Project winning?
A	100	5	0	110	No
B	200	12	0	215	No
C	300	15	8	320	Yes

Round 5 (Final round)

Project	Threshold Cost, EMUs	Your earnings if project wins, EMUs	Your bid, EMUs	Total group bid, EMUs	Project winning?
A	100	5	0	102	No
B	200	12	2	210	Yes
C	300	15	3	298	No

The auction ends, with project B "winning". Since you bid 2 EMUs on project B, you have to give us 2 EMUs. Your bid on project C does not have to be paid, since project C did not win. In addition, you win 12 EMUs (so your net gain from this auction is 12-2=10 EMUs).

Self Test—Let's see how well you understand the procedure.

1. If we give you 20 EMUs for the first auction, and 15 EMUs for the second auction, how many EMUs do you have to bid with in auction 2? ______________
2. If the sample auction above ended after Round 3,
   a. Which projects would "win"? _____
   b. How much would you be required to pay? ___
   c. What would be your earnings from the auction? ____
3. If, at the end of the entire experiment, you have accumulated 45 EMUs from Auction 1, 20 EMUs from Auction 2, 40 EMUs from Auction 3, and 55 EMUs from Auction 4,
   a. How many EMUs have you accumulated at the end? _______
   b. How many dollars would you be paid for your participation? _______

Setup
We use 4 rooms, and a Latin squares design to assign auction types to rooms. Each room will see 4 auctions ("runs"). The assignment of auction types to Rooms is the following:

Runs → Rooms ↓	1	2	3	4
R1 (EEB 025)	T1	T2	T3	T4
R2 (EEB 026)	T2	T3	T4	T1
R3 (EEB 042)	T3	T4	T1	T2
R4 (EEB 054)	T4	T1	T2	T3

Allocation of subjects to auctions

		Auction Type Assignment					Room Assignment		
Subject ID	Run 1	Run 2	Run 3	Run 4		Run 1	Run 2	Run 3	Run 4
1	1	3	2	4		1	2	4	1
2	1	4	2	3		1	3	4	4
3	2	4	3	1		2	3	1	2
4	3	1	2	4		3	4	4	1
5	2	4	3	1		2	3	1	2
6	1	2	4	3		1	1	2	4
7	1	3	4	2		1	2	2	3
8	1	4	3	2		1	3	1	3
9	2	4	1	3		2	3	3	4
10	4	3	2	1		4	2	4	2
11	1	4	2	3		1	3	4	4
12	1	4	3	2		1	3	1	3
13	3	1	4	2		3	4	2	3
14	4	3	1	2		4	2	3	3
15	1	3	4	2		1	2	2	3
16	4	1	3	2		4	4	1	3
17	2	3	1	4		2	2	3	1
18	1	4	3	2		1	3	1	3
19	1	2	4	3		1	1	2	4
20	2	1	4	3		2	4	2	4
21	1	3	2	4		1	2	4	1
22	1	4	2	3		1	3	4	4
23	2	3	1	4		2	2	3	1
24	3	2	1	4		3	1	3	1

25	2	4	3	1		2	3	1	2
26	1	3	4	2		1	2	2	3
27	3	4	1	2		3	3	3	3
28	4	2	1	3		4	1	3	4
29	1	4	3	2		1	3	1	3
30	2	1	4	3		2	4	2	4
31	2	4	3	1		2	3	1	2
32	2	4	1	3		2	3	3	4
33	3	1	4	2		3	4	2	3
34	1	2	4	3		1	1	2	4
35	3	1	4	2		3	4	2	3
36	1	2	3	4		1	1	1	1
37	1	3	4	2		1	2	2	3
38	2	1	4	3		2	4	2	4
39	3	4	2	1		3	3	4	2
40	1	2	4	3		1	1	2	4
41	3	2	1	4		3	1	3	1
42	2	3	1	4		2	2	3	1
43	1	2	3	4		1	1	1	1
44	4	3	2	1		4	2	4	2
45	1	3	4	2		1	2	2	3
46	1	4	2	3		1	3	4	4
47	1	2	3	4		1	1	1	1
48	4	2	1	3		4	1	3	4
49	3	2	4	1		3	1	2	2
50	4	1	3	2		4	4	1	3
51	4	2	1	3		4	1	3	4
52	4	3	2	1		4	2	4	2
53	2	1	4	3		2	4	2	4
54	2	4	1	3		2	3	3	4
55	2	4	3	1		2	3	1	2
56	1	4	2	3		1	3	4	4
57	2	3	1	4		2	2	3	1
58	3	4	1	2		3	3	3	3
59	1	4	3	2		1	3	1	3
60	3	2	4	1		3	1	2	2

Subject Utilities

Uit = alpha(it)*Xt + beta(it)*Yt, where *alpha* is the subject's preference for component X of the proposed project ("carbon") and *beta* is the subject's preference for the component Y of the proposed project ("mature forest habitat")

Subject ID	alpha(i1)	beta(i1)	alpha(i2)	beta(i2)	alpha(i3)	beta(i3)	alpha(i4)	beta(i4)
1	0	1	1	1	2	1	2	1
2	1	1	2	2	2	1	1	2
3	1	1	0	2	1	1	1	1
4	1	2	2	2	2	1	2	0
5	2	2	0	1	2	2	0	1
6	2	2	2	2	2	1	0	2
7	2	2	1	0	1	1	1	0
8	1	1	1	1	2	1	1	0
9	0	1	0	2	2	0	1	2
10	2	1	2	2	0	2	0	2
11	2	2	1	1	2	2	2	1
12	0	1	0	1	1	0	2	2
13	1	1	2	1	2	1	0	1
14	2	2	0	1	1	0	2	2
15	1	2	2	2	1	2	0	2
16	2	2	1	1	1	2	1	0
17	2	0	1	2	2	0	0	1
18	1	2	2	2	1	1	1	2
19	2	1	2	2	0	1	0	1
20	2	1	1	1	1	0	0	2
21	1	1	1	2	0	1	1	2
22	1	1	0	1	1	1	2	2
23	0	1	1	1	1	2	2	2
24	2	2	2	2	1	1	1	0
25	0	1	2	1	2	2	2	2
26	2	1	1	0	2	2	2	1
27	0	2	2	2	2	2	2	2
28	2	1	1	2	1	2	1	0
29	2	0	1	1	2	2	0	2
30	2	1	0	1	1	2	2	1
31	2	2	1	1	0	2	1	0
32	1	2	2	1	1	1	1	0

33	0	1	2	2	1	1	2	1
34	2	2	2	2	1	1	2	2
35	2	0	0	1	2	1	1	1
36	1	2	1	1	1	2	1	2
37	1	2	1	1	1	2	2	1
38	1	0	1	1	1	2	1	2
39	1	2	2	0	1	1	1	1
40	2	1	0	1	1	1	0	2
41	2	2	1	1	2	2	2	2
42	1	2	0	2	2	1	2	1
43	1	0	0	1	2	2	0	2
44	1	2	1	2	2	0	1	2
45	2	0	1	2	2	2	0	2
46	2	0	2	0	1	0	1	1
47	2	1	1	2	0	1	0	1
48	1	1	2	2	1	0	0	1
49	1	2	1	0	2	0	2	0
50	1	1	1	2	0	2	0	2
51	2	2	2	0	1	0	2	1
52	1	1	0	2	2	1	1	2
53	0	1	1	2	0	2	0	2
54	1	1	2	0	0	1	2	0
55	2	1	2	1	1	0	1	2
56	2	0	2	1	1	0	1	0
57	1	1	1	1	0	1	1	0
58	1	2	1	1	2	0	0	2
59	1	2	0	2	0	1	0	1
60	2	1	0	1	1	1	1	2

Subjects are endowed with an amount of EMUs before each auction. Thus, we need to create 4 endowments (w(it)). Subject endowments are drawn from {10,20}. The following table gives the endowments:

Subject ID	w(i1)	w(i2)	w(i3)	w(i4)
1	10	20	20	20
2	20	10	10	10
3	10	10	20	20
4	10	20	10	10
5	20	10	20	20
6	10	20	10	20

7	10	20	20	10
8	10	10	10	10
9	10	10	10	20
10	10	10	10	20
11	10	10	20	10
12	20	20	20	20
13	20	20	10	20
14	20	10	10	10
15	20	10	10	20
16	10	10	20	20
17	10	20	20	10
18	10	20	10	20
19	20	20	20	20
20	10	10	10	20
21	20	10	10	20
22	10	10	20	10
23	20	10	10	10
24	10	20	10	10
25	20	20	20	20
26	10	10	10	20
27	20	10	10	10
28	20	20	10	20
29	20	10	20	20
30	10	10	10	10
31	20	20	20	10
32	20	10	10	20
33	20	10	10	10
34	10	20	10	20
35	20	10	10	20
36	20	20	10	10
37	20	20	20	10
38	20	10	20	10
39	10	20	20	10
40	20	20	10	10
41	20	10	10	20
42	20	20	20	20
43	20	10	10	10
44	20	10	20	10
45	20	20	10	10
46	20	10	10	10
47	10	10	10	20

48	20	20	20	20
49	20	20	10	20
50	10	10	20	10
51	20	20	10	20
52	20	10	20	10
53	20	20	20	10
54	10	20	20	10
55	20	10	10	20
56	20	20	10	10
57	20	20	20	10
58	10	20	10	10
59	10	20	10	20
60	20	10	10	10