The Effective Use of Limited Information: Do Bid Maximums Reduce Procurement Cost in Asymmetric Auctions?

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Abstract

Conservation programs faced with limited budgets often use a competitive enrollment mechanism. Goals of enrollment might include minimizing program expenditures, encouraging broad participation, and inducing adoption of enhanced environmental practices. We use experimental methods to evaluate an auction mechanism that incorporates bid maximums and quality adjustments. We examine this mechanism's performance characteristics when opportunity costs are heterogeneous across potential participants, and when costs are only approximately known by the purchaser. We find that overly stringent maximums can increase overall expenditures, and that when quality of offers is important, substantial increases in offer maximums can yield a better quality-adjusted result.

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Introduction

Many environmental goods and services are generated from natural resources that are privately controlled. Thus, programs to enhance their provision require the participation of non-government actors. In many cases, these programs do not use regulatory approaches. Instead, the government pays owners of the resources to voluntarily change their practices.

Assuming that the government prefers to minimize expenditures, or to maximize social welfare, program implementation needs to consider the design of an enrollment mechanism. The enrollment mechanism can consider a number of goals. These include:

1. Minimizing payment, with a target of paying the reservation price to participants;
2. Encouraging broad participation, so as to attract low-cost providers to the program;
3. Encouraging program participants to improve environmental quality whenever it is cost effective.

Achieving this suite of goals may not be easy. The inherent difficulty arises because of an asymmetry of information – the government has superior information about how particular land-use decisions translate to environmental quality, while private landowners have superior information on the private cost of undertaking specific practices (Cason and Gangadharan (2004)).

Motivation: the case of the CRP

As an important example, consider the USDA's Conservation Reserve Program (CRP), which achieves its habitat and soil protection goals by paying landowners to retire their environmentally sensitive land from active crop production. The CRP's enrollment mechanism is competitive, with interested landowners placing offers for acceptance into the program during scheduled signups. There are three major components of the enrollment mechanism.[2,3]

1. Each parcel offered is scored using an Environmental Benefits Index (EBI). The EBI is a linear combination of several measures of the environmental benefits achieved by retiring the offered land, and the size of the payment demanded by the landowner (the bid). Only offers that achieve a target EBI are accepted.

2. Landowners can increase their EBI score by adopting beneficial conservation practices. However, landowners must incur some out of pocket costs to install these practices, thereby reducing their net revenues.

3. Landowner bids are capped, with the cap based on a soil rental rate derived from adjusting a county average agricultural land rental rate with a measure of the soil productivity of the offered land.

In total, the CRP uses a sealed-bid reverse auction with (i) a maximum bid established by a quick-and-dirty land-rent assessment, and (ii) a quality-adjusted scoring method. That is, there are two mechanisms to limit the economic rent a landowner might achieve by participating in the auction: the soil rental rate (the assessment) and the EBI ranking (the quality-adjusted score).[4]

A critical component determining the total cost of operating the CRP is the asymmetric distribution of landowner opportunity costs. Some landowners have low opportunity costs (e.g. wheat growers in Montana) while others have high opportunity

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2. See Reichelderfer and Boggess (1988), Shoemaker (1989), and Latacz-Lohmann and Van der Hamsvoort (1997) for early reviews of the CRP, and Johansson (2006) and Kirwan, Lubowski and Roberts (2005) for detailed information on the CRP bidding mechanism and the Environmental Benefit Index.

3. The CRP allows enrollment through two distinct mechanisms: the general signup (that accounts for most enrollments) and the continuous signup (that targets parcels eligible for highly desirable practices). The general signup is what we consider here; the continuous signup is not competitive.

4. See Vukina, et al. (2008) for a paper concerned with the joint role of the cost factor and environmental score in determining participant bids.

costs (corn growers in Iowa). Since the CRP is a national program, if a single-price mechanism were used, landowners with low opportunity costs could earn substantial economic rents. The use of some form of price discrimination, such as the bid caps, can deliver substantial savings to the government.

But how effective are these bid caps? Prior work by Kirwan, Lubowski and Roberts (2005) finds that landowners are on average overpaid 20% relative to their opportunity costs, suggesting that landowners accepted into the program would have been willing to accept less. Similarly, Horowitz, Lynch and Stocking (2009) find that bids in an auction where the state purchases farmland development rights are 5-15% above landowner opportunity costs. Lowering the bid caps would, of course, lower the rent accruing to accepted landowners.

On the other hand, lowering the bid caps is not without tradeoffs. If bid caps are lowered too far, potentially attractive offers are lost. Whenever the bid cap is below the actual opportunity cost of a landowner (which is unobservable to the government), the landowner will refuse to participate.[5] Thus setting a bid cap influences the total cost of operating the CRP in two ways: by lowering the rents that accrue to accepted bidders, and by potentially discouraging bidders from participation. This is the tradeoff the government must evaluate when setting bid caps. The government must make sure that the gain from limiting rents is not outweighed by the loss from excluding otherwise competitive bidders.[6]

This insight can be illustrated with the following simple example.

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5. More precisely, the bid a landowner may receive is compared to a broadly defined "opportunity cost" that can include the full distribution of profitability (incorporating average returns and risk), and possible non-pecuniary benefits (i.e.; a landowner's appreciation of natural habitat).

6. This inherent tension is present in the workhorse model of auctions, the single-object Independent Private Values (IPV) model with symmetric bidders. In this model, the buyer sets a maximum bid primarily to prevent "bad outcomes," i.e. to prevent purchase from a particularly high-cost bidder when competition is low. The maximum bid must not be set too low; a low maximum would prevent profitable exchange in many circumstances. See the classic paper by Myerson (1981), which shows the role of reserve prices in optimal auctions, and Bulow and Roberts (1989) to see how the optimal reserve price relates to standard economic theory.

Assume there are 100 landowners, each with a unit of land of homogeneous environmental quality. However, the agricultural profitability is heterogeneous; in fact, it is uniformly distributed between \$1 and \$100. Lastly, assume the government's goal is to retire 50 units of this environmentally homogeneous land, and to do so at minimum total cost.

Consider two scenarios where the government uses imperfect assessments of each unit's opportunity cost, and bases its offer on this assessment.

1. An unbiased assessment: the assessment is either \$1 below the true opportunity cost, exactly equal to the true opportunity cost, or \$1 above the true opportunity cost, with equal probability. That is, the assessment, y_i, is equal to $y_i = i + \varepsilon_i$, where ε_i is random variable that can take a value of -1, 0, or 1. On average, ⅓ of the assessments will be below the true opportunity cost, hence these parcels will not be offered. This yields an expected total cost of $\sum_{i=1}^{50} \tilde{y}_i = \$1,937.50$,where $\tilde{y}$ denotes the ordered assessments, i.e. the assessments ordered from lowest to highest, excluding all assessments that are below the true opportunity cost (all assessments where $\varepsilon_i = -1$).

2. A biased assessment that always adds \$1.00 to the estimate above: $y_i = i + \varepsilon_i + 1$. All units will be willing to offer, and will make (on average) \$1 in rent. The 50 lowest assessments have a maximum cost of \$52, and the total expected cost will be $\sum_{i=1}^{50} \tilde{y}_i = \$1,325$.

Thus: the use of an accurate and unbiased assessment can lead to a markedly worse outcome than would be achieved using a less accurate and biased assessment.[7]

[7] Note: a short MATLAB script that computes the above results is available from the authors upon request.

Given these kinds of issues with the bid cap mechanism, we are interested in several empirical questions that can affect the performance of auctions for environmental services:

1. What are the performance characteristics of a noisy assessment in an auction setting with asymmetric bidders?
2. How does a bidder's ability to increase the quality of an offer, say by adopting more or fewer environmentally friendly conservation practices, affect bidding behavior and procurement costs?
3. How do these results change as the bid caps and scoring functions vary?

Due to the complexity of an asymmetric, multi-unit bidding game, models with a closed form solution are not available. Furthermore, while there is a wealth of data on participants in conservation auctions (such as data on offers made to the CRP), there is little data on potential participants who never actually participate (say, eligible landowners who never submit an offer to the CRP). Therefore, we use laboratory experiments to address the preceding questions. In the lab, we are able to observe both potential and actual bidders, with a constant and observable distribution of costs. In addition, experiment participants can be subject to simultaneous variations in both bid caps and in the ability to increase offer quality.

Experimental Design

Nine 1.5 hour sessions were conducted, each session involving nine or ten participants. All participants were undergraduate students at the University of Maryland. During a session, between 30 and 50 independent auctions were held, with total payout to participants based on the sum of earnings across all the auctions.

All auctions were conducted using customized software. In a given auction, each participant was presented with two tickets. These tickets, depicted onscreen, were the commodity that each participant offered to sell to a computerized buyer. On each ticket a cost was printed, and a text box labeled "offer box" was displayed. Subjects submitted bids simply by entering numbers into the offer box corresponding to the appropriate ticket. In some treatments, subjects were given the option of purchasing quality points (an abstraction of landowner's ability to improve their EBI score by implementing practices on their land) by entering the desired quantity into a second text box. Participant earnings for accepted tickets were simply the offer amount minus the cost printed on their ticket (an induced value; Smith (1976)). When applicable, this cost includes the cost of purchasing quality points. For rejected tickets there was no loss – the cost was only imposed when an offer was accepted.

In each auction, the 12 tickets with the *lowest* scores were accepted (11 tickets in the nine-participant sessions). A ticket's score is calculated simply as the offer (the amount of payment the bidder requested for the ticket) minus the quality points the bidder elected to purchase. That is, quality points are scaled so that one extra quality point improves a bidder's score by the same amount as lowering the offer price by one dollar. After each auction, participants were informed which of their tickets from the prior auction were accepted (if any), and their earnings. Bidders were also informed of the maximum accepted offer from the prior auction. Note that each participant could have zero, one, or two of their tickets accepted in each auction.

To capture the asymmetry of costs, tickets were divided into four groups. The groups can be characterized as *low cost with low variance*, *low cost with medium variance*, *medium cost with medium variance*, and *high cost with high variance*. As described in Table 1a, these groups mimic important features of the CRP applicant pool.

Two crucial assumptions underlie our method of assigning costs: the purchaser (i.e. the government) can identify the group, and all parties (landowners and the government) know the cost distribution within each group. However, actual costs are only observed by the ticket holder (i.e. the landowner) – hence, price discrimination (in the form of an offer maximum) is group-specific (rather than participant-specific).

As detailed in the Appendix, all cost draws are from uniform distributions with supports designed to construct the aforementioned cost groups. This design mimics a salient feature of the CRP – a portion of the opportunity cost of land is observable, and a portion is unobservable.[8] Each participant got one low-cost ticket, and one high-cost

8 Compared to the actual CRP, a ticket's "group" proxies for observable features of an offered land parcel that correlate with profitability, such as the soil quality of offered land and the average cropland rental rate for the county.

ticket. All participants were fully informed of the distribution of ticket costs, but had no information on the actual cost draws of other participants.

A summary of treatments is given in Table 1b. Details of the treatments follow.

Bid Caps

Each ticket had a bid cap based on what group the ticket is in. These group-specific bid caps were imposed in each auction. The bid cap for each ticket was displayed onscreen, and participants were not allowed to exceed this amount.

Quality Points

As previously mentioned, bids with the lowest *score*, not necessarily the lowest-priced bids, were accepted. The score is simply given by: Offer Amount – Quality Points. We did not allow quality points (Q) to be purchased in all auctions, so that we could identify the impact that an endogenous score had on bidding behavior and total procurement cost. When quality points were available for purchase, participants could choose to purchase up to a maximum of $\bar{Q}$ "quality points." Thus, participants entered both an offer amount and quality points. Earnings for accepted tickets were then calculated as

$$\text{Offer Amount} - 0.5 * \text{Quality Points}.$$

Note that each participant was subject to the same constraint on points, $\bar{Q}$, and $\bar{Q}$ varied across treatments. Note also that quality points are valued at more-than-par by the government – they reduce a bidder's score on a one-to-one basis, but reduce a subject's earnings by only \$0.50.

Expectations

It is useful to consider some expected experimental results, and the conditions that might change these expectations.

HYPOTHESIS 1. *The low-cost, low-variance bidders will make offers equal to the bid caps when the bid caps are cost-effective.*

Our expectation is that the bidders with the very lowest opportunity costs will always be constrained by bid caps when these caps are set at cost-effective levels. That is: the marginal bid in each auction is expected to be well above the maximum bid (the bid cap) of every low cost, low variance bidder.[9] Thus we expect these bidders to be constrained by the bid caps under a cost-effective mechanism.

HYPOTHESIS 2. *Auctions will outperform a single-price offered by the purchaser.*

Prior work by Schilizzi and Latacz-Lohmann (2007) suggests that a single-price mechanism results in lower total costs than an auction. However, the environment we construct here is different from that considered by Schilizzi and Latacz-Lohmann.[10] The presence of identifiably distinct groups of bidders with endogenous quality choices more closely parallels the environment of the CRP. As we discussed above, if the government sets a single offer price too low, participation rates of otherwise competitive bidders might well drop significantly. In this environment, it might make sense to impose relatively high bids caps on individual groups of bidders, but to let competition determine the price paid by the marginal bidder.

> HYPOTHESIS 3. *Competitive bidders, i.e. those submitting bids near the margin of acceptance, should purchase quality (Q points) in order to reduce their score and improve their chances of being accepted. Low cost bidders will not purchase quality points.*

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9 Since the participation of low cost bidders is important to cost minimization, the maximum allowable bid should not be set too low for this group. However, in many cases even a generous bid cap will still be well below the marginal bid.

10. Schilizzi and Latacz-Lohmann do, in fact, make experimental subjects aware of their relative competitiveness. They do not, however, attempt to discriminate using different bid caps, as the CRP does, and as we do here.

Bidders that want to reduce their score should do so first by purchasing quality points, as they are valued more than one-to-one by the buyer. Since Q points are valued more than one-to-one by the buyer, for bidders who wish to lower their score it is always optimal to first purchase up to $\bar{Q}$ points, and then lower their asking price if a further score reduction is desired.

HYPOTHESIS 4. *A high $\bar{Q}$ can induce greater competition.*

A high $\bar{Q}$ gives high cost bidders the ability to compete effectively by offering high quality bids (bids with a large amount of Q points). This extra competition may induce low cost bidders to lower their offers.

HYPOTHESIS 5. *If quality is important, increasing bid caps may be advantageous even though this may reduce competition.*

Relaxing bid caps allows low-cost bidders to improve the quality of their offers while increasing their profits, and do this without diminishing their probability of acceptance. While this can lead to an increase in the quality of accepted offers, it also means that low-cost bidders may receive greater rents.

Design Issues

The several questions addressed in this research are not readily characterized as independent decisions. Varying the stringency of bid caps, and increasing the opportunity to add quality points, are both likely to have continuous, but not necessarily linear effects on both individual bidding behavior and on aggregate performance. Moreover, the two effects may have interactions.

These essential features conditioned our experimental design. Given the non-independent nature of our questions, a suitable set of pairwise comparisons of treatments would have been quite complex to administer, and hence difficult to implement. Therefore, our design was structured around providing data for regression analysis, rather then providing data for simpler tests (such as comparisons of means). While a dependence on regression is not the norm in laboratory situations, adopting this strategy did offer several advantages. These included randomization of treatments within a session, testing for several levels of stimuli in various combinations, and using respondent-specific information when combining data across sessions. Similarly, session-specific characteristics (such as due to changes in group size, or experience) can be controlled for.

This strategy also permitted us to adapt our treatment schedule to add more variation where it was needed. In the spirit of Wald (1947), we adapt our design so that "the decision to terminate the experiment depends, at each stage, on the results of the observations previously made." In practice, analysis and inspection of earlier round data provided information on where additional data was required, both in terms of additional rounds with the same treatment (so as to reduce variance by increasing degrees of freedom), and in presenting treatments with untested attributes levels (so as to reduce variance by expanding the range of data coverage). In a colloquial sense, our design strategy encouraged "learning from the experiment", in adapting treatments to insights gleaned during earlier stages of data collection.

Results

Dependent variables

Given the complexity of the bidding game, we focus on aggregate results rather than the behavior of individual subjects. While the micro-level decision making of bidders is interesting in its own right, we are primarily interested in aggregate outcomes such as the total cost of the program and the level of Q points purchased. In particular, we are interested in metrics that capture the cost-effectiveness of each treatment's mechanism.

Two different aggregate metrics are used as dependent variables. The first, a metric we call the *cash rent ratio* (CRR) ignores quality, and just examines the cost of acquisition. The second metric, which we call the *score rent ratio* (SRR) treats quality as commensurate with cost, in terms of acquisition goals. In each case, a normalization is used to condition-out idiosyncratic characteristics of an auction. [11]

The CRR normalizes by the full information cost of obtaining the targeted goal (the normalization is by *optCosts*, a value we describe below). That is, we normalize by the cost of procuring *A* tickets in the hypothetical case when the purchaser can perfectly observe the true costs of all the tickets, and then buy any subset of these tickets at the true costs. Note that purchasing the *A* tickets with the lowest costs is also the most "efficient" mechanism, assuming that the "costs" represent opportunity costs (say, in the context of the CRP, the value of forgone agricultural production). We can write *optCosts(A)*

$$optCosts\left(A\right)=\sum_{i=1}^{A}sCost_i \tag{1a}$$

Where:

A = Number of accepted tickets,

$sCost$ = sorted costs. Thus, $sCost_1$ is the cost of lowest cost ticket, and $sCost_T$ is the cost of the highest cost ticket.

The *cash rent ratio* can then be expressed as

$$CRR \equiv offers/optCosts=\frac{\sum_{t=1}^{T}Offer_t \times Accept_t}{optCosts(A)} \tag{1b}$$

Where:

$Offer_t$ = Actual offer for ticket *t*.

$Accept_t = 1$ if offer is accepted (one of the *A* lowest offers), 0 otherwise.

The *score rent ratio* normalizes by *optQCosts*, a measure which adds to *optCosts* the cost of obtaining the *Q* points obtained in an auction. Note that we do not know the number of *Q* points that will be obtained by the buyer in a given auction *ex ante*. As such, SRR is normalized by the lowest possible cost of obtaining the number of *Q* points that

11 To mimic how conservation programs such as the CRP are structured, our experimental auctions are based on an enrollment target, rather than on budget exhaustion or achieving a quality goal. This feature dictates what we use for normalization variables.

were actually obtained in a given auction, *ex post*. That is, we start with *optCosts*, and then assume that "after the fact" the total quantity of *Q* points obtained in the auction could have been purchased from the lowest-cost tickets.

$$optQCosts\left(A\right) = optCosts\left(A\right) + 0.5 \times \sum_{t=1}^{T} Q_t \times Accept_t \qquad (2a)$$

Where:

Q_t = *Q* points included in ticket *t*'s offer,

0.5 = Cost of a *Q* point.

The *score rent ratio* can then be expressed as

$$SRR \equiv Scores / optQCosts = \frac{\sum_{t=1}^{T} Score_t \times Accept_t}{optQCosts\left(A\right)}. \qquad (2b)$$

Independent variables

The two dependent variables are regressed against several sets of independent variables:

1. Treatment dummies: these capture the effect of different levels of the maximum price, and different $\bar{Q}$ (maximum quality points) values.
2. Treatment and session descriptors: these capture the influence of variation in session participants, such as a measure of their prior experience with auctions. Note that these are based on session-specific statistics, such as the mean number of correct responses to a set of debriefing questions.
3. Session-specific fixed effects. These are dummies that capture unexplained factors specific to a session. Due to problems with rank, only subsets of these dummies can be used.[12]

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12 Several sets of dummies were experimented with. Since the qualitative differences were minor, in this paper we report results using four fixed effect dummies: for the fifth, seventh, ninth, and third or fourth sessions. Hence, sessions one, two, three, six, and eight are treated as having the same level of fixed effect. For those interested, the complete regressions (including the coefficients for the fixed effect dummies) are available from the authors upon request.

4. A single-price cost is computed using the highest cost of an accepted ticket (as may be obtained using a reverse clock auction): $singleCost = A \times sCost(A)$. A cost dispersion variable (*cDispersion*) is then computed as: *singleCost/OptCosts*.

Summary Statistics

In several regressions we compute a feasible, single-price acquisition cost. We use the cost of the smallest rejected offer, as would be the expected result of a multi-unit Vickrey reverse auction in a group of non-colluding rational players.

$$vickreyCost(A) = A \times sCost_{A+1} \tag{3a}$$

Where:

$sCost_{A+1}$ = the cost of the least expensive rejected offer.

We generate a summary statistic that normalizes the above by the measure *optCosts*. That is, in Table 2 we report a summary statistic of:

$$\frac{vickreyCost(A)}{optCosts(A)} \tag{3b}$$

This variable provides a measure of cost variation – roughly speaking, the higher the value, the greater the distance between the "*A+1*" cost and the lowest cost.

We also define *Offers/vickreyCost* as a measure of auction effectiveness

$$\frac{\sum_{t=1}^{T} Offer \times Accept_t}{vickreyCost(A)}. \tag{3c}$$

As reported in Table 2, values of *Offers/vickreyCost* greater than 1.0 signal that the auction does not yield lower costs than a feasible single-price mechanism.

In Table 2 we also report the profit rate:

$$\frac{\sum_{t=1}^{T}\left(\left(Offer_t - Cost_t\right) - 0.5Q_t\right) \times Accept_t}{\sum_{t=1}^{T}\left(Cost_t + 0.5Q_t\right) \times Accept_t}, \tag{4}$$

which is simply the net earnings divided by costs for the accepted tickets. Note that the costs of purchasing *Q* points are included in both the numerator and the denominator.

There were 9 different sessions. A total of 45 treatments were used across all sessions, encompassing about 340 separate auctions. Note that a number of treatments were repeated across sessions (see Table 1). Each auction had a different cost draw, with the first 5 sessions drawing from the "broader cost range," and the next 4 from the "narrow cost range" (as described in Appendix 2).

Table 2 displays summary statistics by cost range and by broad treatment type. The two broad treatment types are treatments with, and treatments without, quality points.

In general, it is not surprising that in the broad cost scenarios greater profit is found. For example, in the scenarios without *Q* points, comparing the treatments with a broad cost range to treatments with a narrow cost range, we see a decline in CRR from 1.6 to 1.48 (though the standard errors are relatively large). Similarly, the *profitRate* is larger in the broad cost range sessions.

There is mixed evidence on how incorporating quality affects efficiency: for the broad cost sessions, the normalized measures are similar (CRR when *Q* points are not available is close to SRR when *Q* points are available), while for the narrow cost sessions incorporating *Q* points seems to increase efficiency (from 1.48 to 1.21).

These summary statistics reveal some insights on the hypotheses we stated above.

The low-cost, low-variance bidders will make offers equal to the bid caps when the bid caps are optimally set.

> Using a criteria that a "low-cost" ticket is one whose maximum allowed bid is less than the round's maximum accepted offer, about 75% (of about 1700 tickets) *should and did* bid at (or within a percent) of their maximum. Over 90% bid at least 90% of their maximum. Note that although a round's maximum accepted

offer is obviously not known at the moment a participant enters an offer, it does serve as a proxy for expectations.

Auctions will perform better than a single price.

Somewhat contrary to expectations, *Offers/vickreyCost* indicates that a "feasible" single-price mechanism is usually better than the receive-your-bid mechanisms used in these experiments. This result holds in both the broad- and narrow-cost scenarios.

As shown in Table 3, this result holds for all but the 90% maximum. That is, even in a receive-your-bid auction where a substantial fraction of the tickets cannot receive a payment at what would be the Vickrey price (because bids are constrained by bid caps that are lower than this Vickrey price), a Vickrey-style auction would still be cheaper.

When Q points are available, participants should purchase the maximum feasible.

Across all auctions, there were about 1,350 accepted offers that could purchase *Q* points to increase their profit without affecting their probability of being accepted. Of these, only 50% chose an optimal level of *Q*. About 40% could have increased their profits by 15% or more, just by increasing their level of *Q*. In fact, almost 25% could have doubled their profits.

In treatments where explicit hints were given on optimal use of *Q*, over 66% adopted an optimal strategy, yet still almost 20% could have doubled their profits.

On the other hand, when low-earnings offers are dropped, these results are ameliorated, with 2/3 of offers purchasing an optimal amount of Q points, and only 2% being able to double their profit. In the rounds where hints were provided, almost 90% select an optimal amount of *Q* points.

Tickets with sufficiently low maximums will not purchase Q points

Tickets whose bid cap was less than the maximum offer accepted in the round were extracted. Confirming our expectation, over 85% of these offered no points, with most of these offers purchasing less than 2 (out of up to 40) points.

A high $\overline{Q}$ can induce greater competition. However, if quality is important, increasing bid caps may be advantageous even though this may reduce competition.

There is mixed evidence on the impacts of allowing for the purchase of Q points. Acquisition costs increase (i.e. for the broad cost sessions, CRR increases from 1.6 to 1.97), but the quality-adjusted measure decreases (for the broad cost sessions, SRR decreases from 1.97 to 1.64). We examine this question more carefully in the next section.

The next section looks more carefully at these issues, using linear regression to identify how different factors (such as level of the maximums) impact efficiency.

Regression Analysis

Each observation consists of outcomes from an auction or a "round"[13], using either the CRR or SRR as dependent variables.

As detailed in Table 4, several types of independent variables are used. Of primary interest are the treatment dummies that control for the type of auction. Of secondary interest are descriptive variables that capture systematic differences between the participant pool of the session and the cost structure of the auctions. Lastly, session-specific dummies are added. These fixed effect parameters capture idiosyncrasies of the sessions. For the purposes of brevity, the session-specific fixed effect coefficients are not reported.

[13] We sometimes refer to an independent auction as a "round". All auctions were one-shot auctions so there should be no confusion about the use of the word round.

Regression results

We used OLS to examine the effects of the treatment and explanatory variables on the normalized cost variables.

We begin with a model that focuses on treatments where no *Q* points could be purchased (Table 5). Note that in all the regressions reported here the first 3 rounds of each treatment are removed, so as to allow for learning.[14]

The most striking result is that the bid cutoff variables (the PCT variables as described in Table 4) are negative – indicating that a moderately stringent maximum of 80% will increase acquisition costs. The least cost results are achieved at 90%. Although the coefficients are not statistically significant, costs increase once the maximum exceeds 90%.

The cost distribution variables suggest that as the spread of ticket costs increases, so does the acquisition costs. This is not surprising, since when there is a wide range of costs (in a given auction) the difference between the low cost tickets and the cutoff (which will be near the median) will tend to increase. Note that a larger average cost (the *avgCost* variable) decreases normalized acquisition cost – if bids do not vary much across rounds, then as costs increase (across all tickets), rents will decrease.

The *9participants* variable is insignificant and small, suggesting that the number of participants did not have a noticeable impact on acquisition costs.

Lastly, the *avgDebrief* variable, which roughly measures the competency of a session's participants, indicates that more competent groups are more competitive, leading to reduced normalized acquisition costs.

The above models do not account for the impact of *Q* points. Table 6 incorporates all treatments, those with and without the opportunity to purchase *Q* points.

Comparing the results in Table 6 with the "no *Q* points" treatments reported in Table 5, the key parameters do not change dramatically. Total acquisition cost is now minimized with a bid cap of 100%.

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[14] We also ran regressions where other quantities of early round tickets were dropped, ranging from one to 6. In addition, we ran a Huber M estimate (as supported by SAS RobustReg estimator), where only the first round per treatment is dropped. Since the results of these several alternatives were qualitatively similar, we only report the results of the "drop 3" regressions.

What is the impact of the capability to purchase *Q* points? First, as expected, in the CRR model points always increase acquisition costs. Since participants can increase their earnings without changing their scores, we expect that acquisition costs will increase as $\bar{Q}$ increases. This is evident from the large coefficient on *Q40*.

Of greater interest is the impact of points on the score. The implicit assumption is that score is what matters – that the purchaser (say, USDA) values additional quality points just as much as dollar savings. As expected, this capability lowers the *score rent ratio* (the quality adjusted acquisition costs*)* with greater magnitude and significance as $\bar{Q}$ increases.

The *P200xQ40* variable supports this (albeit with weak significance). In these auctions, group A bidders (with low maximums and low costs) can now substantially increase their bids. Bids can be raised to a level where competition occurs (that is, their bids can now exceed the maximum accepted bid). Thus, these low-cost, low-maximum bidders have a large incentive to increase their bids, and to purchase points.

The *avgUnder%* variable is a measure of participant competence. At a value of 0, all bidders are optimally using their points (to increase earnings without affecting their ticket scores). The negative value of the coefficient on *avgUnder%,* while not statistically significant, suggests that acquisition costs are lower in rounds where participants are behaving suboptimally. This is unexpected, since in these rounds participants are leaving cash (and points) on the table.

In contrast *to avgUnder%, extraInfo* suggests that when participants are trained to optimally use points (when hints are given), acquisition costs for scores diminish substantially.

Although the *broadCost* variable is not significant, perhaps the overall cost environment (broad vs. narrow) has other impacts. Table 7 considers each cost environment separately, using *SRR* as the dependent variable. Table 8 considers just cost, so it uses *CRR* as the dependent variable.

When comparing across the different cost ranges, both tables indicate that increasing the bid cap (the maximum bid) has greater impact in the broader cost range sessions. This may not be surprising, given the greater rents that are available to low cost tickets in these sessions. Table 8 indicates that the impact of the ability to purchase *Q* points is strong in both the broad and narrow cost range sessions. However, due to a lack of variety in treatments, the impacts of many points and a high maximum is difficult to detect in the broad session (the *P200xQ40* coefficient suggests these two features negate each other).

Summary

Voluntary conservation programs, such the Conservation Reserve Program, often have multiple goals. In addition to the multiple conservation goals (such as protecting water quality and establishing wildlife habitat), there can be several administrative goals. These include minimizing government expenditures, maximizing program efficiency (by avoiding retirement of the most productive lands), and encouraging participation by a broad range of eligible landowners.

To achieve these goals may be difficult, especially when heterogeneous land is eligible for the programs. Thus, some form of a competitive enrollment mechanism is often used. For example, the CRP ranks offers on an index that combines environmental impacts and cost, and accepts the fraction of offers that exceeds a target score. In addition, the CRP imposes an offer maximum based on a measure of the land's agricultural value.

In this work, we consider two concerns with this type of mechanism, focusing on an environment in which the costs of potential participants are heterogeneous and are only approximately known by the purchaser. First, what are the consequences of different bid caps? If bid maximums are set too high, low-cost land may earn excessively high rents. If maximums are set too low, low-cost lands may not be offered by their owners, or attractive but costly land may not be offered. Second, what are the consequences of allowing landowners to improve the quality of their offers, in addition to setting the price of their offers? If quality is a goal of the program, it is important to consider how the stringency of offer maximums may impact landowner willingness to engage in quality improving practices.

To address these questions, we conducted laboratory experiments. A number of treatments were implemented that approximated different characteristics of possible auctions. These included varying the stringency of the offer maximums, the amount of quality that participants could add to their offer, and the distribution of costs. Cost heterogeneity was implemented by assigning participants to groups that had different cost ranges. A purchasing agent possessing imprecise information was incorporated into the experimental design, as the buyer could identify each participant's group membership, but not their actual costs.

The impacts of mechanism characteristics were measured by linear regression on aggregate measures defined for each auction. To focus on efficiency, both in terms of expenditure minimization and social efficiency, a normalized sum of offers was used as the dependent variable, where the normalization factor was the least cost for achieving a fixed number of acceptances (for a given auction).

Our findings support most of our expectations. To start, the more predictable behaviors were observed. Auction participants with a maximum cost sufficiently below the expected threshold (the cutoff price from the prior auction) almost always bid their maximum. These participants rarely purchased *Q* points.

We also found that most participants, but not all, made optimal use of *Q* points—they purchased as many as possible, and adjusted their offers accordingly. However, a non-trivial number of participants did not follow this strategy; which means they left money on the table (or unnecessarily reduced their odds of acceptance). A side experiment, where explicit hints were given on how to use *Q* points, did increase optimal behavior, but did not result in complete adoption of an optimal strategy.

Furthermore, somewhat contrary to our expectations, we found that the use of a pay-as-bid auction, even in cases where a fairly stringent maximum is imposed, is often less cost effective than an idealized Vickrey auction (where all accepted offers receive the cost of the least-expensive rejected offer).

We were especially interested in the impacts of different bid caps, a question we had weaker priors on, especially when participants could improve their probability of acceptance by purchasing *Q* points. Experiments using several different group-specific bid maximums and *Q* points maximums ($\overline{Q}$) were used to examine this issue.

We find that a too stringent maximum (80%) is quite a poor performer. When no *Q* points are permitted, the most cost effective maximum is 90%, with acquisition costs increasing as the maximum is reduced or increased. In fact, somewhat statistically weak evidence indicates that treatments using a 120% maximum tended to have lower acquisition costs than treatments with an 80% maximum.

When *Q* points are allowed, this pattern held. In addition, although total expenditure is increasing in the opportunity to purchase *Q* points, treatments with higher *Q* point maximums tend to be more "score effective".

To check for sensitivity to cost ranges (i.e. the difference between low cost and high cost ticket groups) we also conducted separate analyses for broad and narrow cost treatments. The maximum percent impacts were stronger in the broad costs, while the impacts of *Q* points were somewhat stronger in the narrow cost treatments. This may be an artifact of the distribution of treatments, since the narrow treatments had more complete coverage of the different maximum-*Q* points possibilities.

Conclusions

Our main finding is that aggressive use of cost maximums may be counterproductive. First, low-cost bidders may have maximums that are below their actual costs, hence they will not participate. If a quantity goal (say, number of acres) is maintained, enrolling higher costs acres may be required.

This phenomenon is even stronger when quality enhancements are permitted, and when these quality enhancements are valued by the purchaser. With stringent maximums, low cost bidders who are still willing to participate have little incentive to improve their offers, since profit maximization occurs when they offer their maximum, with no attempt to improve quality. In fact, one often increases quality-adjusted cost effectiveness by increasing maximums, since this will induce low-cost bidders to improve the quality of their bids by more than the cost demanded.

Our observations of the data suggest stringent maximums can have two effects. First, many tickets will never be profitable – their maximum will be below the cost, and thus the tickets will not be offered. Some of these non-offered tickets will be low-cost tickets. Thus, in order to obtain the targeted number of tickets, some higher-cost ticket will have to be accepted ceteris paribus. Second, it is not difficult for medium cost ticket holders to learn this fact (either from these first principles or by observing earlier round cut off prices), and they may respond by raising their offers.

Our findings are based on simple statistics and linear regressions on aggregate (auction-level) measures. While strongly suggestive, and by and large expected, this analysis is somewhat primitive. Additional sessions with greater field context, that focus on pairwise comparisions of selected changes, would be useful. Additionally, analysis using a structural model of bidder behavior, tracking the behavior of individual bidders, is likely to reveal stronger results.

Table 1a: Explanation of cost groups

Group A *Low Cost* *Low Variance*	*As low cost landowners, they should be enrolled.* *A fairly accurate assessment of their costs is available.* Finding a relatively efficient maximum is easiest for landowners in a lower-variance group, in the sense that a simple rule (say, offer something near the expected maximum) will avoid large overpayments and encourage full participation. Encouraging landowners in a low-cost group to improve the quality of their offers is difficult.
Low cost, medium variance	*As low cost landowners, they should be enrolled.* *Assessed values are noisier for this group than for Group A.* Finding an efficient maximum is more difficult when the variance of bidder costs is increased. For a given bid cap above the group-mean, participation is less likely when variance is increased.
Medium cost, medium variance	*It is probable that several of the marginally acceptable offers will come from this group.* Setting a too high maximum means that a few marginal players are overpaid. Set too low and you might end up not meeting your goals, or being forced to take even higher cost offers from group D.
High cost, high variance	*Most of these costs will cause Group D bidders to be uncompetitive.* Maximums in this group may not matter much – if too low and most of this group does not participate, there is little impact on overall cost (tickets from this group are not likely to be accepted. In some cases (i.e.; high maximum offers for group A and B), the presence of offer from this group might induce more competition.

Table 1b – Schedule of Treatments

Session	Cost Range	Number of Treatments	Number of Auctions	Maximums?	Points for Sale?
1 to 5	Broader Cost Range	3 to 7	22 to 41	80% to 120%	0 to 40
6 to 9	Narrower Cost Range	5 to 7	16 to 32	80% to 200%	0 to 40

Table 2 – Summary Statistics for Dependent Variables

	Broad Cost No Q Points	**Broad Cost Q Points**	**Narrow Cost No Q Points**	**Narrow Cost Q Points**
# of auction rounds	90	90	59	105
vickreyCosts/optCosts	1.48 (0.50)	1.51 (0.40)	1.31 (1.04)	1.35 (0.30)
Offers/vickreyCosts	1.02 (0.20)	NA	1.05 (0.10)	NA
***The cash rent ratio* (Offers/optCosts)**	1.6 (0.30)	1.97 (1.80)	1.48 (0.20)	1.8 (0.30)
***The score rent ratio* (Scores/optQCosts)**	NA	1.64 (1.30)	NA	1.21 (0.20)
profitRate	0.45 (0.20)	0.62 (1.30)	0.36 (0.10)	0.3 (0.15)

Table 3: Summary of auction results

The measured variable is the (Sum Of Accepted Offers) / (cost of a feasible Vickrey auction)

Maximums	Narrower Costs Auctions			Broader Costs Auctions		
	N	Mean	Std Dev	N	Mean	Std Dev
80%	16	1.10	0.12	29	1.03	0.16
90%	26	0.92	0.10	29	0.97	0.11
100%	5	1.08	0.11		n.a..	
120%	17	1.10	0.89	26	1.07	0.14

Note: these results only use data from auctions where Q points could not be purchased.

Table 4 – Descriptive Variables

Treatment Dummy Variables

Variable	Description	% equal 1
PCT90	0/1 dummy: 1 if this is a 90% maximum auction	34%
PCT100	0/1 dummy: 1 if this is a 100% maximum auction	3%
PCT120	0/1 dummy: 1 if this is a 120% maximum auction	32%
PCT200	0/1 dummy: 1 if this is a 200% maximum auction	17%
Q10	0/1 dummy: 1 if this is a Q=10 auction	5%
Q20	0/1 dummy: 1 if this is a Q=20 auction	26%
Q40	0/1 dummy: 1 if this is a Q=40 auction	27%
P200xQ40	0/1 dummy: cross of PCT200 and Q40	12%
P90xQ40	0/1 dummy: cross of PCT90 and Q40	7%

Descriptive Variables

Variable	Description	Mean (stdDev)
9Participants	0/1 dummy: 1 if this is a 9 participant auction	33%
broadCost	0/1 dummy: if this is auction uses the broader cost set	50%
extraInfo	0/1 dummy: set to 1 if extra "hints" about optimal bids, when quality points can be purchased, were discussed at earlier time during this auction's session. Note that treatments with hints were only implemented in one of the nine sessions.	7%
avgDebrief%	Percent of debriefing questions answered correctly (in this session)	0.90 (0.05)
avgCost	Average cost of all tickets in the auction	59.8 (4.7)
SdCost	Standard deviation of all tickets in the auction	26.2 (5.8)
cDispersion	Ratio of singleCost and optCosts. This a measure	1.38 (0.2)

	of the dispersion of costs	
avgUnder%	Average amount of forgone profits from non-optimal use of points (in accepted tickets)	0.16 (0.2)

Variable	With fixed effect dummies	Without fixed effect dummies	Robust regression (drop first rounds only)
Intercept	4.46 (7.1)	2.91 (5.8)	3.64 [0.26]
PCT90	-0.18 (-3.7)	-0.13 (-2.6)	-0.06 [0.021]
PCT100	-0.12 (-0.9)	-0.13 (-1.0)	-0.16 [0.05]
PCT120	-0.06 (-1.2)	-0.0015 (-0.03)	-0.13 [0.02]
9Participants	-0.09 (-1.0)	-0.047 (-1.0)	0.075 [0.036]
avgDebrief%	-2.1 (-3.2)	-0.30 (-0.8)	-1.05 [0.26]
broadCost	0.03 (0.4)	-0.15 (-2.8)	0.0032 [0.03]
avgCost	-0.036 (-7.1)	-0.041 (-8.6)	-0.030 [0.002]
sdCost	0.019 (4.1)	0.02 (4.0)	0.019 [0.002]
cDispersion	0.58 (4.5)	0.69 (5.0)	0.093 [0.056]
# of fixed effect dummies	4	0	4
Rsquare	0.83	0.78	0.060
F-stat (prob)	23.6 (p<0.001)	27 (<0.001)	n.a.
#observations	77	77	77
Scale	n.a.	n.a.	0.063

Notes:

Dependent variable: the *cash rent ratio* (offers/optCosts).
The PCT variables are relative to the “80% maximum” base case.
The POINT variables are relative to the “no points” base case.
(t-stats) in parenthesis, [standard error] in brackets (t-stat not reported by SAS).
# of fixed effect dummies refers to the number of session specific dummies included. Note that due to conditioning problems, it was not possible to include a fixed effect dummy for all nine sessions. Estimates of these fixed effect coefficients are available from the authors upon request.

<u>Table 6 – Regression Results, all treatments</u>

Variable	Dependent Variable: Offers/optCosts		Dependent Variable: Scores/optQcosts	
Intercept	4.34	(9.4)	4.6	(9.4)
PCT90	-0.188	(-4.3)	-0.13	(-2.9)
PCT100	-0.26	(-3.2)	-0.25	(-2.9)
PCT120	0.0016	(0.1)	-0.064	(-1.4)
PCT200	0.32	(4.5)	0.0019	(0.03)
Q10	0.19	(2.8)	0.080	(1.2)
Q20	0.15	(3.3)	-0.065	(-1.4)
Q40	0.33	(6.0)	-0.17	(-2.9)
P200xQ40	0.15	(2.0)	-0.13	(-1.6)
avgDebrief%	-1.97	(-4.0)	-2.47	(-4.8)
avgUnder%	-0.14	(-1.4)	-0.059	(-0.6)
extraInfo	-0.099	(-1.2)	-0.37	(-4.3)
<u>broadCost</u>	0.042	(0.8)	0.10	(1.7)
avgCost	-0.034	(-11.0)	-0.031	(-9.3)
sdCost	0.023	(7.4)	0.020	(6.2)
cDispersion	0.36	(4.1)	0.37	(4.0)
# fixed effect dummies	4		4	
Rsquare	0.84		0.79	
F-stat (prob)	44.7	(p<0.0001)	33.7	(p<0.0001)
#observations	183		183	

Notes:

Dependent variable: the *score rent ratio* (Scores/optQCosts).
The first 3 rounds of each treatment are removed.

Table 7 – Regression Results for Each Cost Environment, all treatments

Variable	Broader cost range (sessions 1 to 5)	Narrow cost range (sessions 6 to 9)
Intercept	4.57 (10.1)	2.37 (5.5)
PCT90	-0.17 (-4.1)	-0.0021 (-0.05)
PCT100	-0.35 (-3.3)	-0.082 (-1.1)
PCT120	-0.11 (-2.4)	-0.040 (-0.9)
PCT200	n.a.	0.069 (1.2)
Q10	-0.034 (-0.7)	n.a.
Q20	-0.12 (-1.96)	-0.095 (-2.3)
Q40	n.a.	-0.32 (-7.8)
P200xQ40	0.069 (0.9)	-0.21 (-3.8)
P90xQ40	-0.21 (-2.1)	n.a
avgDebrief%	-1.67 (-2.8)	0.31 (0.8)
avgUnder%	0.045 (-0.23)	0.18 (2.3)
extraInfo	n.a.	-0.23 (-4.9)
avgCost	-0.043 (-9.1)	-0.025 (-8.7)
sdCost	0.026 (5.5)	0.015 (4.6)
cDispersion	0.44 (3.9)	-0.0016 (-0.1)
# fixed effect dummies	0	0
Rsquare	0.79	0.88
F-stat (prob)	23.05 (p<0.0001)	44.5 (p<0.0001)
#observations	91	92

Note:

Dependent variable: the *score rent ratio* (Scores/optQCosts).
The first 3 rounds of each treatment are removed.
n.a. signifies variables that did not appear in any treatment in these sessions.

Table 8 – Regression Results for Each Cost Environment, no points treatments

Variable	Broader cost range (sessions 1 to 5)	Narrow cost range (sessions 6 to 9)
Intercept	3.95 (5.6)	2.87 (5.3)
PCT90	-0.27 (-4.0)	-0.077 (-1.7)
PCT100	n.a.	-0.10 (-1.52)
PCT120	-0.10 (-1.5)	-0.03 (0.7)
avgDebrief%	-1.16 (-1.8)	-0.34 (-0.8)
avgCost	-0.046 (-6.7)	-0.026 (-6.6)
sdCost	0.023 (3.6)	0.019 (4.3)
cDispersion	0.65 (3.9)	0.069 (0.41)
# fixed effect dummies	1	0
Rsquare	0.84	0.79
F-stat (prob)	29.61 (p<0.0001)	12.5 (p<0.0001)
#observations	47	30

Notes:

Dependent variable: the *cash rent ratio* (Offers/optCosts).
The first 3 rounds of each treatment are removed.
n.a. signifies variables that did not appear in any treatment in these sessions.

Appendix: ticket cost range.

When constructing groups, and their associated ticket ranges, our goal was to capture important features of a population of potential participants, such as the population of CRP eligible landowners. For the sake of efficiency, we do not mimic all the features – participants whose costs render them highly unlikely to participate need not be explicitly reflected in the experiment design. In addition, we structure the cost ranges to guarantee some competition – so that at least for a fraction of the participants there is no obvious strategy. That is, given some rough notion as to the probable cutoff score (say, as intuited from prior round results), not everyone has either a maximum bid below this cutoff, or a ticket cost above it.

Table A2.1 displays the cost range used in the experiment sessions. Note that two distributions of ticket costs were used, with the first 5 sessions using the "broader cost range," and the last 4 sessions using the "narrower range".

Table A2.1 : Cost ranges for tickets

Broader cost range

Group	*Bottom of cost range*	*Top of cost range*
A	30	45
B	10	65
C	35	95
D	40	150

Narrower cost range

Group	*Bottom of cost range*	*Top of cost range*
A	35	55
B	20	80
C	40	90
D	45	125

Note: costs are denominated in "E-bucks". E-bucks were converted into real cash at the rate of $0.03 per E-buck.

For example, a group A ticket in session 3 (a broad cost range session) would have a real dollar cost that fell anywhere between $0.90 and $1.35.

References

BULOW, JEREMY, and JOHN ROBERTS (1989). "The Simple Economics of Optimal Auctions," *The Journal of Political Economy*, 97(5): 1060-1090.

CASON, TIMOTHY N., and LATA GANGADHARAN (2004). "Auction Design for Voluntary Conservation Programs," *American Journal of Agricultural Economics*, 86(5): 1211-1217.

HOROWITZ, JOHN K., LORI LYNCH, and ANDREW STOCKING (2009). "Competition-Based Environmental Policy: An Analysis of Farmland Preservation in Maryland," *Land Economics*, forthcoming.

JOHANSSON, ROBERT (2006). "Conservation Program Design: Participant Bidding Enhances Cost Effectiveness," Economic Research Service, USDA.

KIRWAN, BARRETT E., RUBEN N. LUBOWSKI, and MICHAEL J. ROBERTS (2005). "How Cost-Effective Are Land Retirement Auctions? Estimating the Difference between Payments and Willingness to Accept in the Conservation Reserve Program," *American Journal of Agricultural Economics*, 87(5): 1239-1247.

LATACZ-LOHMANN, UWE, and CAREL VAN DER HAMSVOORT (1997). "Auctioning Conservation Contracts: A Theoretical Analysis and an Application," *American Journal of Agricultural Economics*, 79(2): 407-418.

MYERSON, ROGER B. (1981). "Optimal Auction Design," *Mathematics of Operations Research*, 6(1): 58-73.

REICHELDERFER, KATHERINE, and WILLIAM G. BOGGESS (1988). "Government Decision Making and Program Performance: The Case of the Conservation Reserve Program," *American Journal of Agricultural Economics*, 70(1): 1-11.

SCHILIZZI, STEVEN, and UWE LATACZ-LOHMANN (2007). "Assessing the Performance of Conservation Auctions: An Experimental Study," *Land Economics*, 83(4): 497-515.

SHOEMAKER, ROBBIN (1989). "Agricultural Land Values and Rents under the Conservation Reserve Program," *Land Economics*, 65(2): 131-137.

SMITH, VERNON L. (1976). "Experimental Economics: Induced Value Theory," *The American Economic Review*, 66(2): 274-279.

VUKINA, TOMISLAV, XIAOYONG ZHENG, MICHELE MARRA, and ARMANDO LEVY (2008). "Do Farmers Value the Environment? Evidence from a Conservation Reserve Program Auction," *International Journal of Industrial Organization*, 26(6): 1323-1332.

WALD, ABRAHAM (1947). *Sequential Analysis*. New York, NY: Dover Publications, Inc.