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Exploring Environmental Service Auctions

William B. Holmes
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EXPLORING ENVIRONMENTAL SERVICE AUCTIONS

By

William Bruton Holmes

A Dissertation Submitted in Partial Fulfillment
of the Requirements for the Degree
of
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in the
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of
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ACCEPTANCE

This dissertation was prepared under the direction of the candidate's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics in the Andrew Young School of Policy Studies of Georgia State University.

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ABSTRACT

EXPLORING ENVIRONMENTAL SERVICE AUCTIONS

By

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The chapters of this dissertation explore related aspects of the procurement of conservation services from private landowners. In the first chapter, heuristic laboratory experiments reveal the impact of potential government regulation on strategic forces and efficiency properties in conservation procurement auctions. In the second chapter, data from past procurement auctions are analyzed to discover the existence and magnitude of premiums received by auction participants.

The first Chapter, "Procurement Auctions Under Regulatory Threat," examines how strategic forces and efficiency properties are impacted in auctions for the procurement of environmental services when a threat of regulation is levied. Laboratory experiments examining different regulatory environments demonstrate that a threat of regulation will reduce the amount of public funds necessary to purchase a given level of environmental services. However, adverse selection costs and equity are negatively impacted by threat implementation.

The second Chapter, "Estimating Bid Inflation in Procurement of Environmental Services," studies the size of premiums received by program participants in conservation

programs. Predictions informed by economic literature and theory elicit the underlying value distribution for a unique dataset of procurement auctions. Average premiums for auction participants range from almost 50 percent to less than 1 percent across auction periods and institutions. The results demonstrate that both repetition and rule variation may improve the efficiency of procurement auctions. The auctions studied here are shown to yield efficiency improvements of more than 32 percent over standard fixed-payment schemes for service procurement.

Chapter I: Procurement Auctions Under Regulatory Threat

Introduction

Market institutions are gaining popularity worldwide for use in the procurement of environmental services from private landowners. While the potential benefits of using auctions to allocate contracts have been well documented in economic theory (Chan, Laplagne, and Appels 2003; Klemperer 1999; Latacz-Lohmann and Hamsvoort 1997, 1998), research on the use of auctions for the procurement of environmental services is still needed. Procurement auctions for environmental services (PES auctions hereafter) have demonstrated promise for reducing rents to landowners that result from the information asymmetry present between agencies that purchase environmental services and landowners who provide these services (Latacz-Lohmann and Schilizzi 2005). This asymmetry exists because landowners have better information about their opportunity costs of providing services. Competitive processes used to allocate contracts in auctions reduce the incentives for landowners to inflate their opportunity costs relative to the incentives they face when traditional fixed payment allocation mechanisms are implemented. While PES auctions have shown improvements over fixed payment schemes to contract environmental services, there is empirical and laboratory evidence that landowners bid significantly higher than their opportunity costs when participating in discriminatory price PES auctions (Cason and Gangadharan 2005; Kirwan, Lubowski, and Roberts 2005). The resulting informational rents awarded to contract winners create a need for the allocation of a greater amount of public funds to purchase a given level of

environmental services than would be necessary if landowners bid their true opportunity costs of providing services.

Ongoing research programs such as the one conducted by Groth are continuing to explore the efficiency properties of PES auctions (Groth 2008). However, one issue that has been left unaddressed in the literature stems from the fact that the procuring agent is often a government entity, and consequently, may be empowered with regulatory authority by lawmakers. Indeed, government regulation has a long history of use in the United States to prevent activities that are harmful to the public. Miceli and Segerson assert that "courts have long viewed it as a legitimate exercise of the government's police power to 'regulate' property without the obligation to pay compensation, provided that the intent of the regulation is to protect the 'health, morals, or safety' of the community" (Miceli and Segerson 1995). They expand on this concept by saying "actions that limit the use of but do not physically acquire property have generally been viewed as non-compensable." Clearly there are cases in which the land management practices of private landowners may adversely affect the health, morals, and safety of other members of a community. Some common examples of these situations are as follows. One may be found if a landowner over-extracts from a publicly owned environmental stock, such as a river or aquifer, thereby reducing availability to other community members. Another could arise from a landowner's decision to remove critical habitat for endangered species. Still other situations might stem from pesticide usage, manure storage, or other production practices employed by landowners.

As mentioned above, it is within the power of a government to impose regulations to preserve or increase environmental goods. This chapter examines how strategic forces

and efficiency properties are impacted in auctions for the procurement of environmental services when a threat of regulation is levied. Laboratory experiments are conducted to reveal characteristics of bidder behavior in different regulatory environments. The experiments provide insight into the efficiency-equity tradeoffs inherent in regulatory policy applications with respect to the use of procurement auctions for environmental services. Results indicate that it is possible to reduce the amount of public funds necessary to purchase a given level of environmental services by using an explicit threat of regulation in PES auctions. Ceteris paribus, this outcome represents an efficiency gain and improvement in the performance of the auction by increasing the amount of services that may be contracted within a given budget, thereby reducing the need for a government to collect distortionary taxes. However, adverse selection costs and equity considerations that arise from levying a regulatory threat may outstrip the potential benefits gained by paying lower prices to service providers.

The next section of this chapter contains a detailed presentation of background information and motivation for the exploration of this topic.

Background and Motivation

A PES auction is defined as a procurement auction in which one buyer (usually a government entity) seeks to ensure that a certain amount of environmental services are obtained from a group of landowners (often farmers).[1] Landowners that participate in a PES auction bid dollar amounts they are willing to accept from the government in return

[1] Fishermen and other resource users are also potential providers of environmental services. In their case, the environmental services provided consist of use permits that are purchased at auction by the conservation agent.

for maintaining a certain ecosystem to agreed-upon rules. From an efficiency standpoint, the landowner's bids should reflect their true opportunity costs for providing the environmental services. However, contractual relationships arrived at through this bidding process are subject to asymmetries of hidden information and hidden action. Both asymmetries enable landowners to achieve rents, or windfall gains, from the conservation agent by either inflating their bids or failing to perform the services they are contracted to provide. While each asymmetry creates inefficiency with regard to the provision of environmental services, this analysis will focus on the former (hidden information).[2]

Hidden information becomes a problem when the opportunity cost of providing a particular environmental service varies across landowners. Auction theory predicts that bidders will weigh the amount at which they inflate their bid (the windfall gain from winning a contract in the auction), against the probability that their bid will be accepted when formulating bids in multiple unit discriminatory price auctions (Cox, Smith, and Walker 1984; Vickrey 1962). Shoemaker's early analysis (Shoemaker 1989) of the Conservation Reserve Program (CRP), the largest PES initiative in the U.S., finds evidence of informational rents going to landowners. Further study of the CRP by Kirwan et al. quantifies windfall gains in the CRP as constituting between 10 and 40 percent of total contract values in 2002-2003 signup periods, the most recent of their sample (Kirwan, Lubowski, and Roberts 2005). Additionally, *the Economist's* (Economist 1999) report on the California Headwater Forest purchase and Osterberg's

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[2] Cox et al. provide an informative analysis of both information asymmetries in the context of government procurement from private contractors who may engage in costly effort to reduce overall costs of service provision (Cox et al. 1996).

analysis (Osterberg 1999) of a German agri-environment payment program both contain further support for informational rents going to landowners.

Informational rents to landowners are an important problem because they generally come at the expense of tax dollars. Since distortionary tax collections are often used to compensate landowners for providing environmental services, taxpayers will benefit if the payments to landowners are equal to the landowners' opportunity costs of contract compliance, but no more than these costs (Ferraro 2008).

As mentioned in the introduction, an important aspect of PES auctions that is usually kept in the background if mentioned at all in the relevant literature is the fact that the conservation agent is usually a government agency, and the government has the power to order the implementation of ecosystem management practices if lawmakers chose to empower the government agency in such a way. Consider the case of a local river basin that supports a thriving ecosystem of plants and animals while serving as the primary water supply for a local community. Additionally, assume the river is also used by local farmers who extract water to irrigate their crops. Next, consider what might happen if biologists determine that a severe drought will dry up the river and destroy the ecosystem if farmers continue to irrigate their crops in a specific year. In comparable situations, such as in the Flint River Basin of Georgia (U.S.A.), the government decided to implement a PES auction to purchase enough of the water rights back from farmers so that the ecosystem and water supply were protected for the year (Cummings, Holt, and Laury 2004; Laury 2002). If farmers had inflated their bids (in essence, claiming that their opportunity costs were higher than they really were), then the government would have spent more taxpayer money than was socially optimal to contract with the farmers to

suspend irrigation. One possible alternative the government could have pursued was to simply have told the farmers that they were forbidden from irrigating crops in the drought year, and then enforced the restriction through monitoring and strict fines. This second alternative seems problematic from both a political standpoint (politicians generally avoid being perceived as treating farmers unfairly) and from an efficiency point of view (by forcing a heavier portion of the burden of the drought onto the farmers than is socially optimal). Another alternative that combines both scenarios mentioned above is for the government to issue a regulatory threat, i.e., notifying farmers that if the sum of their bids exceeds the government's budget allocation for the auction (determined by the distribution of farmer's opportunity costs), then their irrigation rights would be suspended without compensation.[3] In this way, the government may be able to induce enough farmers to lower their bids to a level equal to their opportunity cost, so that enough of the irrigation rights may be purchased at an efficient price. Of course, other outcomes of such a regulatory threat are possible. For example, the allocational efficiency of the auction could be adversely impacted by the issuance of a threat if the lowest cost service providers are not selected. This could occur if higher cost service providers decrease their bids more than lower cost providers because the higher cost providers have more to lose in the event of a regulation. An even worse case from an efficiency-equity perspective might occur if the budget allocation is exceeded, thereby triggering the threat and causing services to be "taken" without compensation. That outcome would ignore all heterogeneity in costs across service providers and represent a situation in which a

[3] The form of regulation in which all contracts are taken without compensation represents a boundary case that seems to be a logical place to begin the analysis of the impact of threatened regulation on bidding behavior. Of course, there are many different permutations and forms of regulatory threats and consequences that could be tested in future laboratory sessions.

heavier portion of the burden of the drought than is socially optimal is forced onto the farmers.

A less politically sensitive case to motivate this analysis arises from the presence of bio-physical thresholds in certain procurement situations. Consider a section of river that travels through the property of many different landowners. Consider further that the government agency (or conservation agent) charges landowners a fee based on their riverfront acreage to dredge the river every few years in order to mitigate the effects of erosion stemming from their land management practices along the riverside. It may be possible to reduce erosion through the collective action of many different landowners, thereby eliminating the need for periodic dredging. In such a case, landowners have the option of implementing erosion control land-management practices along the river to avoid having it dredged. A conservation agent could conduct an auction to purchase contracts to ensure that areas of riverfront are managed in accordance with specified erosion control practices. If the agent is not able to contract riverfront lands beyond the threshold level to avoid dredging within a specific budget (for example, the total cost of the next anticipated dredging of the river), then the agent would simply refuse all bids and charge the previously mentioned fee for the necessary dredging. Note how this is different from the case of having a maximum reserve price in the auction since landowners will actually suffer a loss in the form of the dredging fee if the agent is unable to contract the threshold level of land. However, this problem is analytically similar to the case of using a regulatory threat to reduce bid inflation among PES auction participants. Here, the dredging fee is congruent with the idea of a “regulatory threat.” Therefore, one would expect individual bids in the auction to be lower than they would

be if there were no consequences for a failure to contract the threshold level of riverfront within a given budget.

Finally, consider the case of a PES auction to protect an overexploited fishery. Here, the conservation agent seeks to purchase enough permits from users of the fishery to meet an environmental objective. Consider further that there is already an ongoing political debate about possible future regulatory actions that may be used to protect the fishery. In this case, many participants in the auction may internalize an inexplicit regulatory threat. That is to say, auction participants may be aware that regulatory action (such as the imposition of a fishing ban or technological restriction) has a higher probability of occurring if the amount of permits purchased within the budget allocated to the auction is insufficient to protect the fishery. Even though this threat is not explicitly levied by the conservation agent, it would certainly be expected to affect bidding behavior in the auction. The experiments reported in this chapter shed light on the nature and magnitude of the effects of threatened regulation in auctions, along with providing predictions about the outcomes of such auctions.

The next section provides a discussion of the relevant empirical and theoretical literature on PES auctions. There is also a review of the primary legal precedents for environmental regulation in the United States.

Literature Review

"An auction is a market institution with an explicit set of rules determining resource allocation and prices on the basis of bids from market participants" (McAfee and McMillan 1987). It is fairly clear that auctions have certain properties that are useful in

the provision of environmental services. Participants are able to deal with uncertainty about the value of such services by allowing the auction institution to determine whether or not a contract is accepted. While this has been recognized as a useful way to lower informational rents to service providers (Latacz-Lohmann and Hamsvoort 1997), there is evidence that the auction mechanism alone is insufficient for eliminating all informational rents. Cason and Gangadharan provide evidence of this persistent problem in laboratory experiments using both uniform and discriminative price auctions (Cason and Gangadharan 2005). In their experiments, the sealed bid discriminatory price auction institution allows the buyer to purchase a larger quantity of services than the sealed bid uniform price auction. However, they find evidence of at least 8 percent bid inflation (meaning that bids to provide the services are at least 8 percent higher than the opportunity costs of service provision) in most offers. The previously mentioned work by Kirwan et al. finds further evidence of substantial bid inflation in CRP auctions (Kirwan, Lubowski, and Roberts 2005). They estimate inflation levels of between 11 and 67 percent in the most recent periods of their sample (2002-2003).

Theoretical predictions of bid inflation in auctions have been constructed beginning with Vickrey's formulations of Nash equilibrium bidding behavior in both single unit and multiple unit auctions for risk neutral economic agents (Vickrey 1961; Vickrey 1962). Harris and Raviv (HR) extended Vickrey's model to explain behavior in multiple unit auctions where all bidders have the same individual concave utility function and values are drawn from a general distribution function (Harris and Raviv 1981). The equilibrium bid function from HR for risk neutral agents was later converted into the

form of computable finite polynomials by Cox, Smith, and Walker (Cox, Smith et al. 1984).

Later work by Latacz-Lohmann and Hamsvoort, presents a theoretical model designed specifically for conservation auctions (Latacz-Lohmann and Hamsvoort 1997). They find that the auction mechanism does improve the efficiency of contracting for environmental services over traditional fixed-payment schemes used by conservation agents. However, they acknowledge the fact that it is difficult for their theory to "provide a cut and dried solution in most real-world settings" because of relaxed assumptions and simplifications. While these theoretical pieces are relevant to this analysis, there is no existing model to predict the outcome of auctions conducted in an environment which contains a threat of regulation. It is here where the experiments reported in this chapter may be used to push this frontier of knowledge and inform more sophisticated theories.

PES auctions have already been conducted in the U.S., Australia, the United Kingdom, and other European nations. Various environmental objectives, such as increasing biodiversity, reducing dryland salinity, protecting groundwater, and extending wildlife habitat have been targeted in these auctions (Latacz-Lohmann and Schilizzi 2005). Markus Groth of the University of Luneburg is conducting a research program to formulate a comparative study of conservation auctions. His empirical work strives to expand our understanding of this innovative environmental policy instrument (Groth 2008).

Cummings, Holt, and Laury make an important contribution to the literature in a paper which depicts the design process and execution of an auction for irrigation permits

in the Flint River basin of Georgia (Cummings, Holt, and Laury 2004). After experimenting in both the laboratory and the field, CHL recommended that the regulatory authority use a first price sealed bid discriminatory price auction with multiple rounds of bid revisions to secure a certain level of irrigation suspension in the Flint River Basin. The auction mechanism induced farmers to decrease offers over time and was considered a success even though certain aspects of the auction design (namely the enforcement of constraints by state officials, i.e., fixed budget, acreage target, average price, and maximum accepted price constraints) differed between experimental design and real-world implementation. The choice of a discriminatory price auction instead of a uniform price auction in CHL is supported by findings in experiments by Cason and Gangadharan (Cason and Gangadharan 2005). Their laboratory procurement auctions compared a discriminatory price institution with a second price uniform auction institution. CG found that even though sellers' bids were not significantly different from their costs in second price uniform auction treatments, there was a substantial inefficiency in procurement. This was because each successful seller received the price per unit of the first rejected bid (as is customary in the uniform price multiunit generalization of the second price auction). Because prices exceeded costs, some inefficiency occurred. At the same time, their discriminative price auction experiments showed smaller differences in the amount that successful sellers were "overpaid." For these reasons, the discriminatory first price auction was chosen for use in the experimental design presented in this analysis.

There is also a relevant thread from the pollution literature that examines how political pressure can change the effect of taxes and subsidies on polluting industries.

Finkelshtain and Kislev have a theoretical model which accounts for the reality of political influences by inserting contributions from industry participants into the politician's objective function (Finkelshtain and Kislev 2004). FK show that when producers are politically active and politicians are willingly influenced, welfare-maximizing policies (such as a pollution tax or a pollution abatement subsidy) will not achieve the maximum level of social welfare. Along these lines, the pollution control literature also studies the effects of monitoring and enforcement on polluter compliance. Glaeser and Schleifer (Glaeser and Schleifer 2003) highlight the importance of enforcement costs to industry regulation, while identifying conditions under which regulatory action may be an efficient remedy for market failure. In their model, GS associate the choice to pursue a regulatory strategy with the "vulnerability of law enforcement in a country to subversion by powerful interests that might be affected." Their model implies that regulatory actions become increasingly efficient tools for dealing with market failures in countries where the government has a firm grip on power, and bureaucrats are not easily swayed by special interests. These avenues of the literature are mentioned here in an attempt at completeness, but they will be largely put aside in the following analysis. This is because the incorporation of both monitoring costs and political processes would introduce unnecessary levels of complexity in the analysis of bidding behavior in PES auctions under regulatory threat. Nevertheless, they are worth mentioning as future work in the area could begin to account for these considerations.

In addition to reviewing the literature with respect to PES auctions, it is also helpful to trace the history of regulation in the United States. Such a discussion would

begin with the eminent domain clause of the Fifth Amendment of the U.S. Constitution. This clause empowers the government to seize private property, or rights in property, for public use provided that it pays "just compensation." According to Miceli and Segerson, it has long been viewed by courts that it is a legitimate exercise of the government's power to regulate property without the obligation to pay compensation as long as the regulation is to protect the "health, morals, and safety" of the community. While government actions that result in the physical acquisition of private property are established as seizures for which compensation must be paid, actions that simply limit the use of property, but do not physically acquire it, have generally been viewed as noncompensable. Others such as Epstein argue that instead of being noncompensable, government regulation should be viewed as a physical acquisition of property and therefore a seizure of private property, or "taking", under the eminent domain clause (Epstein 1985). However, Epstein is consistent with Miceli and Segerson in his belief that the prevailing interpretation of the law in this area is powerfully skewed in favor of government regulation. Epstein cautions that the current interpretation of government regulation on the disposition of private lands modifies the incentives of those in power by reducing their willingness to take and pay for land for public use. In essence, the political group in control, can get what they want at reduced expenditure of their own wealth through regulation. There are several important legal doctrines that have supported policies of noncompensable government regulation through the years beginning with Mugler v. Kansas (1887).[4] That case decision established the "noxious use" doctrine which states that no seizure occurs when the government acts to prevent activities that are harmful to the public. This doctrine was overturned 35 years later in the case of

[4] 123 U.S. 623 (1887)

Pennsylvania Coal Co. v. Mahon (1922).[5] There, Justice Oliver Wendall Holmes ruled that "a regulation that 'goes too far' in reducing the value of the owner's property becomes a taking, regardless of its purpose (Miceli and Segerson 1995)." Holmes suggested that the specifics of 'going too far' should be decided on a case by case basis, and that the status quo view of regulation was such that no such taking occurs and compensation is unnecessary (Epstein 1985). Later, in Penn Central Transportation Co. v. City of New York (1978),[6] the Supreme Court proposed that the character of the government action, the impact of the action on the property owner, and the regulation's impact on "investment-backed expectations" of the property owner were each important in determining whether or not compensation should be paid in response to a regulatory action. Finally, in Lucas v South Carolina Coastal Council (1992),[7] the Court's decision took the position that a seizure is compensable if it renders a property valueless, unless the regulation is aimed at preventing an activity that would not be allowed under the state's common law of nuisance. This exception for nuisances means that compensation is not due for regulations that prevent nuisances as defined by a state's common law standards.

The next section of the chapter contains a detailed description of the experimental design employed in the laboratory sessions.

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[5] 260 U.S. 393 (1922)
[6] 438 U.S. 104 (1978)
[7] 112 S. Ct. 2886 (1992)

Experimental Design

One of the most persuasive reasons to use laboratory experiments to investigate the effect of a regulatory threat on bidding behavior in PES auctions stems from the fact that the experiments may indeed help policymakers avoid costly mistakes from unpredicted outcomes of regulation. An experiment can provide insight into the bidding behavior in procurement auctions under threat of regulation. This leads to the central questions we seek to answer through experimentation: What are the impacts on the strategic forces and on final contract allocations when a threat of regulation is levied in a PES auction? Can a regulatory threat reduce informational rents to landowners and thereby allow for the needed level of service provision to be achieved at an efficient cost? And finally, what efficiency-equity tradeoffs are associated with imposing the regulatory threat in this type of institution.

Overview:

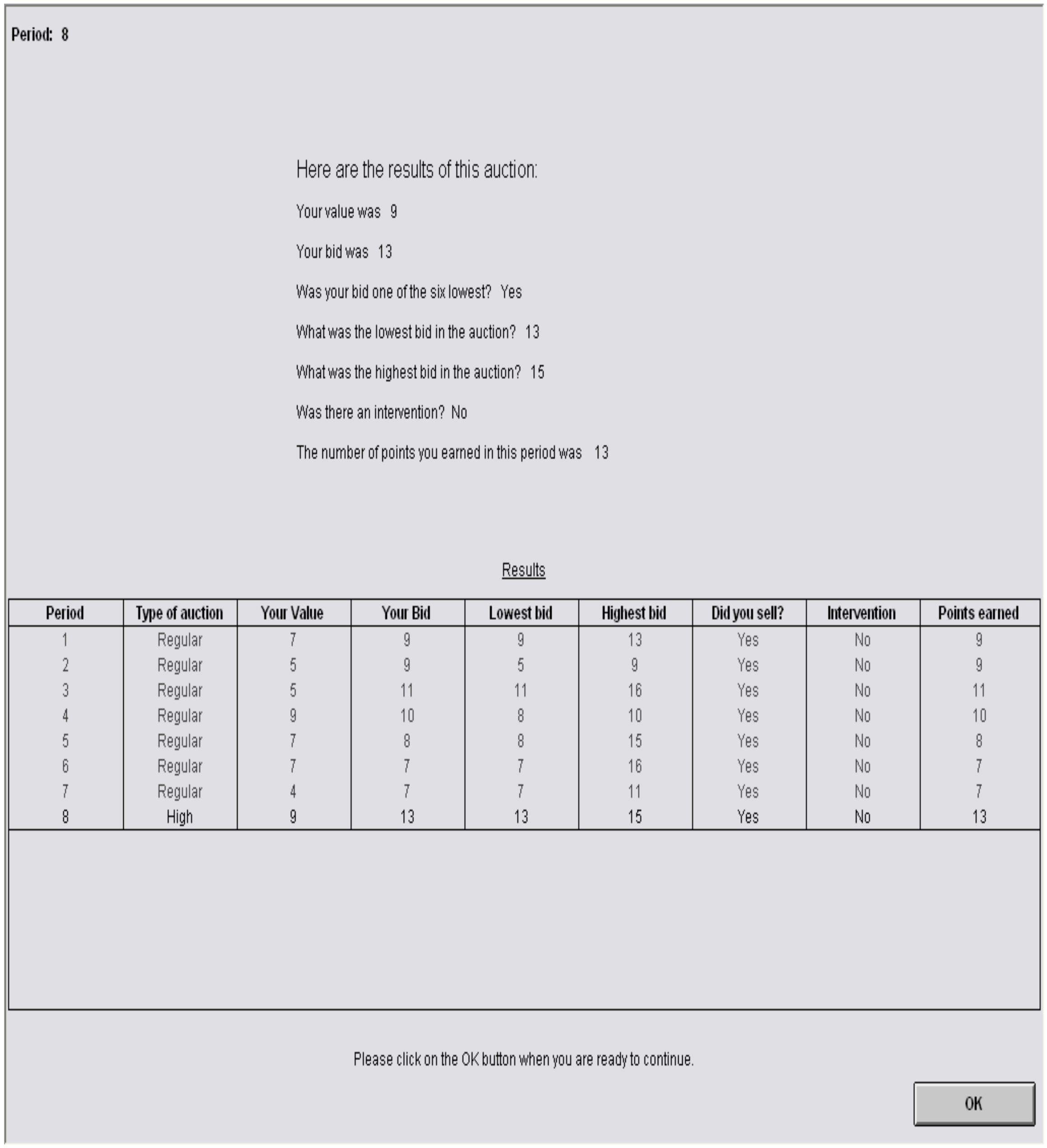
The experiment is run with groups of representative landowners containing N=11 individuals. This was to ensure that group size was large enough to provide the subjects with a complex bidding environment comparable to those found in the field. Each group of subjects participates in several treatments of a procurement auction. Treatments are varied to incorporate three regulatory environments ranging from complete absence of a threat to a level where there is a strong expectation for regulation to occur. While the experiment is designed to mimic a real-world procurement auction between landowners and conservation agents, there is little if any role-playing involved, as subjects are only given the information in their instructions to behave as sellers of a fictitious commodity.

The experiment proceeds as follows. Each participant enters the lab and is seated at a computer. The General Background instructions are next to the computer so that the subjects may begin reading silently to themselves (see the appendix for a copy of all printed instructions). Once the background instructions are read, the Regular Auction (Treatment 1) instructions are handed out. Then there is a question and answer period. Next, subjects participate in several rounds of the Regular Auction treatment. This process is repeated for the remaining High Budget Auction and Low Budget Auction treatments. Before each new set of instructions are handed out, the old ones are collected. Subjects have the opportunity to raise their hands to ask questions at any time but are restricted from talking among themselves during the experiment.

Figure 1 and Figure 2 show sample screenshots of the bidding phases in the Regular and High Budget Auction Treatments. In every auction, each subject is told that they are acting as the seller of a fictitious commodity. They are given a computer generated randomly drawn commodity value between 3 and 10. This is analogous to the opportunity cost of implementing the environmental service in a PES auction. Next, the subject is asked to enter a bid between 1 and 20 into the computer to sell his commodity. The computer program orders the bids from all players and then performs calculations to determine which if any bids are accepted and whether or not the regulatory threat is imposed. A review screen then appears for subjects to give them feedback on the outcome of the auction. If the regulatory threat is realized, each player's payoff for that auction is zero. If the threat is not realized, then the lowest 6 bidders earn points equal to the amount of their bids, while the others earn points equal to their randomly drawn commodity values. Sample screenshots of the High Budget Auction Treatment bidding

phase, Regular Auction Treatment review phase, and subject questionnaire are contained in Appendix A.

Figure 1: Regular Auction Treatment Screenshot


Period: 8

Here are the results of this auction:

Your value was 9

Your bid was 13

Was your bid one of the six lowest? Yes

What was the lowest bid in the auction? 13

What was the highest bid in the auction? 15

Was there an intervention? No

The number of points you earned in this period was 13

Results

Period	Type of auction	Your Value	Your Bid	Lowest bid	Highest bid	Did you sell?	Intervention	Points earned
1	Regular	7	9	9	13	Yes	No	9
2	Regular	5	9	5	9	Yes	No	9
3	Regular	5	11	11	16	Yes	No	11
4	Regular	9	10	8	10	Yes	No	10
5	Regular	7	8	8	15	Yes	No	8
6	Regular	7	7	7	16	Yes	No	7
7	Regular	4	7	7	11	Yes	No	7
8	High	9	13	13	15	Yes	No	13

Please click on the OK button when you are ready to continue.

OK

Figure 2. High Budget Review Phase in Period 8

To ensure saliency of the reward system, subjects are notified in advance that each point they earn in an auction period is to be exchanged for $1.00 at the end of the experiment if that period is chosen for final payoff using a bingo cage. As explained in the General Background instructions, one period from each auction treatment is drawn

for final payoff. The decision to select one period from each treatment for payoff was made to increase the likelihood that subjects bid independently in each round. As a consequence, the maximum possible amount of money awarded to any subject in the experiment is $60 (reflecting the unlikely case where 20 points is earned in each of the three chosen periods). The reward system is designed under the assumption that subjects are trying to maximize their earnings. Complete subject instructions are included in Appendix B.

Treatments:

The following is a brief description of each of the auction treatments that are administered during the experiment.

1. Regular procurement auction (R). In this treatment which is run at the beginning and end of the experiment, the lowest 6 bidders receive points equal to their bids while the remaining bidders receive points equal to their value draws for the period.

2. High Budget procurement auction (H). Subjects are told the computer's total level of expenditure to accept the lowest 6 bids is randomly drawn from [36-40].

3. Low Budget procurement auction (L). Subjects are told the computer's total level of expenditure to accept the lowest 6 bids is randomly drawn from [26-30].

In each of the threat treatments, if the lowest 6 bids sum to less than or equal to a number randomly drawn from a uniform distribution within the range shown above, i.e., [26-30] in the case of treatment 3, then the lowest 6 bidders earn points for the period

equal to their bids while the remaining 5 bidders earn points for the period equal to their commodity values. In the event that the expenditure limit is broken, all payoffs are zero. It should be noted that the information conditions are such that subjects are only informed of the uniform distribution from which the expenditure limit is drawn.

The threat implemented in these experiments is that every bidder will earn zero points if the budget is exceeded. This case is well-suited for our research objective to observe changes in strategic behavior as a result of the threat. If instead we chose a threat with similar but less severe consequences, then we may expect to observe similar changes in strategic behavior, but with a lesser magnitude. The threat studied here is also analogous to situations occurring in the natural environment. For example, it is common for regulators to ban all resource users from extracting from a particular fishery to protect from overharvesting, such as in the California salmon fishery in 2008 and 2009 (Davidson 2010). Faced with a ban, all permits and stamps for the salmon fishery were rendered valueless (CDFG 2010), and all profits from commercial fishing for California salmon were zero. Of course, our design of the threat does not apply to all potential regulatory situations, and other interesting permutations exist which could be explored in future laboratory sessions.

The expenditure limits in the H and L treatments are based on the expectation of the value distribution and are chosen to reflect different regulatory environments. In the H treatment, the expenditure limit range is chosen to be around 40 percent higher than the expectation of the value distribution (here, the expectation of the value distribution is the expectation of the sum of the lowest 6 out of 11 values randomly drawn between '3' and '10' = 29.10). The 40 percent increase above the value distribution expectation in H

treatment auctions is meant to reflect a fairly lenient regulatory environment. On the other hand, the L treatment expenditure limit range of 26-30 encompasses the aforementioned expectation of the value distribution of 29.10. This limit is meant to reflect a strict regulatory environment.

The expenditure ranges for the threat treatments are summarized in Table 1. In addition to being stated in the instructions, the relevant range appears on the bidding screen during each period of the experiment.

Table 1. Expenditure Ranges for Threat Treatments

Group Size	Threat level for treatment H	Threat level for treatment L
N=11	[36,40]	[26,30]

Clearly, the incentives faced by bidders are altered in each of the three treatments. In the R treatment, sellers face a more traditional auction situation in which they try to maximize the utility gained from winning points above their value times the probability of winning in the auction. More formally, $\max\{u(bid - value) * Prob(winning)\}$. Here it would be irrational to enter a bid below one's value. In the H and L treatments, the incentives change dramatically when the possibility of earning zero points is introduced. Here the sellers maximize utility gained from the number of points they would earn if they retain their value and there is no intervention plus the premium they would earn from a winning bid. More formally, $\max\{u(value) * Prob(no\ intervention) +\ u(bid - value) * Prob(winning)\}$. As the amount bid decreases, the probability of not having an intervention increases and the probability of winning increases. Therefore, there may be an incentive for sellers to actually bid below their values, particularly in the L treatment, in order to reduce the

probability of triggering an intervention which would ensure they earn zero points for the auction.

The ordering of the threat treatments is varied across sessions. For odd numbered sessions (I and III): (1,2,3,1); for even numbered sessions (II and IV): (1,3,2,1). Each sequence begins with an R treatment auction. Then a varying series of threat treatments is administered, with a return to the R treatment at the end. This ordering establishes a baseline for subject behavior in an auction process without regulatory threat. Then, the threat treatment order is varied across sessions to help in the identification of effects that might arise from either starting with a severe threat and then relaxing the expenditure constraint, or beginning with a relaxed expenditure constraint and then tightening it in subsequent auctions.

Groups complete seven periods of each treatment before changing to the next auction type, for a total of 28 auction periods. Thirty minutes is spent reading instructions and answering questions. Each auction period lasts approximately one minute. Also, it takes approximately ten minutes for subjects to answer the questionnaire. Therefore, each session of the experiment may be completed in less than 1.5 hours.

Data generated by these treatments consists of all bids and payoffs from every auction. Analysis yields interesting comparisons between bidder behavior in the R auction treatment with behavior in the H and L threat treatment auctions. An inflation measure is calculated for each auction including those where the regulatory threat was

realized by ordering the bids (1,…,n) from lowest to highest and using the following formula:

$$Inflation = \frac{\sum_{i=1}^{6} b_i}{\sum_{i=1}^{6} v_i}$$

The inflation measure captures the ratio of the sum of the lowest 6 bids (b) and hence the potential expenditures for the government to achieve its objective of 6 contracts, relative to the total values (v), analogous to opportunity costs, that are available to subjects for keeping their commodities. Therefore, an inflation level of one would indicate the achievement, on average, of the outcome where contract prices are equal to opportunity costs. This measurement captures bid inflation as an individual property, but it is not capable of finding inefficiency arising from socially suboptimal agents winning the auction.

Another measure of auction performance may be constructed to determine the amount by which the total cost to the buyer exceeds the lowest possible cost of providing the same amount of services across all sellers. This measure, called "total inflation" may be constructed in the following way:

$$Total\ Inflation = \frac{min \sum_{i=1}^{6} b_i\ \forall_{\ i}}{min \sum_{i=1}^{6}\ v_i\ \forall_i}$$

In the above equation, the sum of the lowest six bids (b) is compared with the sum of the lowest six value (v) draws in each round. This broader measure of auction performance compares the winning bids in the auction with the lowest possible costs of service provision across all potential providers. A total inflation score of one would indicate the

achievement, on average, of the outcome where contract prices are equal to the lowest possible opportunity costs across service providers. While this measure does a better job than the first inflation measure of capturing any deviation from the optimal social cost paid by the buyer in each auction, it is still inadequate for measuring inefficiencies arising from adverse selection of service providers. That problem will be addressed with a separate analysis of the efficiency properties of the different threat treatments with respect to the optimal allocation of contracts to the lowest cost providers.

Further analysis of the data incorporates econometric tests of bid inflation levels within and between subjects. Learning effects are studied by comparing the results from sequential auctions in each treatment.

In addition to comparisons of bidding behavior across treatments, we will also test how well existing theory predicts actual bidding behavior in the R treatment auctions. The analysis will compare R auction data with the theoretical prediction formulated for a risk neutral bidder in Cox, Smith, and Walker. They provide a Nash equilibrium bid function for an auction with the following properties.[8] Each bidder $i = \{1, \ldots, N\}$ submits a bid b to purchase a single unit, and the Q highest bidders win (note how this is the reverse of the experimental auctions, where each bidder submits a bid to sell a single unit, and the Q lowest bidders win). The parameter v is the bidder's underlying value, while $\bar{v}$ reflects the bidder's belief of the highest underlying value held among all auction participants. In the above formula, participants construct their bids by evaluating the probability that at least N-Q other bids will be lower than their own bids. The reverse is true in procurement auctions where participants construct their bids by evaluating the

[8] See pages 984-985 of CSW, 1984 for the relevant formula and a complete exposition of the proof.

probability that at least N-Q of the other bids will be higher than their own bids. Figure 3 depicts the theoretical prediction of bids for the treatment 1 parameterization. Double arrows are drawn to indicate how the difference between bids and values are related for traditional and reverse auction predictions. In the traditional auction, buyers at the lower end of the value distribution are predicted to shave their bids by the same amount that sellers at the higher end of the value distribution are predicted to inflate their bid in a reverse auction.

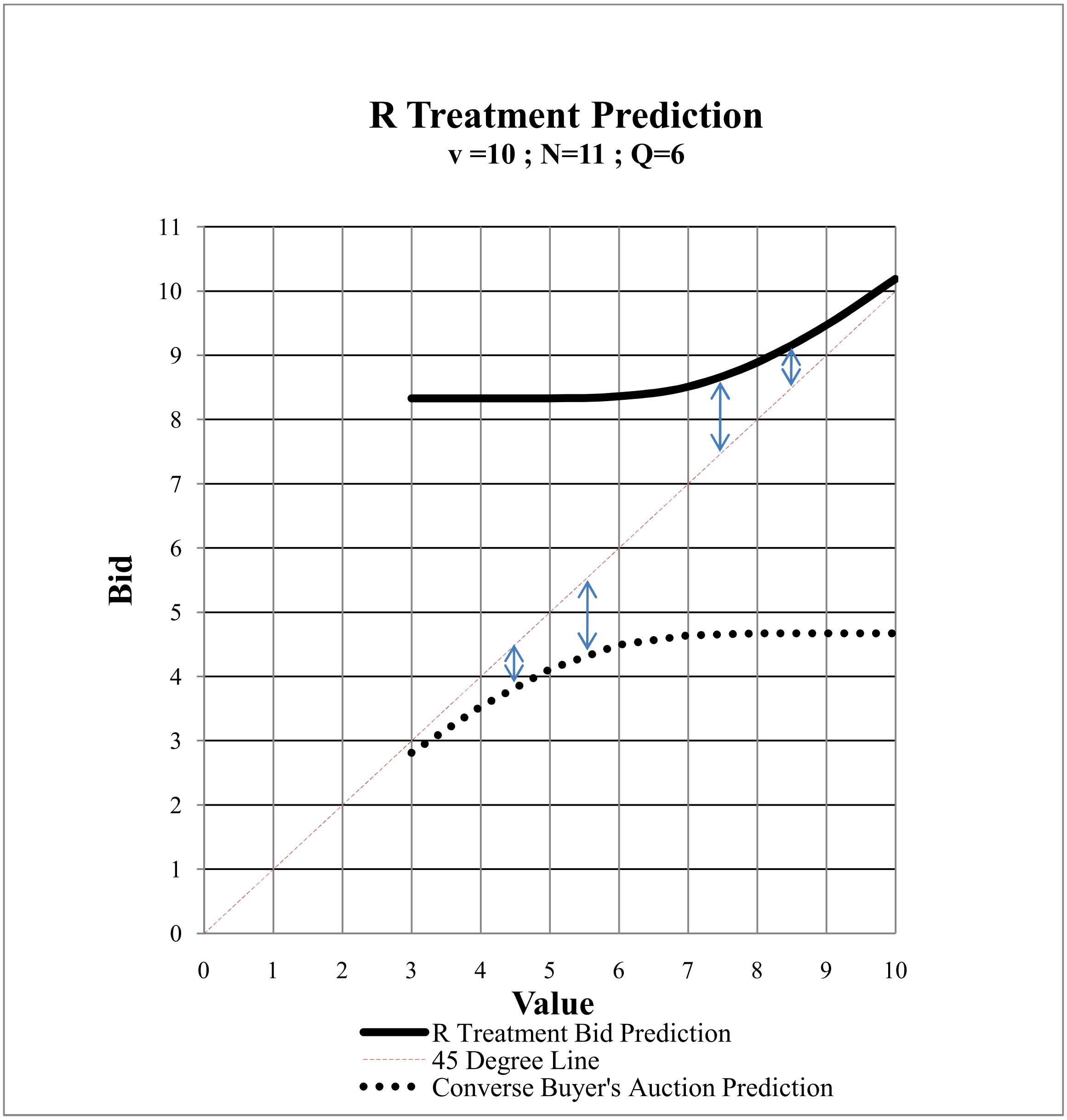


Figure 3. Predicted Bidding

One potential weakness of this experiment stems from the use of $1.00 bid increments. This may be too large of an increment to capture all of the subtlety in bidder behavior. Furthermore, the theory to predict bidding in R auctions is formulated in continuous space, a factor which will be addressed in the results section. In spite of these

weaknesses, we believe the $1.00 bid increment is a convenient simplification that helps to reduce subject confusion.

Data from four experimental sessions are reported in the next section.

Experimental Data and Results

The experiment was programmed and conducted using the Ztree software (Fischbacher 2007). All forty-four subjects were recruited from the undergraduate student population at Georgia State University. Both male and female subjects with ages ranging from 19 to 29 participated in the session. The experiment took place in the Experimental Economics Laboratory located within the Experimental Economics Center of the Andrew Young School of Policy Studies at GSU. Data generated in the experiment consist of 28 bids for each subject, yielding a total of 1232 observations. Subjects also provided answers to a questionnaire at the end of the experiment (see the appendix for a screenshot of the questionnaire). In accordance with the protocol, the treatment ordering was (1,2,3,1) for Sessions I and III, and (1,3,2,1) for Sessions II and IV.

Summary statistics presented in Table 2 are separated between the Regular (R) auction treatment, High Budget (H) auction treatment, and Low Budget (L) auction treatment. It is clear that the mean bid and mean inflation increment (calculated as bid-value) were much lower on average in the auctions that were run with some level of threat. In particular, the mean bid in R auctions exceeded the mean value by 2.87. This may be compared with a mean bid in the H treatment that was only 2.07 higher than the mean value, and a mean bid in the L treatment that was only 1.12 higher than the mean

value. Similarly, the percentage of bid inflation equal to (bid-value)/value decreased from a mean of .56 in the R treatment to .42 and .21 in the H and L treatments respectively. It is also interesting to note that the average winning bid of 7.71 in the R auctions fell to 6.17 in H auctions and 4.98 in the L auctions. Finally, the binary intervention variable shows that interventions occurred in 36 percent (10 out of 28) of H auctions and 46 percent (13 out of 28) of L auctions.

Table 2. Descriptive Statistics of the Full Sample

Regular Treatments

Variable	Obs	Mean	Std. Dev.	Min	Max
Value	616	6.48	2.23	3	10
Bid	616	9.35	2.62	1	20
Average Winning Bid	336	7.71	1.63	1	11
Inflation Increment	616	2.87	2.16	-4	13
Percent Inflation	616	0.56	0.55	-0.67	4
Highest Bid	56	13.86	2.57	10	20
Lowest Bid	56	5.54	1.83	1	8

High Budget Treatments

Variable	Obs	Mean	Std. Dev.	Min	Max
Value	308	6.35	2.24	3	10
Bid	308	8.43	3.84	2	20
Average Winning Bid	168	6.17	1.25	2	9
Inflation Increment	308	2.07	3.50	-6	16
Percent Inflation	308	0.42	0.67	-0.625	4
Highest Bid	28	15.57	4.41	10	20
Lowest Bid	28	4.61	0.94	2	6
High Budget	28	37.64	1.74	36	40
Intervention	28	0.36	0.48	0	1

Low Budget Treatments

Variable	Obs	Mean	Std. Dev.	Min	Max
Value	308	6.68	2.16	3	10
Bid	308	7.80	4.86	1	20
Average Winning Bid	168	4.98	1.71	1	14
Inflation Increment	308	1.12	4.47	-9	17
Percent Inflation	308	0.21	0.70	-0.9	5.67
Highest Bid	28	15.57	4.83	8	20
Lowest Bid	28	2.93	1.00	1	5
Low Budget	28	28.14	1.75	26	30
Intervention	28	0.46	0.50	0	1

Data from the questionnaire regarding subject understanding reveals that all of the subjects found the instructions to be clear. However, one subject in Session I reported a lack of understanding in the beginning of the experiment that the least amount of points

she could earn in the R auctions was her commodity value. As a consequence, the subject bid below her value in the early periods (in fact, her bid was only one point in two of the first 7 R auction periods). The subject then realized her error when reading the H treatment instructions and subsequently changed her behavior for the remainder of the experiment. Fortunately, robustness checks including and excluding Session I observations have ensured that enough data has been gathered so that the outlier behavior of one subject does not exert a substantial influence on the experimental results. For this reason, no observations have been excluded from this analysis.

Figure 4 depicts a summary graph of auction outcomes in all sessions across all auction periods. Here, the treatment ordering in Sessions II and IV are renumbered (periods 8-14 are changed to 15-21 and vice-versa) for the sake of convenience. Charts of individual session results are contained in the appendix. The summary graph shows both the average procurement payment paid and the lowest possible opportunity cost for each of the 28 auction periods. Because the same random value draws in Session I were implemented for all other sessions, the line representing the sum of the minimum six values does not change across sessions. Note that the Regular auction treatment periods (1-7 and 22-28) have the highest procurement payments. It is clear from the graph that procurement costs were considerably lower in the H and L treatments. Also, payments appear to roughly track the value draws in each period. This indicates that some subjects may inflate their bids by a fixed percentage of their costs. Further econometric tests explore this relationship later in the chapter. Finally, it should be noted from the summary graph that the six lowest value draws in four out of seven of the L periods were higher than the possible range of the budget draw (26-30). In those periods, it would be

necessary for the average winning bidder to submit a bid below their value in order for the threat to be avoided. Somewhat surprisingly, this behavior occurred on many occasions.

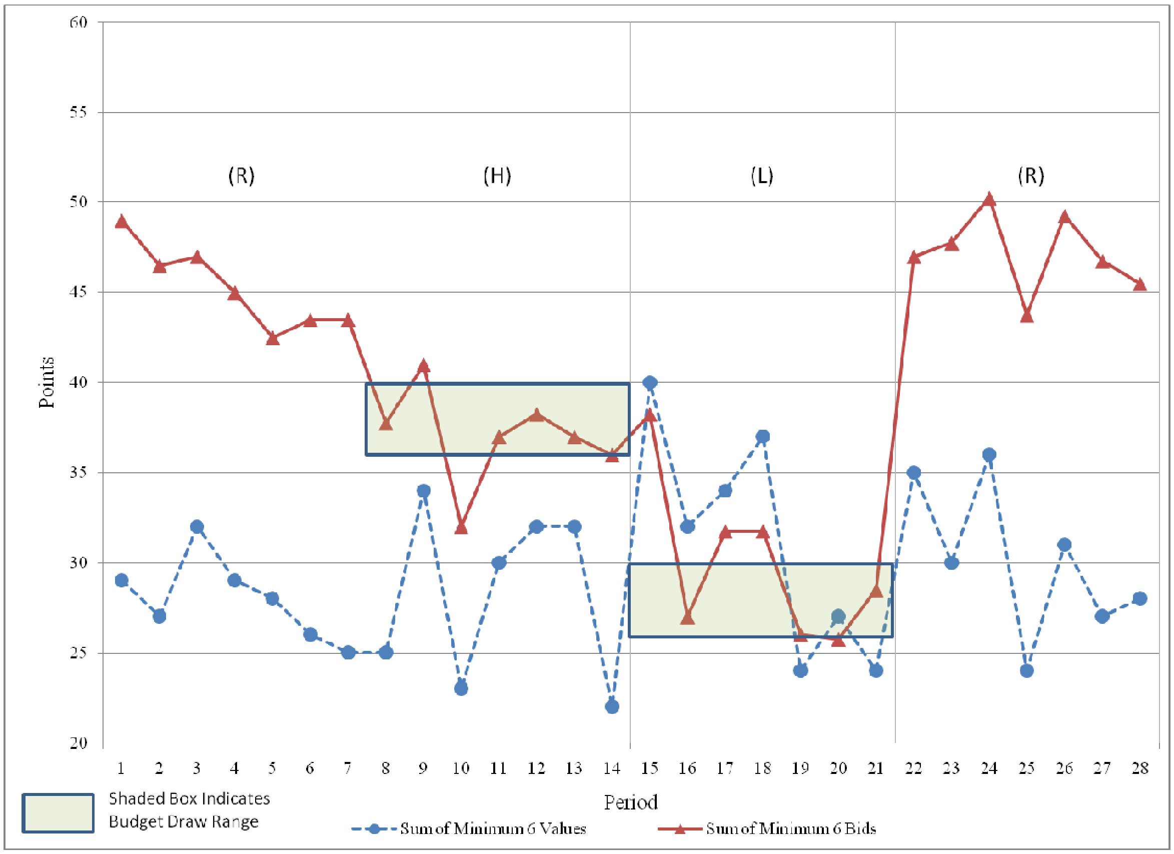


Figure 4. Summary Graph of Auction Outcomes

Next, Figure 5 shows a plot of the inflation increment (bid-value) for every decision made in all four sessions. Observations are separated into bins which correspond to one of the three treatments, for example, observations 1 through 308 show the inflation increment for every participant in every round of the baseline treatment.

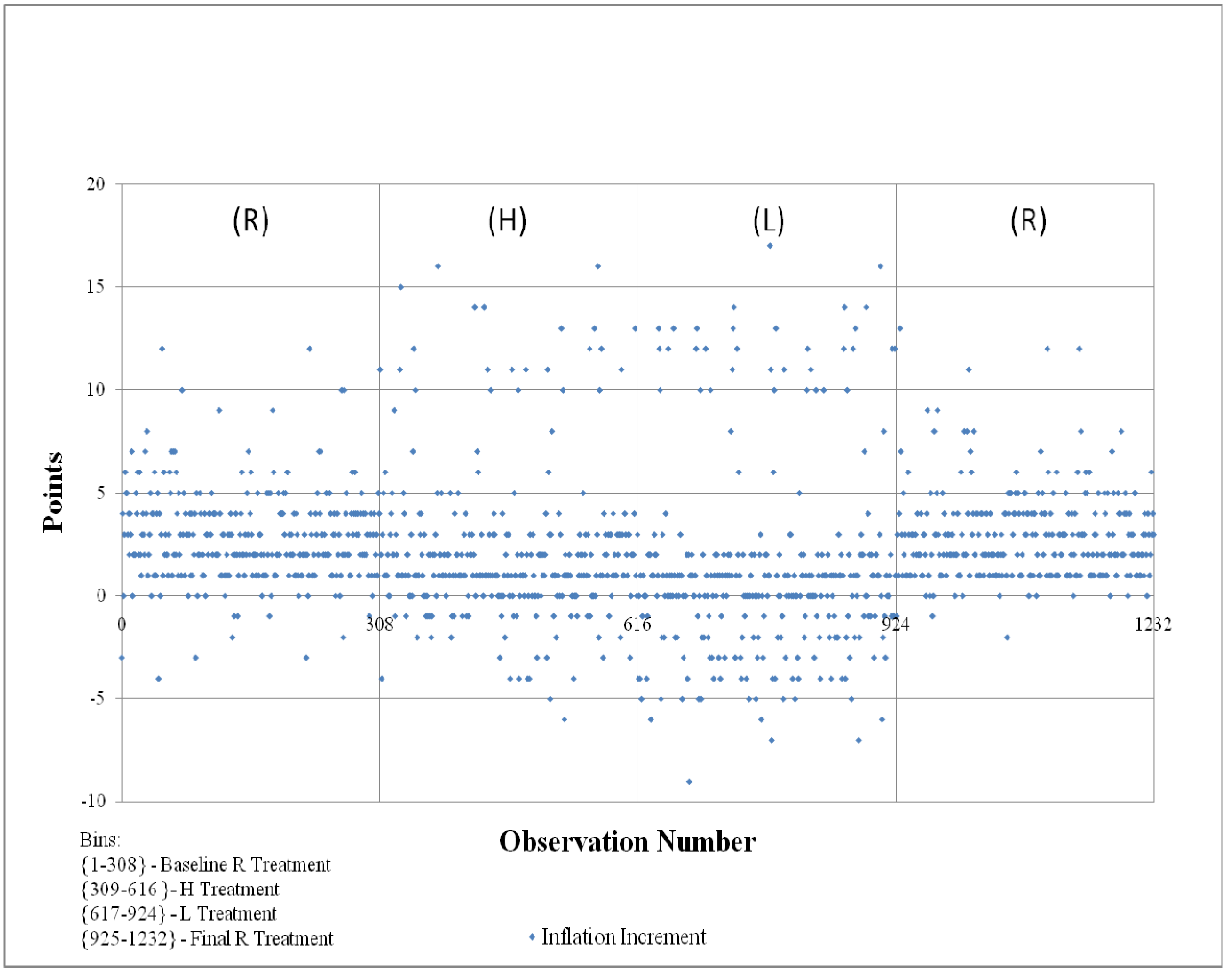


Figure 5. Inflation Increment for All Decisions

Looking at Figure 5, it is apparent that bids are almost always above values in the R treatment. However, there are many bids equal to or below values in the H and L treatments. In fact, there appear to be quite a few observations in which the inflation increment is equal to zero in both of these treatments. A zero inflation increment corresponds to an instance where the landowner would bid exactly his opportunity cost to provide the conservation service to the government. Finally, it is important to note that there are observations of extraordinarily high inflation increments (those that are between 10 and 17 points), in the H and L treatments. These observations are significant outliers

from the mean levels of bid inflation observed in these treatment periods. Further investigation of these observations reveals that they are the result of a few subjects bidding the maximum 20 points in several of the H and L periods. Figure 6 depicts a frequency diagram of each subject's bid of 20 in all auction treatments. It is apparent from the diagram that four subjects in Session III and three subjects in Session IV were responsible for most of the 20 point bids. Indeed, subject number 25 bid 20 points in all seven L treatment periods and in three out of seven H treatment periods. Survey responses from these subjects indicate that they understood the auction rules and were simply bidding the maximum in order to secure their commodity value in the event that the threat was avoided. None of the survey responses indicate that bids of 20 were made as signals to protest the auction institution as was first suspected by the author.

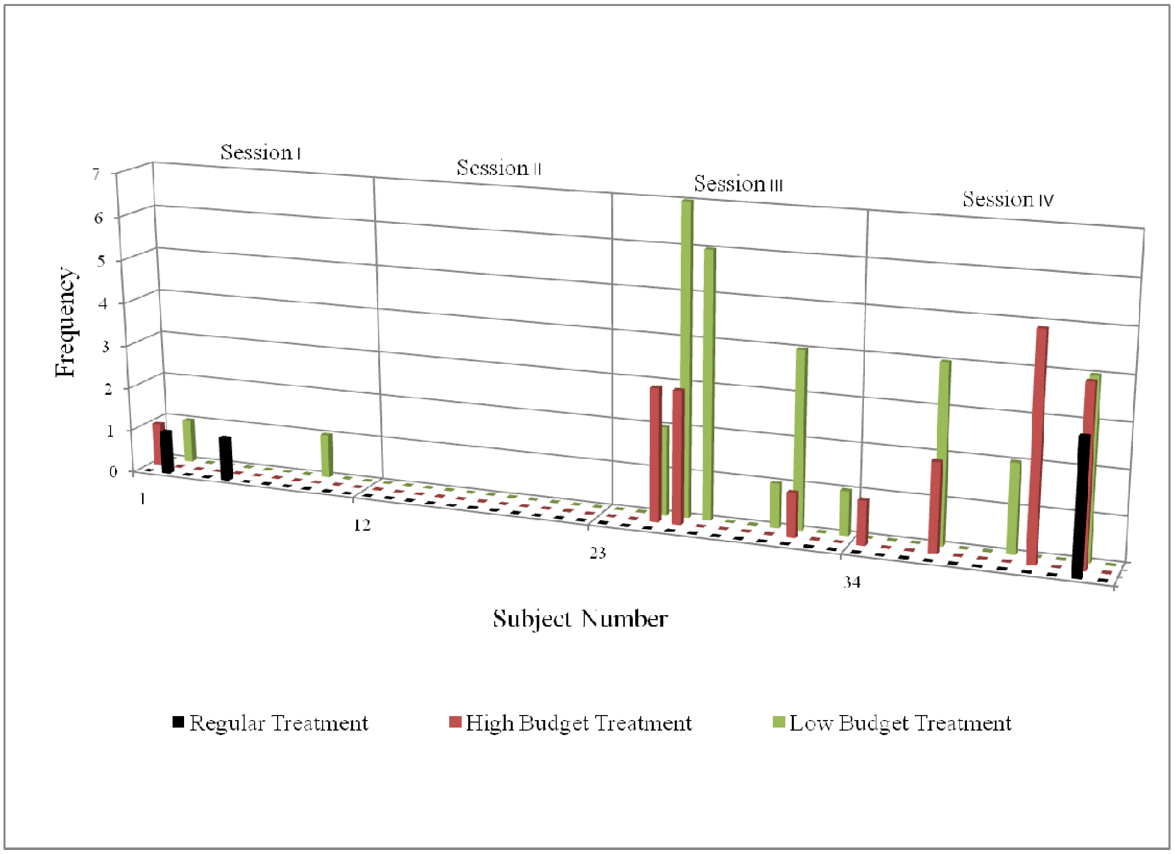


Figure 6. Frequency of Bid = 20

Figure 7 shows a scatterplot of the inflation increment for the winners (defined as those with the lowest six bids) in each treatment. Observations 1-168 correspond to the first seven R auctions for each session, 167-336 to the H auctions, 337-504 to the L auctions, and 505-672 to the final seven R auctions. From the graph it is clear that bid inflation was highest in the R periods and lowest in the L periods. Here the trend in Figure 5 reappears but is more pronounced in magnitude. Winners in the L auctions often bid at a level equal to or below their value. This happened with less frequency in the H auctions and almost never in the R auctions. Also, there are many observations in the R auctions in which the inflation increment is four or greater, while that rarely occurred in the H and L treatments.

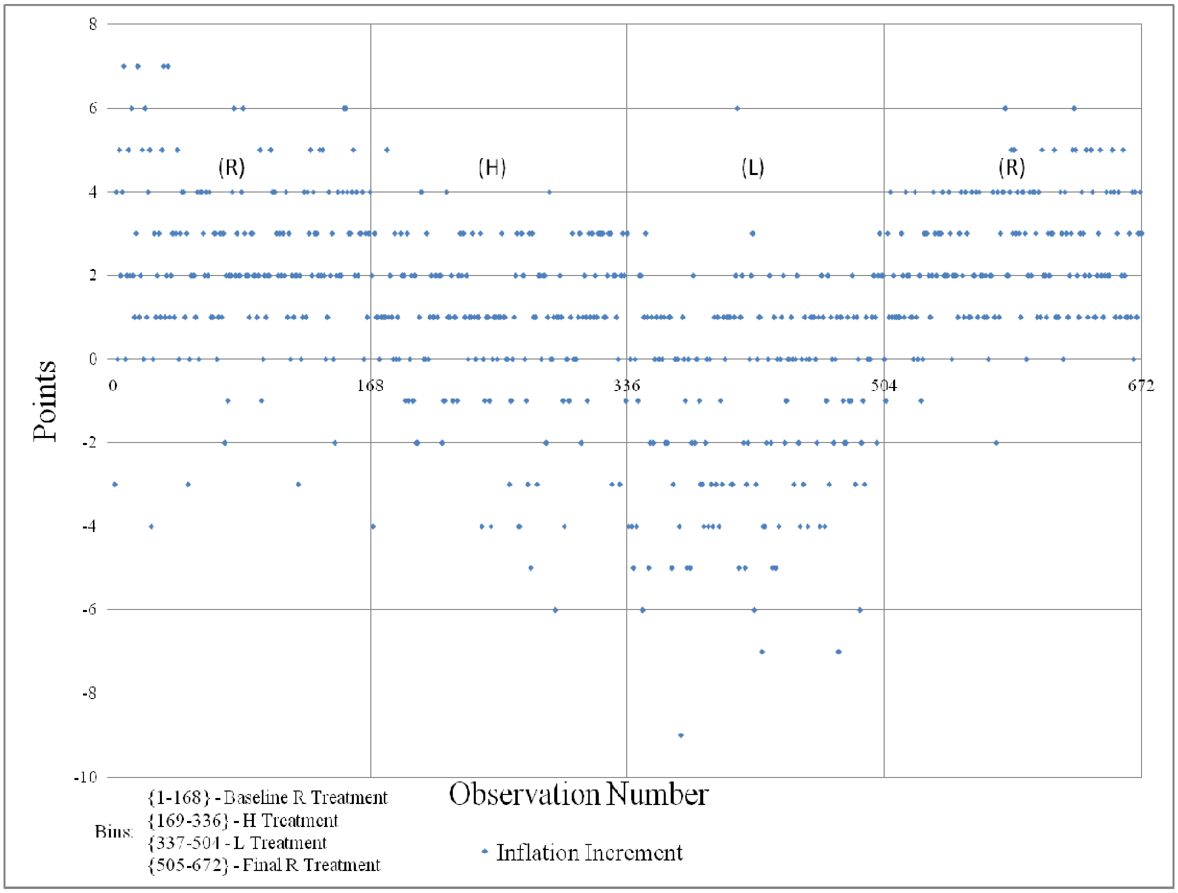


Figure 7. Inflation Increment for the Winners

After examining the summary data, it becomes apparent that in addition to analyzing the entire dataset as a whole, it may also be useful to look at two subgroups. The first subgroup consists of all bids in every auction except for those equal to the maximum of 20. Excluding bids equal to 20 in this subgroup (the ex-20 group) will allow for a closer observation of bidding behavior by the majority of subjects who did not raise their bids to the maximum in order to secure their commodity values. After all, the same objective could have been accomplished by bidding one's value instead of the max. Another natural subgroup of bids that warrants closer examination is one that consists only of winning bids (those that are the lowest six bids in each auction). The winner

subgroup will allow for an analysis of the behavior and characteristics of those participants who were able to successfully sell their unit. Descriptive statistics of these two subgroups are presented in Table 3.

Table 3. Descriptive Statistics of Ex-20 and Winner Subgroups

	Regular			High			Low		
	Obs	Mean	St.Dev.	Obs	Mean	St.Dev	Obs	Mean	St.Dev
Bid	616	9.35	2.62	308	8.43	3.84	308	7.80	4.86
Bid ex 20	611	9.25	2.45	288	7.62	2.40	275	6.33	2.52
Bid Winner	336	7.71	1.63	168	6.17	1.25	168	4.98	1.71
Inflation Increment	616	2.87	2.16	308	2.07	3.50	308	1.12	4.47
Inflation ex 20	611	2.80	2.02	288	1.38	2.30	275	-0.19	2.45
Inflation Winner	336	2.46	1.74	168	0.77	1.93	168	-0.92	2.44
Pct Inflation	616	0.56	0.55	308	0.42	0.67	308	0.21	0.70
Pct Inflation ex 20	611	0.55	0.55	288	0.32	0.53	275	0.03	0.38
Pct Inflation Winner	336	0.58	0.53	168	0.25	0.41	168	-0.06	0.39

It is evident from Table 3 that there are significant differences in bidding behavior in the winners and ex-20 subgroups. Winners inflate their bids by a lower than average amount in all three treatments (2.46, .77, and -.92 points in the R,H, and L treatments respectively). This may be compared with an average of 2.87, 2.07, and 1.12 points of average inflation in all R, H, and L treatments. Interestingly, the percentage of inflation is slightly larger for winners in the R treatment when compared with the average percentage of inflation for the full sample (58% for the winners versus 56% for the full sample). This would indicate that a subject’s value is a major determinant of their success in selling their unit in the R treatment. Also, the increasing percentage for winners versus the entire sample indicates that low value holders inflate more than higher value holders in the R treatment which is consistent with auction theory. That is not the

case in the H and L treatments where the percentages of inflation for the winners are substantially lower than those of the average bidder, (.25 vs. .42 in the H and -.06 vs. .21 in the L). The same idea that inflation percentages are lower for winners in the H and L treatments also holds when comparing the winner and ex-20 subgroups, thereby indicating that those subjects who respond to the threat by decreasing their percentage of bid inflation are most likely to sell their unit in these treatment periods.

Table 4 reports mean inflation measures for each group of treatments that are calculated in accordance with the previously mentioned formula. Scores were closer to 1 in both the H and L threat treatments, thereby indicating that the computer was able to purchase each unit at a price closer to the seller's value in those treatments. Interestingly, the ratio went below 1 for the L treatment as the severity of the threat caused bids to be driven below values on average for the lowest 6 bidders. This could partially stem from the higher random value draw in the L treatment periods (6.68 vs. an H treatment mean of 6.35 and an R treatment mean of 6.48). Since the low budget in the L treatment was designed to contain the expectation of the value distribution (specifically, the expectation of the sum of the lowest 6 out of 11 values randomly drawn between '3' and '10' = 29.10), the greater random value draws in L treatment periods (31.14 on average for the sum of the lowest 6 values) was too high for subjects to avoid the threat without lowering their bids to a level below their values.

Table 4. Mean Inflation Scores

Mean Score	Treatment
1.47	R
1.14*	H
.84**	L

*Threat was realized in 10 out of 28 periods
**Threat was realized in 13 out of 28 periods

The same pattern is found in the calculation of the mean "total inflation" scores reported in Table 5. Here the scores are slightly higher because we are now comparing bids of the lowest six bidders with the values of the lowest six value holders. The different scores in each treatment indicate that not all winning contracts are being allocated to the lowest value holders, a phenomenon which will be explored later with specific measures of adverse selection in each treatment.

Table 5. Mean Total Inflation Scores

Mean Score	Treatment
1.59	R
1.31*	H
0.96**	L

*Threat was realized in 10 out of 28 periods
**Threat was realized in 13 out of 28 periods

Further sensitivity analyses of the inflation scores are reported below in Table 6 and Table 7. In Table 6 it is apparent that the average percentage by which bids exceed values is highest for the low value holders. A similar result is found by comparing Table 7 with Table 4. Here we find that the ratio of bids to values for the lowest value holders is larger than the ratio for contract winners, again confirming the existence of adverse selection in the auctions.

Table 6. Sensitivity Analysis – Geometric Means of Bid to Value Ratios

Treatment	R	H	L
∑(b/v) for all observations	1.56	1.42	1.21
∑(b/v) for observations of the lowest 6 bidders	1.59	1.25	0.94
∑(b/v) for observations of the lowest 6 value holders	1.72	1.58	1.25

*Threat was realized in 10 out of 28 periods
**Threat was realized in 13 out of 28 periods

Table 7. Sensitivity Analysis – Ratio of Bids to Values For the Lowest Six Value Holders

∑(b)/∑(v) for observations of the lowest 6 value holders	Treatment
1.63	R
1.50	H
1.20	L

*Threat was realized in 10 out of 28 periods
**Threat was realized in 13 out of 28 periods

Table 8 reports the average of a measurement of adverse selection costs in each treatment. These costs are calculated for each period as the difference between the sum of values for the 6 accepted bidders and the sum of the 6 lowest overall values. Adverse selection costs are highest in the H treatment and L treatments. Two sample t-tests confirm that the mean adverse selection costs are significantly higher in the H and L auction periods at the α=.01 significance level. A high adverse selection cost is undesirable and inefficient as it corresponds to the case where individuals with a relatively high opportunity cost engage in contracts with the conservation agent. Another way to examine adverse selection costs is presented in Table 9. As the table shows, 83.93 percent of the contracts in the R auction periods were allocated to the individuals with the lowest opportunity cost. This may be contrasted with only 74.40 percent of the contracts in the H and L auction periods.

Table 8. Adverse Selection Costs (a)

Mean Cost	Treatment
2.43	R
4.07*	H
4.21*	L

*Threat was realized in 10 out of 28 periods
**Threat was realized in 13 out of 28 periods

Table 9. Adverse Selection Costs (b)

Percentage of Contracts Allocated Efficiently	Treatment
83.93	R
74.40*	H
74.40**	L

*Threat was realized in 10 out of 28 periods
**Threat was realized in 13 out of 28 periods

Results of an OLS regression of the inflation increment on subject's values and a dummy variable for each of the H and L auction periods using subject fixed effects are presented in Table 10. The equation estimated is as follows:

$$(Bid_i - Value_i) = a + B_1 Value_i + B_2 High_i + B_3 Low_i + e_i$$

The r-squared of the regression is .28 and all variables are statistically significant at the α=.01 level. The constant term of 4.33 reflects the average amount of bid inflation that one would expect to observe in the R auctions for a subject with a value of zero. Of course the lowest possible value is 3 and the average is 6.48 in all R auction periods. The coefficient on value of -.23 reveals that bid inflation decreases with higher value draws. The regression indicates that an individual with an average value draw of 6.48 would be expected to inflate their bid by 2.84 points (a substantial 44 percent above underlying value) in R-type auctions. Looking at the coefficient on the H auction dummy, it appears

that the presence of the threat in the H treatment serves to reduce the inflation increment, as is reflected in the coefficient value of -.82. This result shows that the ordinary level of bid inflation may be reduced by the introduction of a relatively modest threat. The coefficient on the L auction dummy of -1.70 shows an even greater reduction of the inflation increment in L treatment auctions.

Table 10. Inflation Increment Results Using OLS With Subject Fixed Effects

Value	-0.23
	(6.13)*
High	-0.82
	(4.12)*
Low	-1.7
	(8.54)*
Const	4.33
	(16.31)*
R^2	0.28

*Absolute t-ratios are significant at the a=.01 level

Table 11 reports results from an OLS regression of the inflation increment on value and period for all R observations as well as those in the ex-20 and winner subgroups. The equation estimated is as follows:

$$(Bid_i - Value_i) = a + B_1 Value_i + B_2 Period + e_i$$

The coefficient of 0.00 on period (albeit with no statistical significance) indicates that subjects treated each R auction independently. There is no evidence of learning or convergence in the R auctions. The lower coefficient on value for winners indicates that value was a more important factor in lowering the inflation increment among the winners.

Table 11. Inflation Increment Results in Regular Treatment Using OLS with Subject Fixed Effects

	R1	R2	R1 ex 20	R2 ex 20	R1 win	R2 win
Value	-0.28	-0.28	-0.31	-0.31	-0.55	-0.55
	(9.00)*	(9.00)*	(10.62)*	(10.61)*	(15.49)*	(15.46)*
Period		0.00		0.00		0.00
		(0.02)		(0.23)		(0.28)
const	4.69	4.69	4.80	4.82	5.33	5.31
	(21.88)*	(20.03)*	(24.09)*	(22.16)*	(27.47)*	(25.68)*
R^2	0.41	0.41	0.43	0.43	0.70	0.70

*Absolute t-ratios are significant at the a=.01 level

Table 12 reports results from the H auctions of an OLS regression of the inflation increment on value, period, and the dummy variable lastinter which equals 1 if there was an intervention in the last period and zero otherwise. The equation estimated is as follows:

$$(Bid_i - Value_i) = a + B_1 Value_i + B_2 Lastinter_i + B_3 Period + e_i$$

In the ex-20 subgroup and winner subgroups, it is evident that having an intervention in one period caused individuals to lower their level of inflation by around half a point in the next period. As was the case of the R auctions, the winners in the H auctions lowered their inflation increments with each increase in value more than the average bidder (-.70 vs. -.45 in the ex-20 subgroup and -.20 for the entire sample).

Table 12. Inflation Increment Results in High Budget Treatment Using OLS with Subject Fixed Effects

	H1	H2	H3	H1 ex20	H2 ex20	H3 ex 20	H1 win	H2 win	H3 win
Value	-0.21	-0.22	-0.22	-0.44	-0.45	-0.45	-0.68	-0.70	-0.70
	(2.82)*	(2.84)*	(2.89)*	(8.63)*	(8.85)*	(9.02)*	(16.70)*	(17.30)*	(17.21)*
Lastinter		-0.24	-0.18		-0.59	-0.51		-0.41	-0.40
		(0.72)	(0.52)		(2.65)*	(2.32)**		(2.65)*	(2.50)**
Period			-0.10			-0.12			-0.02
			(1.24)			(2.34)**			(0.56)
const	3.44	3.53	4.60	4.14	4.37	5.69	4.44	4.67	4.87
	(6.77)*	(6.73)*	(4.55)*	(12.29)*	(12.71)*	(8.62)*	(19.36)*	(19.44)*	(11.01)*
R^2	0.48	0.48	0.49	0.51	0.52	0.53	0.85	0.86	0.86

*Absolute t-ratios are significant at the (*)a=.01 level and (**)a=.05 level

(Threat was realized in 10 out of 28 periods)

Results from an OLS regression for the L auctions of the inflation increment on value, period, and lastinter are reported in Table 13. The equation estimated is as follows:

$$(Bid_i - Value_i) = a + B_1 Value_i + B_2 Lastinter_i + B_3 Period_i + e_i$$

As in the H auctions, having an intervention in one period reduced the levels of bid inflation in the next period. Not surprisingly, the winners in L auctions lowered their inflation increments with each increase in value more than the average bidder in those auctions. In fact, the above regressions for the H and L treatments showed a larger coefficient on value than the R treatment regressions reported in Table 11. This is not too surprising given our earlier supposition that individuals will be seeking to maximize the following in the H and L treatments:

$$\max\{u(value) * Prob(no\ intervention) + u(bid - value) * Prob(winning)\}$$

It appears as though the left side of the above maximization equation takes priority over the right side for the highest value holders in threat treatments. In order to reduce the probability of losing their comparatively large value from an intervention, the higher value holders bid a smaller amount above their value or a larger amount below their value than lower value holders.

Table 13. Inflation Increment Results in Low Budget Treatment Using OLS with Subject Fixed Effects

	L1	L2	L3	L1 ex20	L2 ex20	L3 ex 20	L1 win	L2 win	L3 win
Value	-0.15	-0.15	-0.13	-0.47	-0.48	-0.50	-0.80	-0.80	-0.85
	(1.64)	(1.65)***	(1.44)	(8.99)*	(9.25)*	(9.15)*	(11.68)*	(12.06)*	(12.27)*
Lastinter		-0.56	-0.55		-0.63	-0.62		-0.74	-0.72
		(1.47)	(1.48)		(2.96)*	(2.90)*		(3.02)*	(2.97)*
Period			0.05			-0.06			-0.14
			(0.48)			(1.03)			(2.20)**
const	2.09	2.33	1.42	2.91	3.21	4.31	3.77	4.09	6.85
	(3.38)*	(3.65)*	(0.72)	(8.09)*	(8.72)*	(3.83)*	(9.05)*	(9.79)*	(5.18)*
R^2	0.57	0.57	0.57	0.59	0.60	0.61	0.73	0.75	0.76

*Absolute t-ratios are significant at the (*)a=.01, (**)a=.05, and (***)a=.10 levels
(Threat was realized in 13 out of 28 periods)

Of critical importance in the results of these experiments is the fact that the threat was triggered in 36 percent of H auctions and 46 percent of L auctions. This corresponds to an outcome of a PES auction in which heterogeneity across opportunity costs is ignored and landowners bear the full burden of service provision. Both equity and efficiency arguments may be made against such a case. Indeed, the implementation of the threat presented here would essentially be considered a "taking" under Epstein's interpretation of the eminent domain clause, although prevailing legal opinion is more in favor of non-compensable regulation when the outcome is sufficiently justified. One of the main factors contributing to the frequent occurrence of interventions is the high

random value draw in several periods. Indeed, in the cases where the value draw is less than the expectation of the distribution (as previously mentioned, 29.1 for the lowest 6 of 11 randomly drawn values from '3' to '10'), the incidence of intervention falls to 17 percent (2 out of 12) of H auctions and 25 percent (3 out of 12) of L auctions. This may be contrasted with the frequency of interventions when the value draw is greater than 29.1. With the higher value draws, the frequency increases to 50 percent (8 out of 16) of the H auctions and 63 percent (10 out of 16) of the L auctions. A summary of these observations is presented in Table 14. This result emphasizes the importance of accurately estimating the distribution of opportunity costs across service providers in these forms of auctions. If actual costs are higher than the estimated distribution, then there will be a considerably higher incidence of threat realizations relative to the case where costs are not underestimated.

Table 14. Percentage of Interventions in Threat Treatments

	H		L	
All Values	35.71%	10 of 28	46.43%	13 of 28
Values ≤ 29	16.67%	2 of 12	25.00%	3 of 12
Values > 29	50.00%	8 of 16	62.50%	10 of 16

29.1 = Expectation of the sum of the lowest 6 of 11 values drawn randomly from 3 to 10

Next, we construct a benefit-cost analysis of bid inflation versus allocative inefficiency from the implementation of a regulatory threat in the auctions. In Table 15 we compare across treatments the nominal outcomes in these auctions (adjusted by a realistic excess burden, or distortionary cost, for raising the required revenue) with the best case outcome from a social perspective. The difference between these two scenarios may be thought of as the net benefit accruing to the auction from implementing the threat

treatments. Again, the nominal outlays must be adjusted because the social cost arising from bid inflation is not simply the amount by which payments exceed underlying values, but instead it is that difference adjusted by an appropriate average cost of funds. The average cost of funds chosen was 30 percent, following Feldstein's analysis of the United States' income tax (Feldstein 1999).[9] The calculation of the net benefit measure is as follows:

$$Net\ Cost = Actual\ Costs - Best\ Social\ Costs$$

$$Actual\ Costs = (.30 * 6 * mean\ of\ the\ lowest\ six\ bids) + (6 * mean\ of\ the\ values\ held\ by\ the\ lowest\ six\ bidders)$$

$$Best\ Social\ Costs = (.30 * 6 * mean\ of\ the\ lowest\ six\ values) + (6 * mean\ of\ the\ lowest\ six\ values\ )$$

The net cost measure represents the inefficiency of the deadweight loss from extra tax dollars from bid inflation plus the excess costs from misallocations. From Table 15, it is apparent that net costs of the auctions are lower on average in the H and L treatments. Table 16 then compares the average percentage improvement in net cost from implementing each of the threat treatments. Net costs are improved by 12 percent and 49 percent on average from the implementation of the H and L treatments, respectively. However, this measure ignores the fact that the threat was actually triggered in several cases, and enthusiasm over the improvements in net costs must be tempered by this knowledge.

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[9] Estimates of the marginal cost of the last unit of revenue raised range as high as 200 percent, considerably greater than the estimate of 30 percent for the average distortionary cost used here.

Table 15. Social Costs of the Auctions

Net Cost of the Auction	Treatment
7.58	R
6.69	H
3.83	L

Table 16. Benefit from Threat Implementation

Percent Reduction in Net Cost From Threat Implementation	Treatment
11.75%	H
49.47%	L

Finally, we look to the performance of auction theory with respect to the R auction results. The mean bid in R auctions was 9.35 versus a mean predicted bid for risk-neutral bidders of 8.77, conditioned on the value draws. Although these means are fairly close, a Wilcoxon signed- rank test indicates that the distributions of actual bids versus risk-neutral predictions are significantly different with a p-value of 0.001. Paired t tests conditioned on each value show that bids were significantly lower than the risk neutral prediction when values were between 3 and 5, while they were significantly higher when values were between 8 and 10. Lower than predicted bids could be explained by the presence of risk aversion among low value holders. However, risk aversion does not explain why the majority of bids among high value holders (8-10) are above the risk-neutral prediction. Figure 8 shows a plot of actual bids versus the risk-neutral prediction. Bids have been slightly dispersed with spherical noise so that they do not overlap, however each point in a cluster corresponds to the nearest integer value on the y axis. In the picture there are many more observations below (above) the prediction when the corresponding value draw is low (high).

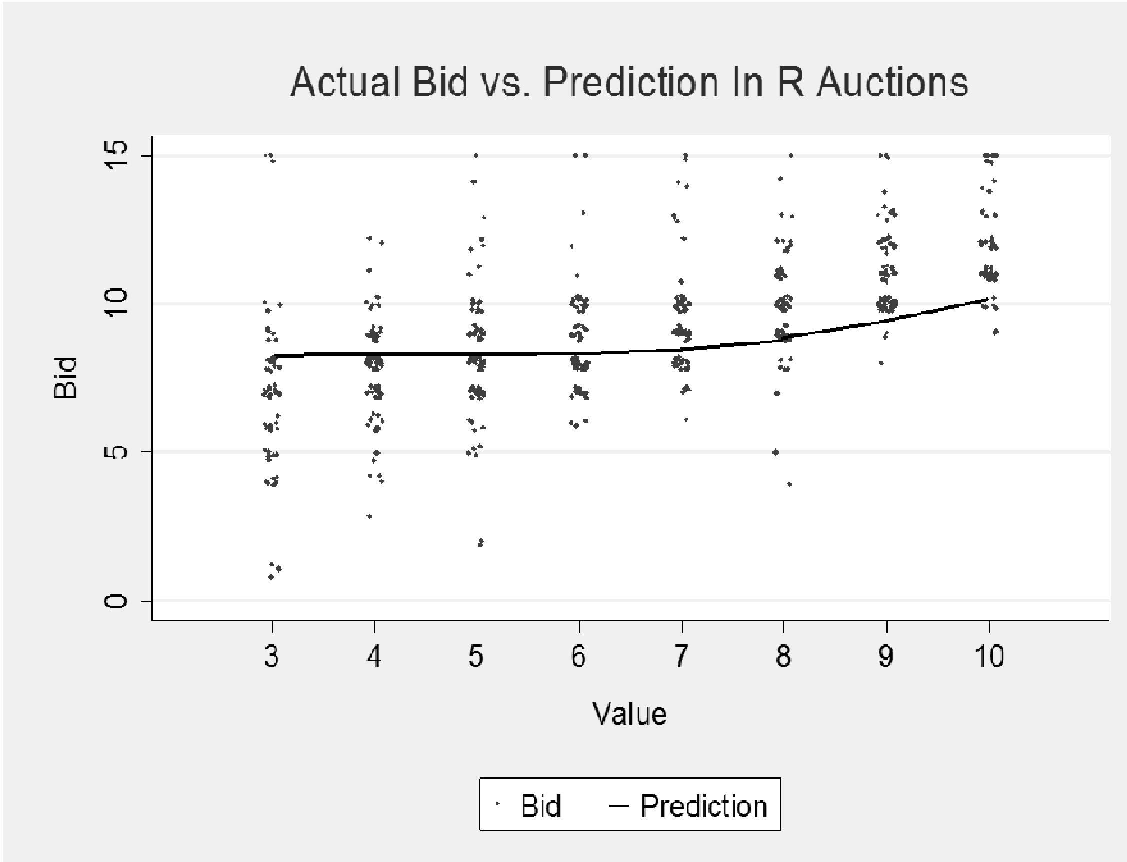

Figure 8. Actual Bid Versus Prediction in Regular Treatment Auctions

Discussion and Concluding Remarks

Overall, the results from the experiment highlight important tradeoffs that arise from the issuance of a regulatory threat. On the one hand, the presence of a regulatory threat reduces the level of bid inflation in procurement auctions. On the other hand, the realization of the threat in 36 percent of the H auctions and 46 percent of the L auctions is undesirable, as it represents the case in which an undue portion of the costs of service provision are forced onto landowners. However, the incidence of threat realization is considerably lower for auction periods in which the actual value draws are equal to or

less than the expectation of the value distribution. This result underscores the importance of correctly estimating the distribution of opportunity costs in this regulatory scheme. Another problematic effect of issuing a regulatory threat is the increase in adverse selection among contract allocations. In this experiment, the adverse selection costs in the auctions increased about 70 percent for both the H and L treatments.

In terms of equity and efficiency, it becomes apparent that both may be adversely affected by the implementation of the regulatory threat in this experiment. To balance those negatives is the positive effect of reduced bid inflation among auction participants. This experiment represents a boundary case in which the regulation is applied to all stakeholders. Other permutations of the regulation that fall between forcing each participant to provide the service and doing nothing may have different impacts on the incidence of threat realization, adverse selection costs, and overall provision costs. Those experiments have yet to be run. Here, the form of regulation punishes service providers for inflating their bids above their costs while ensuring that the environmental service is provided, regardless of the bidding behavior of participants. This structure may be of use in circumstances characterized by a tight public budget, ambiguous property rights, and a keen need for the environmental service. Evaluating these criteria is beyond the scope of this chapter, but the results obtained here highlight the tradeoffs that one would expect to observe from the implementation of such a scheme.

Chapter 2: Estimating Bid Inflation in Procurement of Environmental Services

Introduction

Auction mechanisms are gaining popularity as tools for the procurement of environmental services from private landowners. This trend is occurring because the competitive processes used to allocate contracts in auctions reduce the incentives for landowners to inflate their opportunity costs of service provision relative to the incentives they face when traditional fixed payment allocation mechanisms are implemented. In spite of these improvements, theoretical, empirical, and laboratory evidence all suggest that landowners bid significantly higher than their opportunity costs when participating in auctions for environmental services (Cason and Gangadharan 2005; Cox, Smith, and Walker 1984; Kirwan, Lubowski, and Roberts 2005; Laury 2002). For example, when looking at U.S. Conservation Reserve Program (CRP) auctions, Kirwan et al. estimate that payments to landowners are at levels from 11 to 67 percent above opportunity costs in 2002-2003, the most recent periods of their sample. These estimates represent profits above opportunity costs to program participants of a substantial amount, considering the program has disbursed more than $30 billion dollars since inception in 1985. From an efficiency perspective, these windfall gains create a need for the allocation of a greater amount of public funds to purchase a given level of environmental services than would be necessary if participants bid their true opportunity costs of providing services.

The size of windfall gains to participants in conservation auctions will likely depend on numerous factors including auction rules, frequency of auctions, types of conservation practices contracted, and the duration of contracts. Furthermore, estimating

gains is difficult when the auction is not incentive compatible, and thus, reservation prices are unobserved. Such is the case with one of the most commonly used auction mechanisms, the discriminatory price auction. Empirical studies of the CRP have been informative, but they only examine one specific auction design, albeit the one used in the world's largest conservation auction. Other smaller auctions with differing designs have been used to contract conservation services in the U.S., Australia, Germany, and England. More research is needed to obtain greater understanding of the performance characteristics of different conservation auctions. Specifically, it will be necessary to explore auctions for different kinds of services, as well as those which employ different rules. Whether or not the magnitude of windfall gains to auction participants varies greatly with respect to the type of service being contracted or to the specific choice of auction rules (even among auctions that use some form of discriminatory pricing) remains an open question. This analysis helps answer the question by estimating gains to participants in auctions for irrigation suspension in Georgia (U.S.). Predictions informed by economic literature and theory are used to elicit bidder's implied values distributions, and these distributions are compared across multiple iterations of the auction. Because the data were collected during the implementation of two separate discriminatory pricing rules in 2001 and 2002, it is possible to compare the performance of auctions for the same service under those different rules. Multiple iterations of auction rounds allow for an analysis of how participants adapt their bidding behavior in the face of new information. In addition, we use the underlying value distribution to compare auction performance with hypothetical fixed payment schemes of permit procurement.

The findings of this chapter show the existence of substantial and varying levels

of bid inflation in discriminatory price auction institutions. Over repeated rounds, rent-seeking participants reduce their bids toward the maximum accepted price on average. The implementation of a maximum reserve price also improves auction performance. Finally, a greater number of permits were procured under both auction mechanisms than would have been possible within the same budget using a fixed payment protocol.

The next section of the chapter contains a concise review of the relevant economic literature.

Literature Review

An auction is defined as a market institution with an explicit set of rules determining resource allocation and prices on the basis of bids from market participants (McAfee and McMillan 1987). Clearly auctions have properties that are helpful for the provision of environmental services. Participants are able to deal with uncertainty about the value of services by allowing the auction institution to determine whether or not a contract is accepted.

In their theoretical analysis of PES auctions, Latacz-Lohmann and Hamsvoort (herein referred to as "LH") develop a model of conservation auctions in which each landowner compares potential profits after implementing the conservation practice plus the nonstochastic conservation payment with the profit from remaining at the status quo (not winning a contract) (Latacz-Lohmann and Hamsvoort 1997). In their model, landowners weigh the probability of having their bid accepted against the increased gains that would result from a larger conservation payment. Operationalizing the theory in LH requires an assumption of the distribution of participant's expectations of what will be the

highest accepted bid in the auction, an external assumption to the model. While this is a departure from traditional auction theory where the optimal bid is determined endogenously by the number of auction participants and contracts accepted, along with the assumption of the expectation of the highest value held among all of the auction participants (which is external to the model when the maximum reserve price is unannounced), LH assert that it is appropriate to incorporate the formulation of the distribution of participant's expectations since conservation auctions often have external factors associated with them that would enter into the optimal bid function such as the amount of money appropriated to the auction program, or a projected contract target. After applying their model to a hypothetical conservation program, LH conclude that the auction mechanism does improve the efficiency of contracting for environmental services over traditional fixed-payment schemes used by conservation agents. However, they acknowledge the fact that it is difficult for their theory to "provide a cut and dried solution in most real-world setting" because of relaxed assumptions and simplifications. In this chapter, we test the actual performance of the Georgia irrigation auctions against various hypothetical fixed payment schemes.

Prior theoretical work also addresses the inclusion of a reserve price in multiunit auctions. A reserve price is a minimum acceptable bid in a buyers' auction where there are multiple buyers and a single seller. In a sellers' auction with multiple sellers and a single buyer, a reserve price is a maximum acceptable bid. McAfee and McMillan assert that optimal auction design should utilize a maximum reserve price when there are multiple units contracted and no firm budget constraint (McAfee and McMillan 1987). McMillan later cautions that the maximum reserve price will only be effective when

bidding competition is relatively strong (McMillan 1994). LH report results from the application of their model which suggest that the maximum reserve price in discriminatory price conservation auctions should be calibrated to a level 30 percent higher than the average opportunity cost of service provision to realize the full efficiency potential of the auction. Here, we find the maximum reserve price in the final period data to be less than 30 percent above our estimate of the average opportunity cost of service provision.

In spite of the deficiency of theory in providing unassailable solutions to real-world conservation auctions, particularly those studied in this dissertation, there is a general foundation on which to stand that began with Vickrey's formulations of Nash equilibrium bidding behavior in both single unit and multiple unit auctions for risk neutral economic agents (Vickrey 1961; Vickrey 1962). Harris and Raviv (HR) extended Vickrey's model to explain behavior in multiple unit auctions where all bidders have the same individual concave utility function and values are drawn from a general distribution function (Harris and Raviv 1981). The equilibrium bid function from HR for risk neutral agents was later converted into the form of computable finite polynomials by Cox, Smith, and Walker (Cox, Smith, and Walker 1984). As detailed in the upcoming section on data and methods, their formulation of the risk-neutral equilibrium bid function in a standard buyers' auction can be adapted to provide a prediction of behavior in procurement auctions.

In the previously mentioned paper by Kirwan et al., windfall gains are measured by estimating the endogenous relationship between windfall gains and the overall CRP

bid score.[10] This is accomplished by using exogenous components of the overall score as instruments for the total score. Other researchers have also found evidence of information rents accruing to landowners in the CRP. Shoemaker's analysis depicts how these rents may be capitalized into land values for lands which are eligible for the CRP (Shoemaker 1989). Additionally, *the Economist's* (Economist 1999) report on the California Headwater Forest purchase and Osterberg's analysis (Osterberg 1999) of a German agri-environment payment program both contain further support for informational rents going to landowners in procurement programs.

One empirical paper which is closely related to the analysis presented here is Laury's 2002 study of the performance of the two different auction institutions used in Georgia's irrigation auctions. Her report discusses factors which led to the change of institutions, the results of laboratory experiments to explore various auction rules, and the eventual outcome of the 2002 auction (Laury 2002). Laury finds offers to be substantially lower under the maximum reserve price institution in 2002. While Laury provides a great deal of information with regard to the development and implementation of the Georgia irrigation auctions, as well as an informative comparison of auction outcomes across institutions, she does not attempt to quantify the windfall gains to auction participants. In order to measure bid inflation, one must uncover the underlying value distribution, which is the approach taken in this chapter.

Cason and Gangadharan find evidence of bid inflation and thus windfall gains

[10] Overall bid scores in the CRP are comprised of many factors in addition to a specified payment. These factors include the specific conservation services proposed, environmental benefits accruing from many factors, whether or not the location of a parcel is in a state or national conservation priority area, and others. Note how this contrasts with the GA irrigation auctions where all eligible acreage is assumed to provide the same per acre benefit and bids are only differentiated by the proposed payment per acre of irrigation reduction.

accruing to auction participants in laboratory experiments using both uniform and discriminative price auctions (Cason and Gangadharan 2005). In their experiments, the sealed bid discriminatory price auction institution allows the buyer to purchase a larger quantity of services than the sealed bid uniform price auction. They find evidence of at least 8 percent bid inflation in most offers. By comparison, the experiments reported in Chapter 1 (Holmes 2009) find evidence of inflation to be over 40 percent on average in different parameterizations of discriminatory price reverse auctions.

Cummings, Holt, and Laury also examined the implications of different auction institutions in a paper which describes the design process of the 2001 Georgia irrigation auction (Cummings, Holt, and Laury 2004). After experimenting in both the laboratory and the field, CHL arrived at the recommendation that the regulatory authority use a first price sealed bid discriminatory price auction with multiple rounds of bid revisions to secure a certain level of irrigation suspension in the Flint River Basin. They found that the auction mechanism used in 2001 induced farmers to decrease offers over time and was considered a success even though certain aspects of the auction design (namely the enforcement of constraints by state officials, i.e., fixed budget, acreage target, average price, and maximum accepted price constraints) differed between experimental design and real-world implementation. Similarly to Laury (2002), the CHL paper did not address the magnitude of windfall gains to auction participants.

Previous studies of repeated auctions have shown that repetition degrades the efficiency properties of conservation auctions. In looking at the early signup periods of the U.S. CRP, Reichelderfer and Boggess find that the average bid converges to the maximum accepted payment in the previous round over time (Reichelderfer 1988). Later

work by Hailu and Schilizzi simulates repeated auctions using an agent based model with learning. They also find that repeating the auction process over time degrades efficiency (Hailu and Schilizzi 2004). In this chapter, we analyze five consecutive auction periods to empirically examine any effects of repetition on auction efficiency.

Finally, there are several cases in the literature where researchers have used observables gathered from field data from auctions to estimate the underlying parameters in those auctions. Athey and Haile provide a discussion of approaches to structural estimation of auctions, focusing on first price sealed bid and ascending auctions (Athey and Haile 2007). Wolak presents empirical techniques for recovering cost function estimates for the early months of operation of the National Electricity Market in Australia (Wolak 2003). Zulehner has an empirical study of bidding behavior in sequential cattle auctions in Austria (Zulehner 2003). Other researchers have conducted empirical studies of auctions for different commodities such as the U.S. government's sale of electromagnetic spectrum for personal communication services, oil and gas leases, and timberland harvesting contracts (Haile 2001; Hendricks, Porter, and C.Wilson 1994; McAfee and McMillan 1996).

This concludes the literature review. The next section of the chapter presents a detailed description of the data and methodology employed.

Data and Methodology

The data used in this analysis come from the previously mentioned auctions for irrigation services that were conducted in the Flint River Basin of Georgia in 2001 and 2002. These auctions were a result of legislation passed in Georgia in 2000, which

directed the state's Environmental Protection Division (EPD) to conduct auction-like processes to purchase irrigation rights from landowners in drought years. The goal of the legislation, termed the Flint River Drought Protection Act,[11] was to ensure a sufficient water flow in the Flint River to maintain healthy ecosystems and populations of aquatic life during drought years.

Reverse discriminatory price auction institutions were used in 2001 and 2002 to purchase contracts for irrigation suspension from landowners. Each one year contract covered all of the acreage attached to a specific irrigation permit. The locations of acreage eligible for participation in the auctions were largely similar in both years, with the following exceptions. Specifically, 84 out of the 576 total permits were eligible in 2001 but not in 2002. Similarly, 203 out of 695 total permits were eligible in 2002 but not in 2001. At the intersection, 492 "common" permits were eligible in both auction years. There was some modification to the eligible acreage in 330 of the 492 common permits across years, but the total acreage eligible was virtually unchanged at 85,755 acres in 2001 and 86,001 acres in 2002. Of the common permits, 212 were offered in 2001 and 255 were offered in 2002. The size of permits bid in both auctions ranged from 1 to 1442 acres with a mean parcel size of 180 acres in 2001 and 167 acres in 2002. Standard deviations from the mean acreages for all common parcels bid was 187 acres in 2001 and 165 acres in 2002.

While both the 2001 and 2002 auctions employed a form of the reverse discriminatory price auction institution, each year's institution had specific aspects which made them substantially different from one another. In 2001, a sealed bid auction in

[11] O.C.G.A. 12-4-540 through 12-5-550

which provisional winners and losers were privately notified whether or not their bid would have been accepted in each auction round was used. The maximum average price paid per acre was designated by the EPD director (but not disclosed to bidders) in each round, and these prices rose during the auction process from $104.88/acre in round 1 to $135.85/acre in round 5. The round at which to end the auction was also decided by the EPD director during the 2001 auction process. It is important to note that a priori, bidders did not know the total number of rounds or if there would be more than one round. In contrast, the 2002 auction implemented a stated maximum reserve price per acre of $150 for a single round sealed bid discriminatory price reverse auction. The 2001 process generated five rounds of bidding from 333 bidders for 60,193 acres of land to be removed from irrigation. 33,101 acres were contracted in the fifth and final round at a mean price of $135.85 per acre. In contrast, the 2002 auction allowed for the removal of 40,386 acres from irrigation at mean price of $127.92 per acre (all bids of $145/acre or less were accepted). These results are summarized in Table 17.

Table 17. Summary of 2001 and 2002 Georgia Irrigation Auctions

Year	Number of Eligible Contracts	Total Eligible Acres	% of Contracts Offered	Total Acres Offered	Acres Contracted	Mean Price Per Acre
2001	576	98,170	58	60,193	33,101	135.85
2002	695	111,336	49	52,723	40,386	127.92

Ceteris paribus, it appears that modifying the institution to a single round auction with an announced maximum reserve price in 2002 did result in a lower expenditure per acre of land taken out of irrigation in that year relative to the cost in 2001. That finding would reinforce earlier work from McAfee and McMillan which suggests that the inclusion of an appropriate maximum reserve price will improve auction efficiency.

However, several factors which could affect this outcome did indeed vary across years. Examples of these factors are the inclusion and exclusion of different eligible parcels, varying levels of surface water, changing parcel sizes covered under a permit, changing crop prices, and the varying decisions on choice of crop by landowners. Fortunately, the richness of our dataset allows us to match common parcels across years and account for changing planting decisions.[12] Moreover, each of the above factors is held constant across the five rounds of the 2001 auction. Because of this consistency in 2001, an analysis of changes in the underlying value distributions as implied by participant's bidding behavior in each of the five rounds will provide robust evidence of bid inflation, so long as the assumption of rationality among landowners holds. This assumption implies that landowners never make bids below their opportunity costs.[13]

A logical first step in the analysis of bid inflation, both within the repeated rounds of 2001 and across the outcomes of both years, is to look toward economic theory for a benchmark approximation of the underlying value distributions implied from actual bidding behavior in those auctions. If there is no inflation, then stability in the implied value distributions should be observed across auction periods. Auction theory of multiunit discriminatory price auctions provides a way to accomplish this approximation with the following three assumptions. First, we assume an independent, private-values information environment. In this environment, no individual knows with certainty the

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[12] Changing numbers of competing bidders, total eligible acreage, and total acres bid in different auction years would also influence bidding behavior. These concerns will be addressed in the theoretical discussion that follows.

[13] An alternative idea might be that landowners concerned about the potential damages from reduced stream flows could rationally make offers that are below values. But, this is unlikely given that plenty of money was available to achieve the goal of protecting the river basin ($10 million set aside from a large tobacco settlement in 2001, of which only $4,478,842 was spent). Furthermore, there were a large number of auction participants, each of whom had only a limited ability to influence the final outcome of the auction.

values possessed by other auction participants, and if they did have this knowledge, it would not affect their own private value (Krishna 2002). Although some common value components exist in the auctions, such as expectations of the weather, future crop prices, etc., private values is a more appropriate choice because the value of irrigating is realized through increased production of crops for which each farmer in the river basin is a price taker competing in a large regional and possibly national or global market. Moreover, each farmer likely has greater knowledge of their own production function than anyone else. Alternatively, it can be argued that farmers' values are better characterized by the affiliated private values information structure. In this structure, each farmer knows only their own value of the water in irrigation, but, if they have a high (low) value for the water, then it would be more likely that other farmers have a high (low) value. While this information structure is appealing, differences in the cost of pumping water, dryfarming techniques, management skill of the farmer, the amount of capital employed per acre, and the choice of crops planted are not necessarily affiliated. However, prices received for the crops at market and weather expectations are likely to result in some affiliated components of value. Laboratory experiments by Kagel, Harstad, and Levin (KHL) find that affiliated values auctions for a single unit indicate may yield a higher selling price (less bid shading) in first price auctions if public information is announced beforehand (Kagel, Harstad, and Levin 1987). In the auctions studied here, public information was not announced, but landowners were able to talk amongst themselves before and during the auctions. The results from KHL imply that our assumption of independent instead of affiliated private values may result in larger estimates of bid inflation, although KHL examine single unit instead of multiple unit auctions. Another assumption made in the

application of theory is that bidders are risk neutral holders of equal sized units.[14] The average unit size in our data was 180 (160) with a standard deviation of 186 (167) acres in the 2001 (2002) auctions. Some units were differentiated by the fact that they had multi-year crops growing, such as peach trees (USDA 2007),[15] that would not be planted in the upcoming April. However, 75 percent of survey respondents indicated that they planted corn, peanuts, or cotton in 2001 – this percentage fell to 70 percent among the same farmers in 2002 (Laury 2002). Although there are differences in the size and quality of units held in each auction, this departure from the theoretical assumption is mitigated by the large number of permits contracted in each period : ranging from 50 to 272; and the total number of acres that were contracted in both years: 33,101 (40,386) in 2001 (2002). It seems unlikely that a relatively low number of permits covering acreage of either a large size or with an unusual choice of crop would exert much influence on bids of other participants, especially given the private information sealed bid design employed in the auctions. Lastly, we join this analysis to existing economic theory by making the assumption that farmers formulate their bids as if they know the total number of irrigation permits that will be purchased in each auction period before the auction takes place.

With the three assumptions mentioned above, traditional auction theory allows us to approximate underlying value distributions in each auction period. The values

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[14] If instead, we assumed risk aversion among bidders, then the implied value distributions in each period would be shifted upward by similar magnitudes. Given that we find large differences in implied value distributions across periods under risk neutrality, it is unlikely that a small upward shift in value estimates for each period would substantially change the results.

[15] While the value per acre of a crop of peach trees would likely be worth considerably more than that of more commonly planted crops, there are only a few peach farms in the eligible permit area. Specifically, of the seven counties with the most eligible land in 2002 (over 80%), there are peach farms on less than 3% of the parcels.

recovered depend on the amounts bid (b_i) by individual permit holders $i = \{1, \ldots, N\}$ in the auctions, the total number of bidders (N), the total number of permits purchased (Q), and the highest value auction participants believe to be held by all permit holders ($\bar{v}$). Of course, theory predicts that sellers will try to earn a profit in the auction by increasing their bids above their values and this prediction has been shown to be true in both experiments and empirical studies mentioned earlier. The amount by which a bid exceeds underlying value, otherwise referred to as the quantity of bid inflation, increases with increasing Q or decreasing N. According to the theory, bid inflation is also higher when $\bar{v}$ is higher. Since $\bar{v}$ is the only parameter that must be chosen in our estimation of 2001 value distributions (in 2002 $\bar{v}$ is equal to the specified maximum reserve price of $150 per acre), careful consideration must be taken in its selection.

Again, $\bar{v}$ is the value which individuals bidding in the auction believe to be the highest value held by other bidders. Although this value is unknown in 2001, there are different ways to determine a plausible choice for $\bar{v}$. One way is to examine the percentage of eligible contracts that were offered between 2001 when $\bar{v}$ is unknown and 2002 when $\bar{v}$ is known to be $150 per acre (because of the maximum acceptable reserve price). In 2001, 58 percent (333 out of 576) of eligible contracts were offered in the auction. This compares to 49 percent (343 out of 695) of eligible contracts that were offered in the 2002 auction. Because a larger portion of eligible contracts were offered in the 2001 relative to 2002, it is likely that in 2001, $\bar{v}$ was greater than its value of $150 per acre in 2002. Another way to determine $\bar{v}$ is to think of it as the difference in returns for the highest possible yield from irrigated farming versus the lowest possible yield from dryfarming. This is reasonable to do since the majority of farmers chose to plant crops

after they sold their irrigation permits (87 and 90 percent in 2001 and 2002, respectively). Fortunately, researchers (Faircloth and Rowland 2006; Faircloth et al. 2005) have already examined the returns to irrigation in the Flint River Basin. They estimated differences between dryland and irrigated returns on peanuts using controlled experiments in Dawson, GA occurring from 2002 through 2005. In their analysis, dryland returns are actually higher than irrigated in two out of three years. However, there is one year in which they observe a difference in profit of $228.66 per acre between optimally irrigated and dryland acreages. Calculations using data for corn and cotton yield similar estimates of maximum profit differentials. Therefore it seems reasonable as a first approximation to use $229 and $150 for $\bar{v}$ in years 2001 and 2002 respectively. Interestingly, this estimate is below the highest bids observed in the 2001 auctions. The theoretical prediction of bid inflation does not account for this discrepancy, as theory indicates that the bid should equal to underlying value when value $v = \bar{v}$. It is possible that a small number of peach farmers (whose values per acre of peaches far outstrip those of other farmers) could have participated in the auction and bid above the estimated $\bar{v}$, but the number of these farmers is limited (less than 3 percent of total eligible units in the seven most aggressively targeted counties of the river basin - Macon, Webster, Sumpter, Taylor, Randolph, Lee, and Calhoun counties -which accounted for over 80 percent of the total eligible permits) (USDA 2007). Another possible explanation for the impetus behind bids exceeding $\bar{v}$ could arise from the possibility that some landowners feel a repugnance or reluctance to sell their existing right to irrigation. This would explain very low ($.01 per acre) and very high (up to $8000 per acre) bids as being protests to the institution. Cummings, Holt, and Laury explain how an individual in 2001 who bid $.01

per acre never cashed his check, instead opting to frame it and appear photographed in multiple news stories, while criticizing the auction (Cummings, Holt, and Laury 2004). In this analysis, we will treat all observations of bids above $\bar{v}$ as if they are equal to value v. More formally, $b = v \ \ if \ \ b > \bar{v}$. A rigorous analysis will be made of observations that are within the hypothesized range of the value distribution $\{0, \dots, \bar{v}\}$ in 2001 and those that fall outside of the range $(b > \bar{v}\ )$. Additionally, we theorize that bids greater than $\bar{v}$ may form a repugnance index for the general auction process and implementation. It is important to clarify the consistency across auction years with which $(\bar{v})$ is interpreted. In each year, $(\bar{v})$ is the maximum value of irrigation across permit holders who choose to participate in the auction. In 2001, $(\bar{v})$ is chosen as \$230/acre based on observations of crop prices, historic improvements in crop yields from irrigation, and results from controlled experiments on returns to irrigation in the Flint River Basin. Bids above $(\bar{v})$ = \$230/acre in 2001 are believed to be protests of the auction institution. Protest bids are not feasible in 2002 where only bids of \$150/acre or less are accepted. In 2002, the maximum value of irrigation across all bidders in the auction, $(\bar{v})$, is chosen as \$150/acre. Although the highest value of irrigation across eligible participants is still believed to be \$230/acre, the reserve price precludes any profit-seeking permit holder with a value above \$150/acre from participating.

Once $\bar{v}$ is selected, the theoretical prediction for a risk neutral bidder in Cox Smith and Walker (1984) may be inverted to recover the underlying value distribution for participants in the 2001 auctions. The relevant formula for a traditional multiple unit discriminatory price auction is as follows.

$$b_n(v) = \frac{\bar{v}\sum_{k=0}^{Q-1}\frac{(-1)^k (v/\bar{v})^{N-Q+k+1}(Q-1)!}{(N-Q+k+1)k!(Q-1-k)!}}{\sum_{k=0}^{Q-1}\frac{(-1)^k (v/\bar{v})^{N-Q+k}(Q-1)!}{(N-Q+k)k!(Q-1-k)!}}$$

In this formulation, each bidder $n = \{1, \dots, N\}$ submits a bid b to purchase a single unit, and the Q highest bidders win (note how this is the reverse of the Georgia irrigation auctions, where each bidder submits a bid to sell a single unit, and the Q lowest bidders win). The parameter v is the bidder's underlying value, while $\bar{v}$ reflects the bidder's belief of the highest underlying value held among all auction participants. In the above formula, participants construct their bids by evaluating the probability that at least $(N - Q)$ other bids will be lower than their own bids.[16] The reverse is true in procurement auctions where participants construct their bids by evaluating the probability that at least $(N - Q)$ of the other bids will be higher than their own bids. The relationship between predicted bidding in a traditional buyer's auction to the behavior in the reverse auctions studied here may be characterized in the following way. In a traditional buyer's auction, buyers at the lower end of the value distribution are predicted to shave their bids by the same amount that sellers at the higher end of the value distribution are predicted to inflate their bid in the reverse auctions studied here. An example of this relationship is illustrated in Figure 9. Double arrows are drawn to indicate how the differences between bids and values are related for traditional and reverse auction predictions.

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[16] See Cox, Smith, and Walker, 1984 for a complete exposition of the proof.

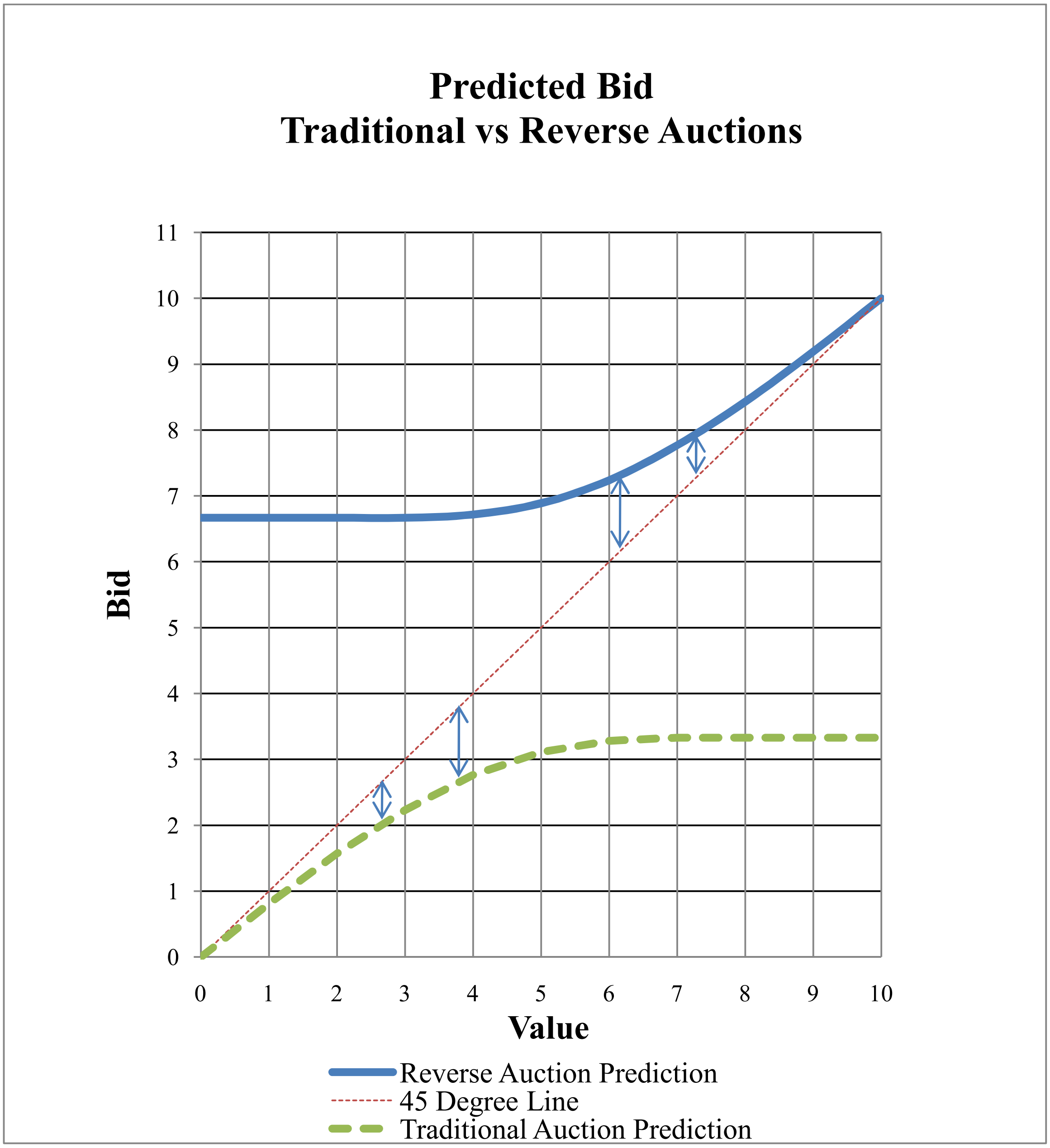


Figure 9. Predicted Bid Versus Value

The next section of the chapter contains estimation results of auction performance.

Results

Predicted values are tabulated with respect to those which are above and below $\bar{v}$ in each of the five 2001 auction periods. These counts are reported in Table 18. The number of bidders whose bids are above the range of $\bar{v}$ drops from 175 out of 333 in period 1 to 119 out of 333 in period 5. As mentioned earlier, we believe those bids which are over $\bar{v}$ may be indicators of participant's objections to the auction procedure. Another plausible explanation could be that our chosen $\bar{v}$ is too low, in spite of our best efforts to accurately approximate the parameter. Or perhaps there are strategic forces related to the possibility of repeating the auction in future years. Regardless, the number of participants who bid above $\bar{v}$ fell in each successive period.

Table 18. Proportion of Plausible Bids in Each Round

Period	Number of Contracts with Implied Values	
	<230	≥230
1	158	175
2	191	142
3	205	128
4	209	124
5	214	119

The implied value distributions across auction periods are compared to confirm the existence of bid inflation. For each period, the approximate value distribution is calculated as if individuals have a priori knowledge of how many contracts will be accepted. If there is no inflation, then the implied value distributions should be stable across all auction periods. Figure 10 shows how the densities of the implied value distributions change in each successive auction period for bids that were less than or

equal to $\bar{v}$ in period 1. It appears as though the distributions are different from one another until around period 4 where the overlay between 4 and 5 is fairly close.

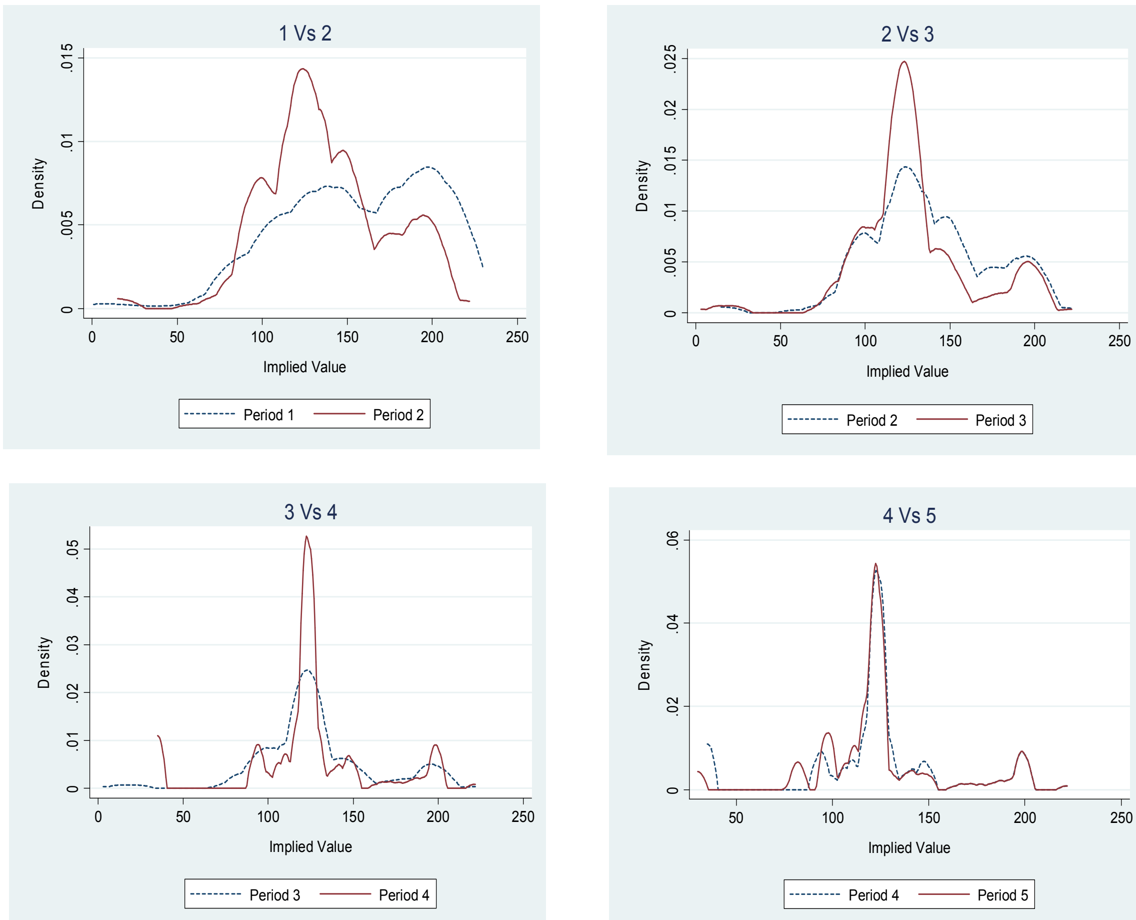


Figure 10. Implied Value Distributions Across Periods

Table 19 reports two-sided Kolmogrov-Smirnov tests for differences in the implied value distributions across periods. The distributions are significantly different at the α=.01 level when comparing periods 1 vs 2, 2 vs 3, and 3 vs 4. Thus, the hypothesis of stability in the implied values across auction rounds is rejected and there is evidence of bid inflation. However, the KS test does not reject the hypothesis that the distributions are the same in periods 4 and 5 at the α=.01 level. These tests reinforce our casual

observation from Figure 10 that the implied value distributions are stabilizing at the end of the 2001 auction.

Table 19. Kolmogrov-Smirnov Tests for Equality of Distributions

			Period 1 vs Period 5
	D	P-Value	Corrected
Combined K-S	0.000	0.000	0.000
			Period 1 vs Period 2
	D	P-Value	Corrected
Combined K-S	0.177	0.000	0.000
			Period 2 vs Period 3
	D	P-Value	Corrected
Combined K-S	0.204	0.000	0.000
			Period 3 vs Period 4
	D	P-Value	Corrected
Combined K-S	0.147	0.001	0.001
			Period 4 vs Period 5
	D	P-Value	Corrected
Combined K-S	0.111	0.033	0.026

A stark contrast in implied values is revealed by comparing the period 1 and period 5 densities in Figure 11. From the graph, it is evident that the peak of the density corresponds to an implied value of around $120 per acre of irrigation suspension in the fifth period. That can be contrasted with the density from period 1, where the peak is concentrated around an implied value of about $200/acre.

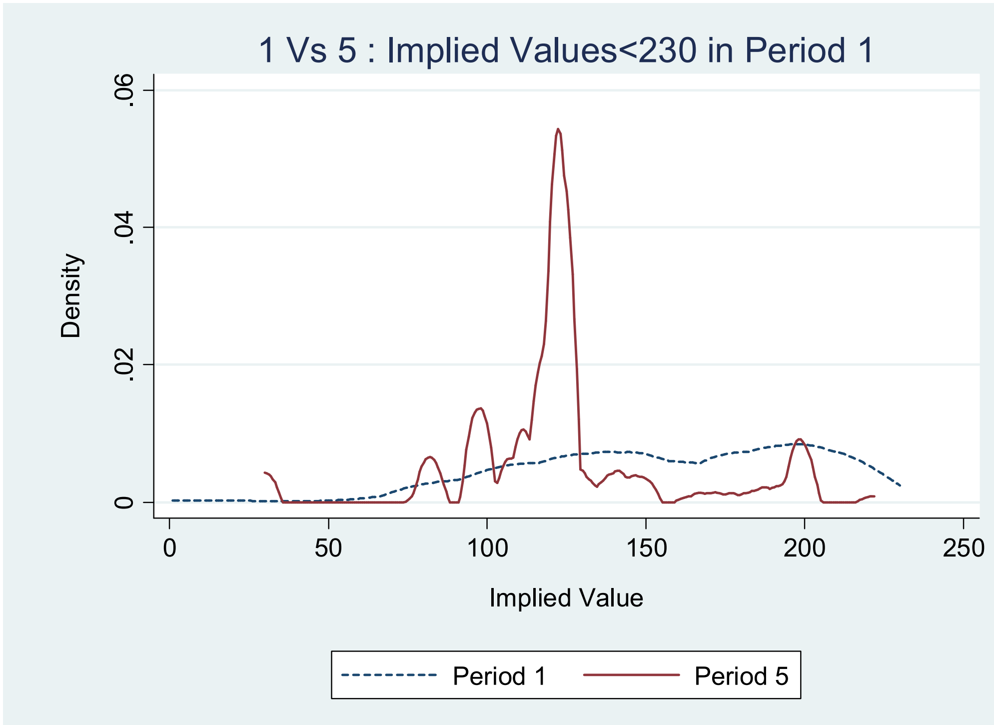


Figure 11. Implied Value Distributions in Period 1 Versus Period 5

While the above findings confirm the existence of bid inflation, there is a question about why the relationship between bids and values changes in periods 1 through 4. The answer is found by looking at the repeated nature of the auction. In experimental auctions, it is not uncommon to look for convergence to the equilibrium condition. Vernon Smith's early paper on auction experiments describes how different conditions such as repetition and varying information environments enable auctions to converge to equilibrium over time (Smith 1962). In our field data, we find convergence from above in period 4 of the 2001 auction. The implication of this convergence is that values recovered from the early periods of the 2001 auction are higher than the true underlying values revealed after convergence in the later periods of the auction. Our general measure of bid inflation is made by comparing amounts bid in each period with the

minimum predicted values revealed by bids, of which the majority occurred in period 5 (51%).

We measure the mean bid inflation in each of the $t = \{1, \ldots, 5\}$ periods of the 2001 auction with the following formula:

$$mean\ bid\ inflation_t = \left(\frac{1}{N}\right)\sum_{i=1}^{N}\{bid_{it} - minimum\ \hat{v}_i\}$$

which shows the mean difference between individual's bids and their minimum implied values ($\hat{v}$) across each of the five periods. More formally, $\{minimum\ \hat{v}_i = min_{t=1,\ldots,5}\ bid_i^{-1}(bid_{it})\}$. Table 20 reports the mean bid inflation in each period for three groups of observations. Group 1 is comprised of observations for those individuals who bid less than 230 in every period. Group 2 is made up of observations from individuals who bid less than 230 in at least one period. Lastly, the Winners group contains observations from those individuals selected to contract with the E.P.D. in period 5. Separating the results into these groups allows for a comparison of the bid inflation level among those participants who's implied values were below $\bar{v}$ for the entire 2001 auction (Group 1) with the level for the group of individuals who's implied values were below $\bar{v}$ in at least one period of the auction, as well as with the level of those participants who ultimately entered into irrigation suspension contracts. Mean bid inflation estimates in Group 1 range from $38.62 in the first period to $7.32 in the final period. For Group 2, estimates range from $62.66 in period 1 to $5.96 in period 5. In the Winners group, the mean estimates of bid inflation range from $62.59 in period 1 to $6.13 in period 5. The similarity of results between Group 2 and the Winners group is

inescapable since the Winners group is a subset of Group 2 sharing 208 out of 214 observations.

Table 20. Bid Inflation by Period

Period	Group 1: v < 230 in all periods (158 Observations)	Group 2: v<230 in some period (214 Observations)	Winners (208 Observations)
	Bid inflation = (bid - minimum implied value)		
1	38.62	62.66	62.59
2	18.50	30.92	30.37
3	10.02	13.74	13.55
4	9.29	10.27	10.51
5	7.32	5.96	6.13
	Mean individual inflation percentage= Mean [(bid - minimum value)/minimum value]		
1	41.23%	58.77%	59.60%
2	24.23%	31.58%	31.83%
3	16.81%	17.15%	17.38%
4	16.92%	16.20%	16.64%
5	15.18%	13.12%	13.50%
	Mean inflation percentage= Mean (bid-minimum value) / Mean (minimum value)		
1	32.47%	48.64%	49.61%
2	15.55%	24.00%	24.07%
3	8.42%	10.67%	10.74%
4	7.81%	7.97%	8.33%
5	6.15%	4.63%	4.86%

The mean individual inflation percentage is calculated for each of the five auction periods $t = \{1, \ldots, 5\}$ and for each subgroup in accordance with the following formula:

$$Mean\ Individual\ Inflation\ Percentage_t = \left(\frac{1}{N}\right)\sum_{i=1}^{N}\{(bid_{it} - minimum\ \hat{v}_i)/minimum\ \hat{v}_i\}$$

This measure of inflation captures the mean percentage above their underlying value by which individual's bid in each round. Group 1 estimates range from a high of 41.23% in

period 1 to 15.18% in period 5. This may be compared with Group 2 estimates which range from 58.77% in period 1 to 13.12% in period 5. In the Winners group, percent inflation falls from a high of 59.60% in period 1 to a low of 13.50% in round 5. The mean individual inflation percentage for each group in all five periods of the 2001 auction is shown in Figure 12. In all groupings, the percentage of inflation falls in each successive period of the auction, thus implying efficiency gains to repeated bidding rounds. It appears as though some farmers start out bidding far above their values and then realize they are going to leave money on the table unless they revise their bids downward toward their true values. High levels of bid inflation in the early rounds are substantial and economically significant, as the total dollar expenditure on irrigation services in 2001 was about $4.5 million. By contrast, in the later periods 4 and 5, these levels of bid inflation are lower in each group as the competitive forces of the auction mechanism drive bids closer to underlying values.

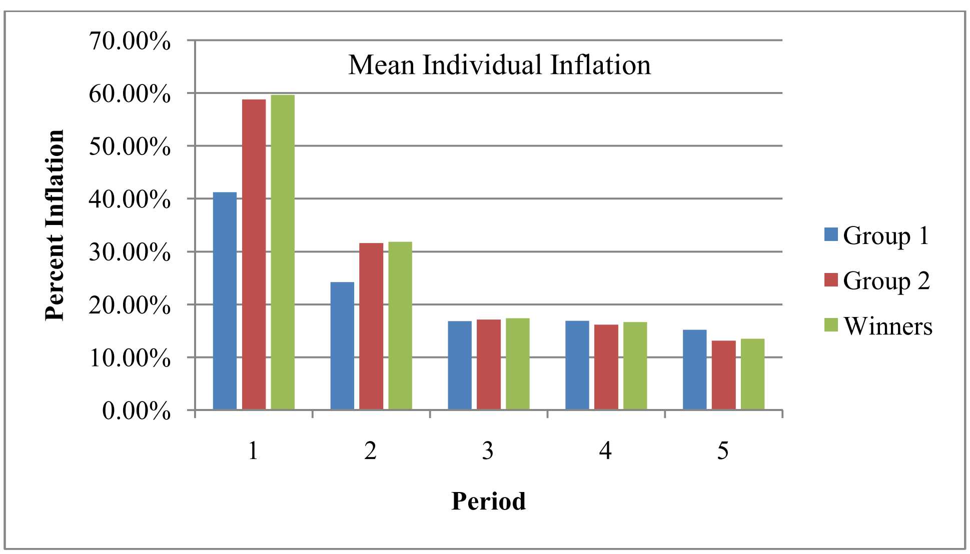


Figure 12. Mean Individual Inflation Percentage

One potential problem with the previous measure of inflation stems from the fact that individual observations with unusually high percentages of inflation coupled with low minimum implied values could bias the mean individual inflation percentage upwards and not accurately characterize the auction's performance in terms of how well the mechanism keeps average premium payouts close to average underlying values. In response to this problem, we construct another measure of the inflation percentage called the mean inflation percentage.

The mean inflation percentage is calculated for each period in accordance with the following formula:

$$Mean\ Inflation\ Percentage_t = \frac{\left(\frac{1}{N}\right)\sum_{i=1}^{N}\{bid_{it} - minimum\ \hat{v}_i\}}{\left(\frac{1}{N}\right)\sum_{i=1}^{N} minimum\ \hat{v}_i}$$

This measure of inflation captures the mean size of the premium by which individual's bid above their underlying value with respect to the mean underlying value for all auction participants. The measure is different from the mean individual inflation percentage reported previously in that it divides the mean individual inflation by the mean minimum value implied by all bidders, rather than dividing each individual's bid inflation by their own implied value. Therefore this measure provides a better description of the overall performance of the auction mechanism, in terms of the amount by which payments (bids) exceeded minimum implied values. The results of this measure are presented in Table 20 and graphically in Figure 13 for Group 1, Group 2, and the Winners group. The mean inflation percentage is lower than the mean individual inflation percentage in each group and period, ranging from 32.47% for Group 1 in period 1 to 6.15% in Group 1 for period

5. Group 2 estimates range from 48.64% in period 1 to 4.63% in period 5. Lastly, the Winners group estimates range from 49.61% in period 1 to 4.86% in period 5. Again, these premiums are of significant size and substantial amount considering the total dollar expenditure of about $4.5 million in 2001.

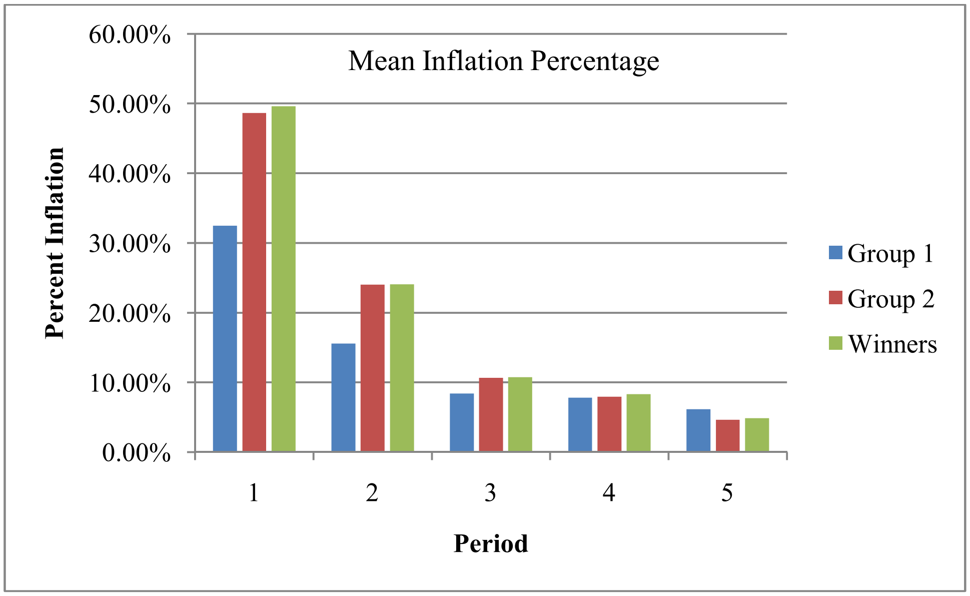


Figure 13. Mean Inflation Percentage

Another important question to address is how bidders change their behavior over time in the 2001 auction. Table 21 reports results from an OLS regression of implied value on auction period using fixed effects. More formally, $\{implied\ value = bid^{-1}(bid_t)\}$. The results indicate a significant and substantial downward trend in implied values over time. For Group 1 observations, the effect is -$7.94/acre per period. The effects in Group 2 and the Winners groups are even larger at -$14.02/acre per period and -$13.90 per period, respectively. The adjusted r-squared is 0.80 for Group 1, 0.73 for Group 2, and 0.71 for the Winners group.

Table 21. Implied Value Results Using OLS with Subject Fixed Effects

	Group 1	Group 2	Winners
period	-7.94	-14.02	-13.90
	(17.99)*	(22.29)*	(21.77)*
const	157.85	194.23	191.12
	(107.80)*	(93.13)*	(90.21)*
R^2	0.80	0.73	0.71

*Absolute t-ratios are significant at the a=.01 level

To further investigate bidding behavior over time in these auctions, it will be helpful to isolate the effect of new information on individual bidding behavior. In Table 22, the differences in mean implied values across periods, calculated as $\left(\frac{1}{N}\right)\sum\{\hat{v}_{it} - \hat{v}_{i(t-1)}\}$, are shown for all auction participants. These differences are also computed for subgroups of individuals which are separated according to whether they received a provisional acceptance or rejection in the previous auction period. For all observations, the mean implied value fell at a decreasing rate in successive periods. On average, the implied values in period 2 are $26.84 per acre lower than the implied values in period 1, whereas the implied values in period 5 are only $1.27 per acre lower than the implied values in period 4. Focusing on differences in implied values across time conditional on whether a bid was provisionally accepted or rejected shows a clear divergence in bidding behavior as participants respond to new information. Implied values do not appear to change in a clear direction in the subsequent period when a bid is provisionally accepted. The change in implied value from one period to the next when a provisional acceptance is received is on average negative ($-1.46 and -$3.12) for periods 3 vs. 2 and periods 4 vs. 3, and on average positive ($.47 and $2.46) for periods 2 vs. 1 and periods 5 vs. 4. There is however a clear propensity for individuals to revise their bids downward as a response

to a provisional rejection. In this case, average implied values fall at a decreasing rate in each period, from an average change of -$31.66 between periods 2 vs. 1 to an average change of -3.42 between periods 5 vs. 4. These changes are illustrated in Figure 14.

Table 22. Implied Values Changing with New Information

	Mean [v(t) - v(t-1)] All Observations		Mean [v(t) - v(t-1)] Provisional winners in the prior period		Mean [v(t) - v(t-1)] Provisional losers in the prior period	
		(N)		(N)		(N)
Period 2 vs Period 1:**	-26.84	(333)	0.47	(50)	-31.66	(283)
Period 3 vs Period 2:**	-13.60	(333)	-1.46	(82)	-17.57	(251)
Period 4 vs Period 3:*	-5.93	(333)	-3.12	(120)	-7.51	(213)
Period 5 vs Period 4:**	-1.27	(333)	2.46	(122)	-3.42	(211)

2 group mean comparison tests show the means for the winners and losers are significantly different at the a=.01 and a=.05** levels

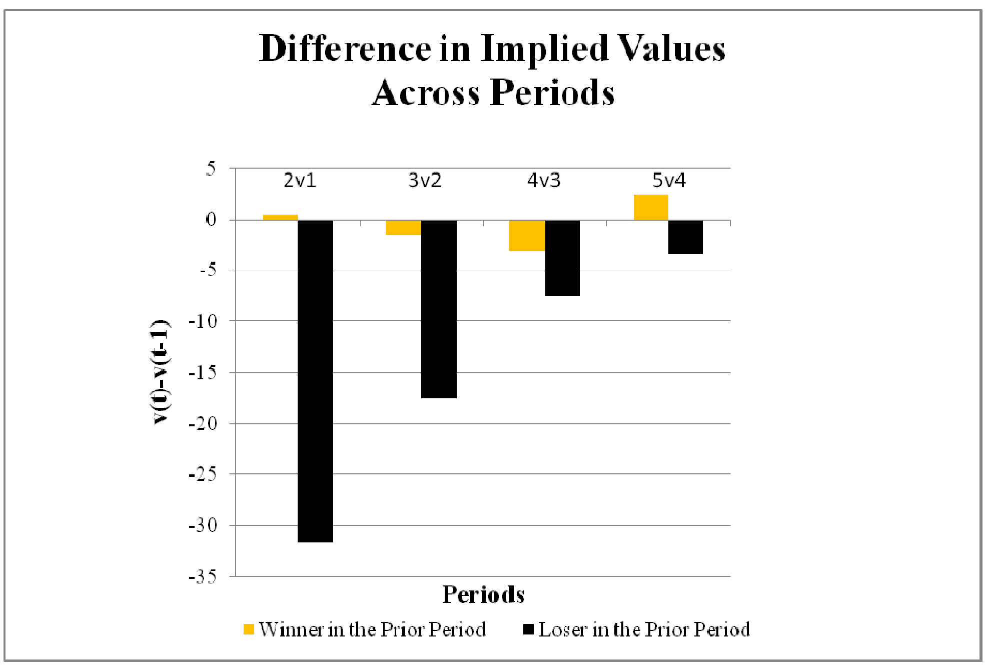


Figure 14. Implied Values Changing with New Information

Another factor of interest is whether or not permit size influences the amount of bid inflation. If a landowner is successful in contracting with the E.P.D., then the nominal amount of the gain received is increasing as permit size increases, holding the amount of bid inflation constant.

More formally:

$$Gain\ to\ landowner\ =\ permit\ size * (bid - value)$$

$$\frac{d(Gain)}{d(permit\ size)} = (bid - value) > 0$$

If farmers have some degree of loss aversion, then we may expect to observe smaller levels of bid inflation as permit size increases. Also, when single individuals own multiple permits which are bid in the auction, we may expect to see a higher level of bid inflation across those permits as they are able to construct a portfolio of bids to reduce the risk of failing to contract at a price above their value (and hence losing out on a potential windfall). Alternatively, we might observe that multiple permit holders behave as if they have a larger amount of total acreage at stake, in which case, we may again expect to see smaller levels of bid inflation. These arguments are constructed into the following testable hypotheses:

Size Hypothesis: Larger parcels will have lower levels of per-acre bid inflation.

Portfolio Hypothesis: Multiple parcels bid by a single owner will have higher levels of bid inflation.

Panel regression using random effects of bid inflation on period, permit size (Acres), the number of other permits offered in the auction by the same bidder (Otherpermits), and a squared term to capture the curvature of the Otherpermits term are reported in Table 23 for Groups 1, 2, and the Winners. The equation estimated is as follows:

$$(Bid_{it} - Value_{it}) = a + B_1 Period_{it} + B_2 Acres_{it} + B_3 Otherpermits_{it} + B_4 Otherpermits_{it}{}^2 + e_{it}$$

As before, there is a major and statistically significant effect of period on the level of inflation. However, the results of both of the above hypothesis tests are insignificant. The coefficient on Acres is negative indicating that there may be a lower level of bid inflation for larger permits, but without statistical significance these results are inconclusive. The z-statistics for Otherpermits are even smaller than those on acreage and the directional effect changes across groups, indicating that bids on multiple contracts may not be constructed differently from those of single parcel owners. The low significance levels of these effects are also apparent in the low between r-squared of .0052, .0097, and .0111 for Group 1, Group 2, and the Winners, respectively.

Table 23. Bid Inflation Results Using Panel Regression with Random Effects
Bid Inflation = (bid-minimum value)

	Group 1	Group 2	Winners
Period	-7.181	-13.405	-13.28
	(17.01)*	(21.50)*	(20.97)*
Acres	-.0012	-.0150	-.01428
	(.14)	(1.32)	(1.25)
Otherpermits	.3804	-.7037	-1.1189
	(.22)	(.31)	(.49)
Otherpermits2	-.1647	.0272	.0552
	(.55)	(.07)	(.14)
constant	38.78	68.08	67.89
	(15.33)*	(20.53)*	(20.24)*
Within r-squared	.31	.35	.35
Between r-squared	.0052	.0097	.0111

Absolute z-statistics are significant at the a=.1 and a=.01** levels

In addition to looking at the behavior of those participant's whom we believe to be formulating "plausible" bids and thus revealing values that are within our hypothesized range of $\bar{v}$, we also consider the bidding behavior of all 2001 auction participants together as well as the separate behavior of those participants who made implausible bids. Figure 15 shows a plot of implied value densities in periods 1 and 5 for all bids excluding one observation of $8,000 per acre.[17] There is a clear leftward shift of the entire distribution as individuals reduce their level of inflation from period 1 to period 5.

[17] This observation was excluded from all graphs for the sake of scale and convenience. It appears as though the individual who bid $8000 per acre to suspend their irrigation in all five periods of the 2001 auction was registering a protest to the auction and did not have any expectation of contracting with the E.P.D.

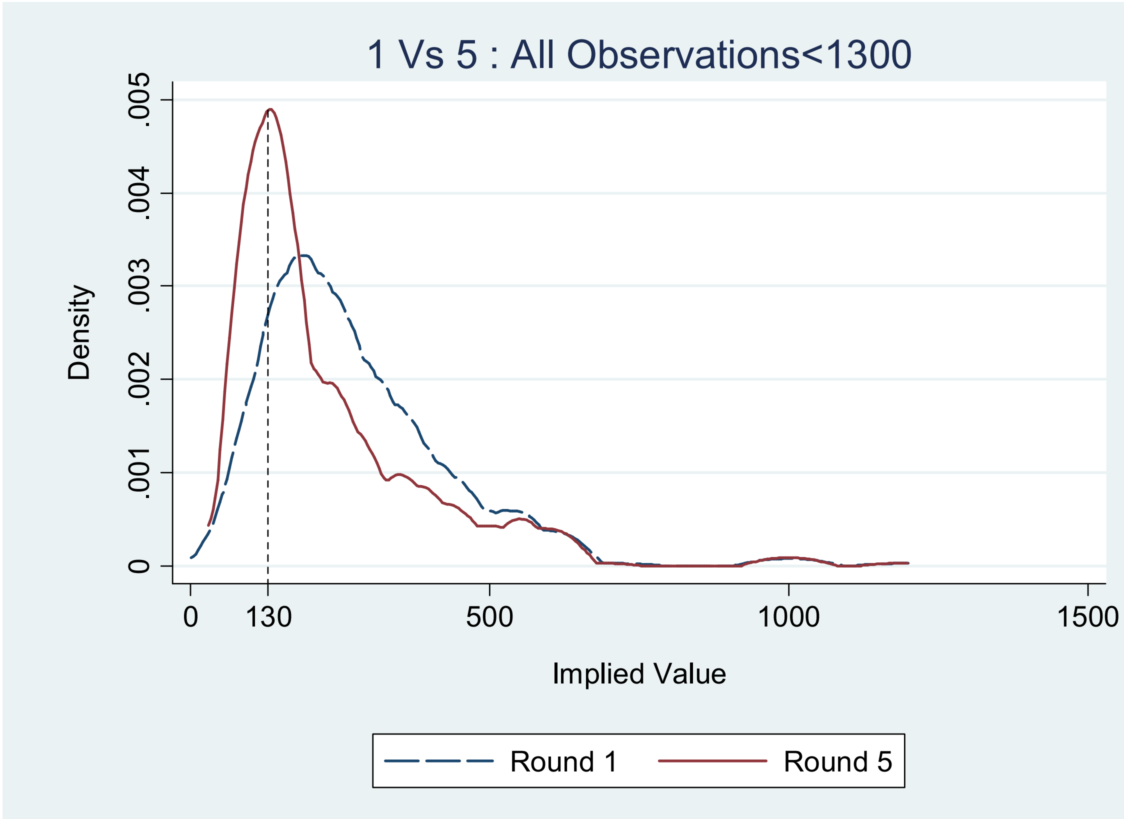


Figure 15. Implied Value Distribution Between Periods 1 and 5 for All Bids

Figure 16 shows the implied value distributions in all periods for observations which were above $\bar{v}$ in period 1 (above $\bar{v}$, the implied value is assigned to be equal to bid since bids are predicted to approach values as they rise to the level of $\bar{v}$). The graphs in Figure 16 appear to be shifting leftward as participants reduce their level of inflation.

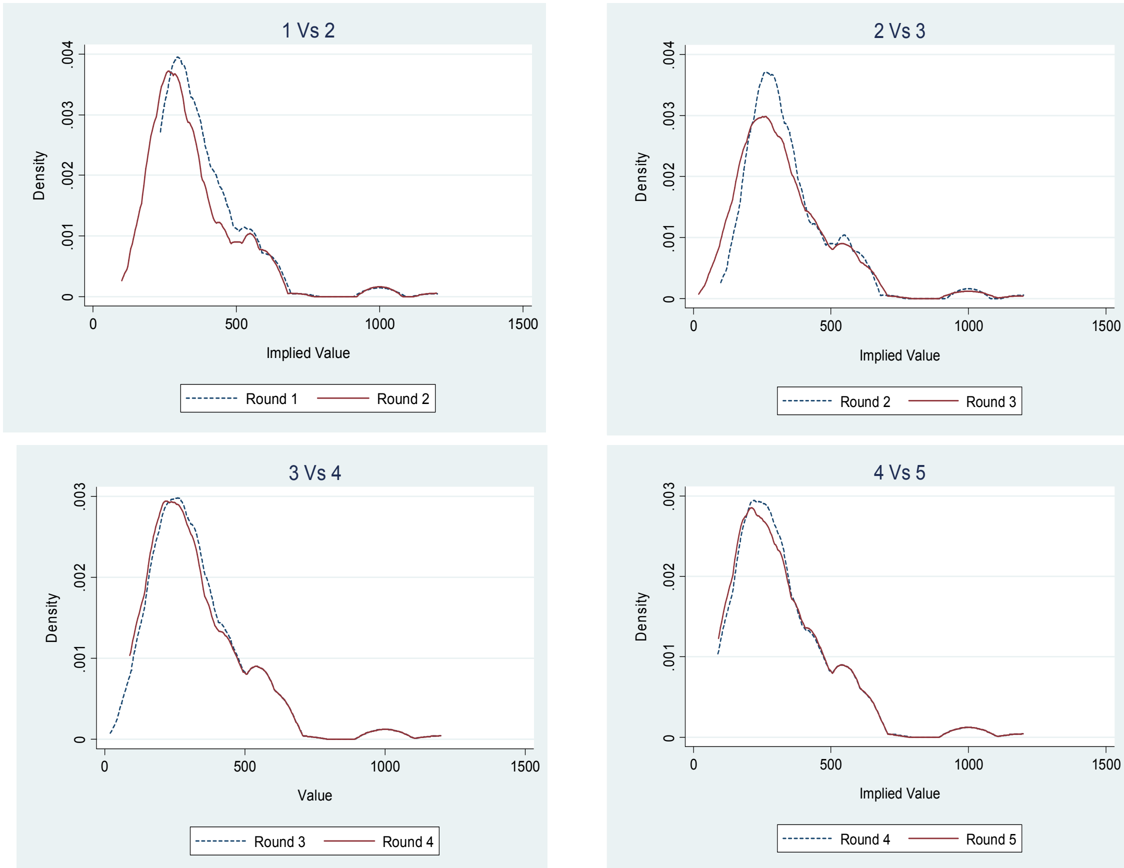


Figure 16. Implied Value Distributions Across Periods for Implausible Bids

This leftward shift may be more easily identified by comparing the densities from periods 1 and 5 for those values which were above $\bar{v}$ in period 1 as shown in Figure 17.

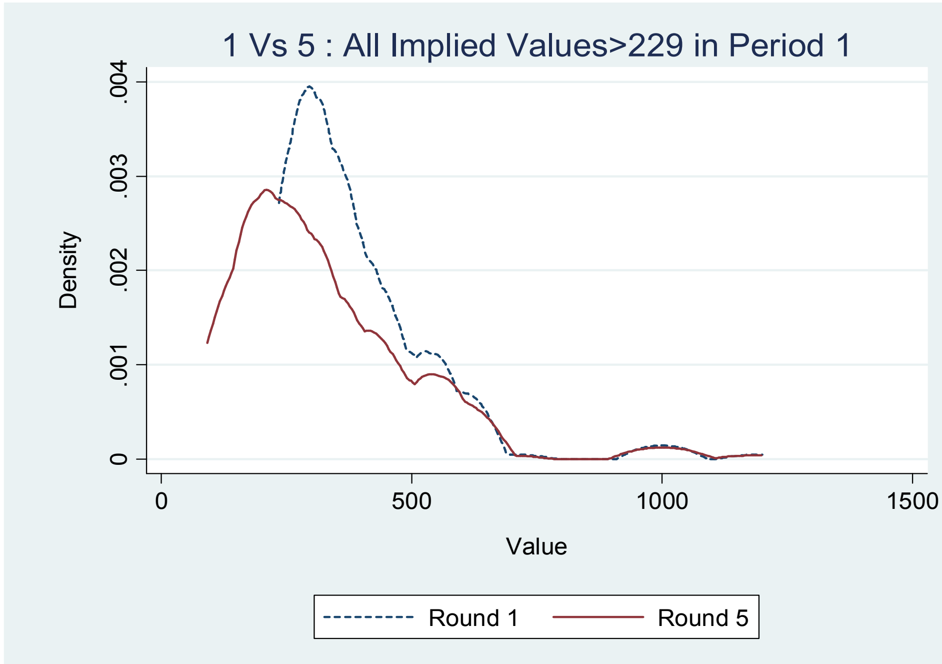


Figure 17. Implied Values in Period 1 Versus Period 5 for Implausible Bids

Kolmogrov-Smirnov tests for the equality of distributions for these bids across all five periods are reported in Table 24. It is clear from the table that participants significantly lower their bids in periods 1 through 3, while the distributions stabilize in periods 4 and 5.

Table 24. Kolmogrov-Smirnov Tests for Equality of Distributions

	D	P-Value	Period 1 vs Period 5 Corrected
Combined K-S	0.349	0.000	0.000
	D	P-Value	Period 1 vs Period 2 Corrected
Combined K-S	0.194	0.003	0.002
Period	D	P-Value	Period 2 vs Period 3 Corrected
Combined K-S	0.189	0.004	0.003
Period	D	P-Value	Period 3 vs Period 4 Corrected
Combined K-S	0.103	0.313	0.269
Period	D	P-Value	Period 4 vs Period 5 Corrected
Combined K-S	0.057	0.938	0.920

Next, we examine the relative performance of different institutions by comparing the amounts bid in 2002 with the minimum implied values from 2001 on the 212 parcels which were offered in both auctions. The 2002 auction results for parcels bid in both years are summarized in Table 25. Looking at the table, it is apparent that there was a divergence in behavior for parcels that entered plausible and implausible bids in 2001 (those which implied a value above and below $\bar{v}$). The mean 2002 bid inflation is calculated as follows:

$$Mean\ 2002\ Bid\ Inflation = \left(\frac{1}{N}\right)\sum_{i=1}^{N}\{2002\ Bid_i - minimum\ \hat{v}_i\}$$

The mean 2002 bid inflation for the 172 plausibly bid parcels from 2001 which were also bid in 2002 is $.55 per acre. This may be compared with a mean 2002 bid inflation of -$238.09 for the 40 implausibly bid parcels from 2001 which were also bid in 2002. The large disparity in 2002 bid inflation between parcels which received plausible versus implausible bids in 2001 provides further evidence that bids exceeding $\bar{v}$ in 2001 were simply protests to the auction institution. It appears as though some individuals who protested the auction in 2001 decided that the money they left on the table by not bidding plausibly was worth more than the benefit gained from drastically overbidding. Indeed, several individuals reduced their bids from $1000 per acre in 2001 to less than the $150 per acre maximum reserve in 2002.

Table 25. 2002 Results for Parcels Bid in Both Years

	Plausible in 2001 (v<230) N=172	Implausible in 2001 (v>230) N=40
Mean Bid Inflation	$0.55	-$238.09
(min , max)	(-$145.91 , $103)	(-$862.50 , -$93.02)
Mean Individual Inflation Percentage	19.45%	-57.26%
(min , max)	(-66.35% , 566.67%)	(-86.25% , -38.60%)
Mean Inflation Percentage	0.42%	-63.45%

Mean individual inflation and mean inflation percentages are calculated using the same formulas presented earlier with 2002 bids in place of those from 2001. In percentage terms, the 2002 auction outperformed the 2001 action with a mean inflation percentage of 0.42% for plausible parcels. This estimate is lower than those found in the literature for other auction mechanisms and supports the theoretical proposition from McAfee and McMillan and Latacz-Lohmann and Hamsvoort that implementing a

maximum reserve price improves auction performance. It is also below the lowest previous estimates of bid inflation in the Conservation Reserve Program by Kirwan, et al.

Finally, we look at how the auction mechanism compares in performance to a suite of hypothetical fixed payment mechanisms. If a bidder has revealed a value during the auction which is equal to or below the fixed payment, then we assume that they would participate in a fixed payment scheme and earn a premium equal to the following:

$$Premium\ From\ Fixed\ Payment = Payment - Value$$

Therefore, the participation constraint in a fixed payment scheme is as follows:

$$\begin{Bmatrix} If\ (Payment - Value) > 0 & ,\ Accept\ Contract\ with\ the\ E.P.D. \\ Otherwise & ,\ Don't\ \ Contract\ with\ the\ E.P.D. \end{Bmatrix}$$

Table 26 compares potential fixed payment outcomes in 2001 using our knowledge of the underlying implied value distribution. In order to contract 33,006 acres (a total amount of acreage similar to the amount contracted in the 2001 auction of 33,101), the E.P.D. would have been required to offer farmers \$200 per acre. At that fixed price, the total expenditure would have been \$6,601,200. This represents a 64.15% higher per acre expenditure than the actual expenditure achieved in the 2001 discriminatory price auction. Moreover, it is important to note that the conservation agent may not have enough prior knowledge of the underlying value distribution to allow for the optimal choice of fixed payment in any given procurement scenario.

Table 26. Potential Fixed Payment Outcomes

Fixed Price Per Acre	Total Acres	Total Payment	Fixed Price Per Acre	Total Acres	Total Payment
$75	2093	$156,975	$165	25765	$4,251,225
$80	2093	$167,440	$170	25855	$4,395,350
$85	2093	$177,905	$175	26632	$4,660,600
$90	2093	$188,370	$180	26948	$4,850,640
$95	3739	$355,205	$185	27120	$5,017,200
$100	6673	$667,300	$190	27597	$5,243,430
$105	7157	$751,485	$195	27713	$5,404,035
$110	8818	$969,980	$200	33006	$6,601,200
$115	10516	$1,209,340	$205	33006	$6,766,230
$120	13447	$1,613,640	$210	33232	$6,978,720
$125	20141	$2,517,625	$215	33232	$7,144,880
$130	22378	$2,909,140	$220	33273	$7,320,060
$135	22667	$3,060,045	$225	33933	$7,634,925
$140	23128	$3,237,920	$230	33933	$7,804,590
$145	23940	$3,471,300	$235	34653	$8,143,455
$150	25688	$3,853,200	$240	35088	$8,421,120
$155	25688	$3,981,640	$245	35349	$8,660,505
$160	25688	$4,110,080	$250	40035	$10,008,750

Figure 18 and Figure 19 illustrate potential outcomes of fixed payment schemes in terms of acres contracted and total program costs for fixed payment programs ranging from $75 to $250 per acre.

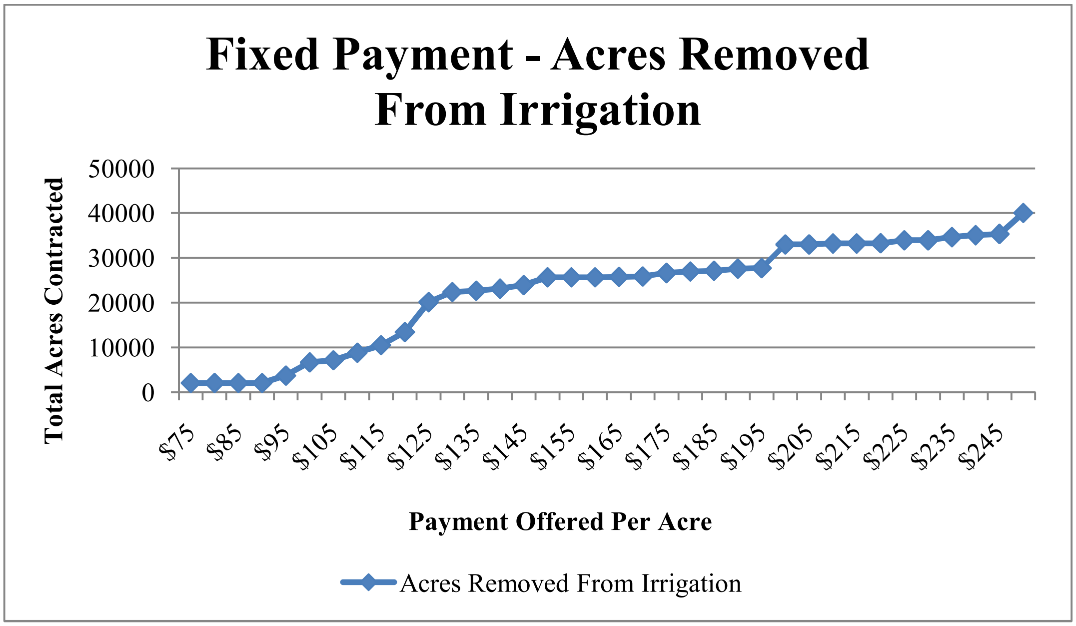


Figure 18. Potential Acres Removed From Irrigation at Each Fixed Price Offer

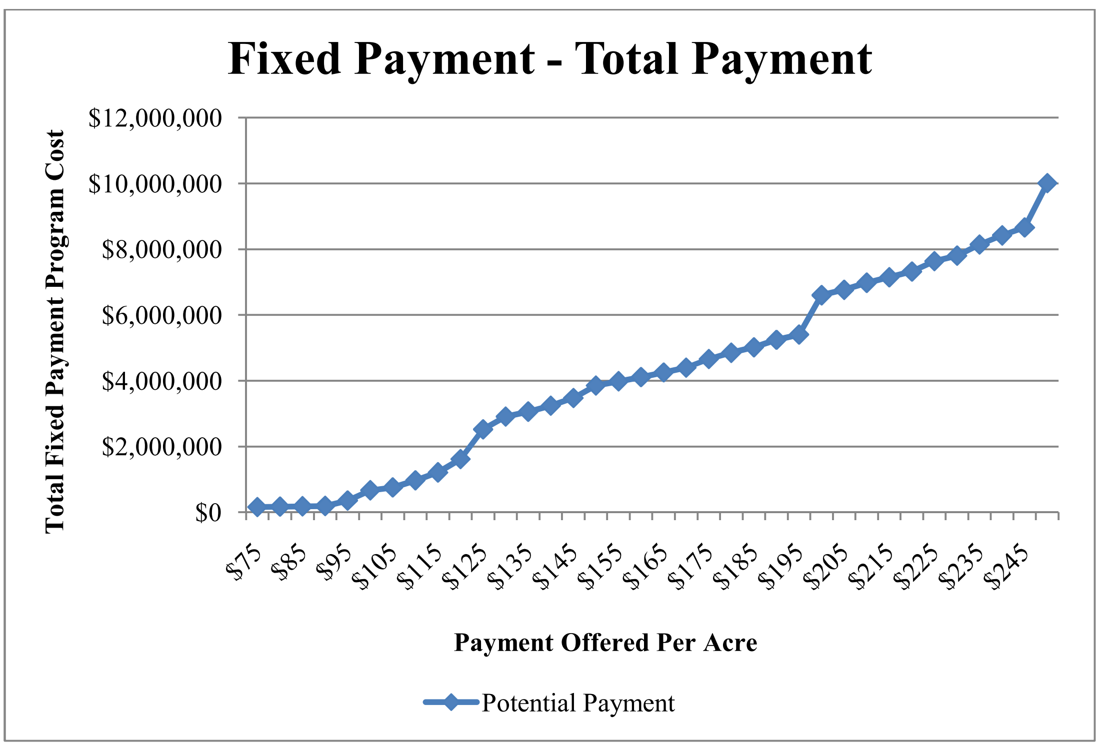


Figure 19. Potential Payments at Each Fixed Price Offer

The final section of the chapter will conclude with general remarks and discussion.

Discussion and Concluding Remarks

Accurate estimation of bid inflation levels in procurement auctions for environmental services is an issue of growing importance, as these kinds of auctions are becoming increasingly popular worldwide. The amount by which auction participants are paid above their opportunity costs will either reduce the amount and quality of environmental services which may be contracted within a given budget, or increase the amount of public funds that must be collected through distortionary taxes in order to meet a particular environmental objective. In addition to providing estimates of bid inflation in irrigation suspension auctions, this analysis increases our understanding of general conservation auctions by comparing performance characteristics under different rules.

Estimates of bid inflation in the Georgia irrigation auctions are largely consistent with previous results from empirical studies of the CRP and experimental studies of first price discriminatory auctions, with the exception of the 2002 auction which shows lower inflation levels. This implies that there may be a common level of inflation for different kinds of environmental services when similar auction institutions are used. The lower variance of our estimates may be explained by the use of different estimation techniques or by the fact that only one service is at stake in the irrigation suspension auction rather than the suite of potential conservation services and land characteristics which factor into CRP bid scores. These results indicate that the optimal choice of auction institution will likely be independent of the type of conservation service procured, so long as there is

sufficient heterogeneity across the opportunity costs of providers to motivate the use of an auction rather than a traditional fixed payment mechanism for procurement.

With respect to auction rules, it appears as though the imposition of a $150 per acre maximum reserve in 2002 allowed for a reduction in the mean inflation percentage among plausible 2001 bidders from 4.63% in period five of 2001 to 0.42% in 2002. The maximum reserve price chosen in 2002 is estimated to be 14.54% percent higher than the mean implied value of our subsample of plausible parcels bid in both years. This gives empirical support to the theoretical claims of McAfee and McMillan and Latacz-Lohmann and Hamsvoort that an appropriately chosen maximum reserve price may improve auction performance.

Repeated rounds in the 2001 auction allow for the observation of changes in bidding behavior over time. In each successive period of the 2001 auction, the mean value implied by participants' bids falls about $8 ($14 dollars for those participants who lowered their bids to a level below $\bar{v}$ in at least one of the five periods). When reactions to new information are incorporated in the time trend analysis, we find that auction participants do not significantly modify their bids upwards or downwards in response to a provisional acceptance in the previous period. However, when bids are provisionally rejected in the prior period, participants reduce their bids by a decreasing amount over time. These findings indicate that bid inflation may be reduced in auctions which are repeated over multiple signup periods, as winners leave their bids unchanged across time while losers reduce their bids to increase their probability of winning in future rounds. This empirical evidence of increasing efficiency from repetition of the auction process contradicts previous empirical findings from a study of the early signup periods of the

Conservation Reserve Programs. Our findings also indicate a more efficient outcome of repetition in auctions than previous research using simulations of an agent based model with learning. Of course, all five periods of the 2001 irrigation suspension auction occurred in the same afternoon, so the ability of each participant to learn from any other's experience was limited by time.

As far as testing the behavior of large landholders versus small, we find negative but statistically insignificant effects of parcel size on bidding behavior. This would indicate that the auction participants do not demonstrate a large degree of loss aversion. Regression results looking for portfolio effects which might arise from bidding more than one parcel in the auction are also inconclusive.

Finally, we find that the 2001 auction yielded a 64.15% improvement in the procurement outcome over the optimal standard fixed payment protocol in that year. While this result does not account for higher administrative costs from conducting an auction instead of a fixed payment scheme, it does reveal a substantial and economically significant reduction in per-acre payments to contract holders. Moreover, the auction mechanism was implemented by the E.P.D. without perfect knowledge of the distribution of the value of irrigation across permit holders. It is unlikely that the E.P.D. would have been able to choose the optimal fixed payment price before implementing such a program. Therefore, the disparity in actual performance between the two institutions could have been much greater.

Appendix A: Sample Screenshots from the Regulatory Threat Experiment

This Appendix contains sample screenshots of the High Budget Auction Treatment bidding phase, Regular Auction Treatment review phase, and subject questionnaire from the experiments on procurement auctions under regulatory threat.

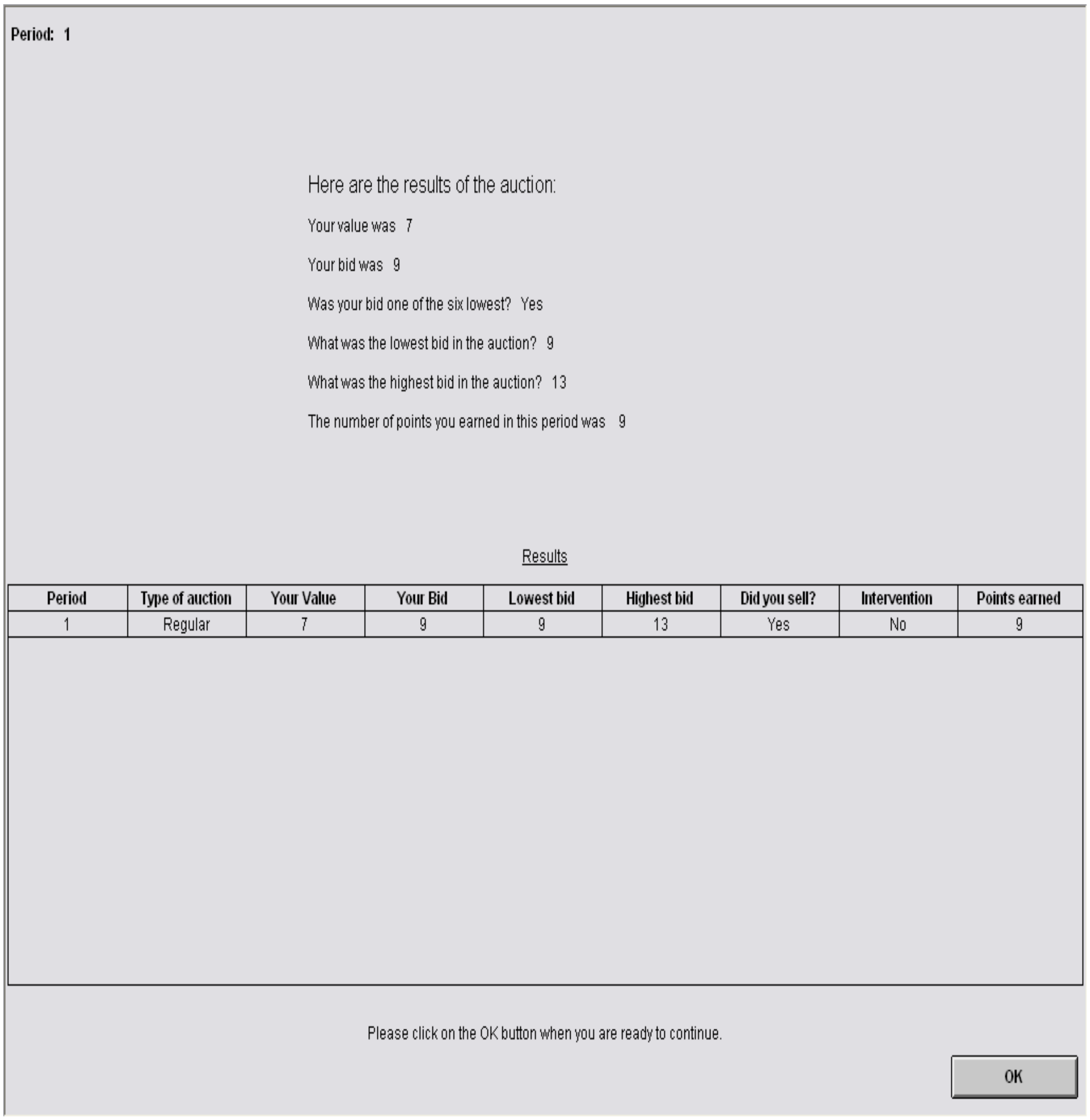
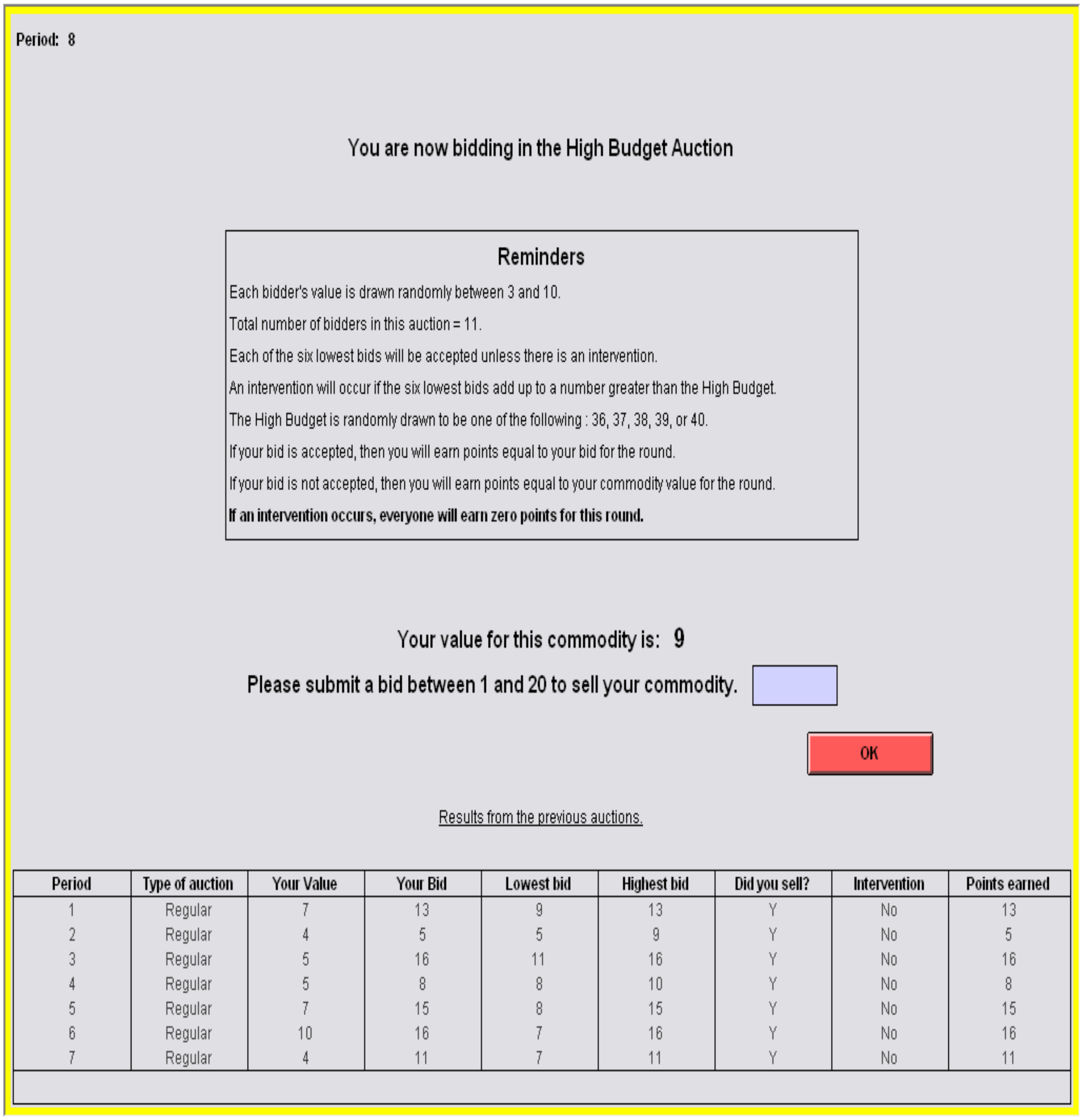


Figure 20. Subject Review Screen After Period 1



Period: 8

You are now bidding in the High Budget Auction

Reminders

Each bidder's value is drawn randomly between 3 and 10.

Total number of bidders in this auction = 11.

Each of the six lowest bids will be accepted unless there is an intervention.

An intervention will occur if the six lowest bids add up to a number greater than the High Budget.

The High Budget is randomly drawn to be one of the following : 36, 37, 38, 39, or 40.

If your bid is accepted, then you will earn points equal to your bid for the round.

If your bid is not accepted, then you will earn points equal to your commodity value for the round.

If an intervention occurs, everyone will earn zero points for this round.

Your value for this commodity is: 9

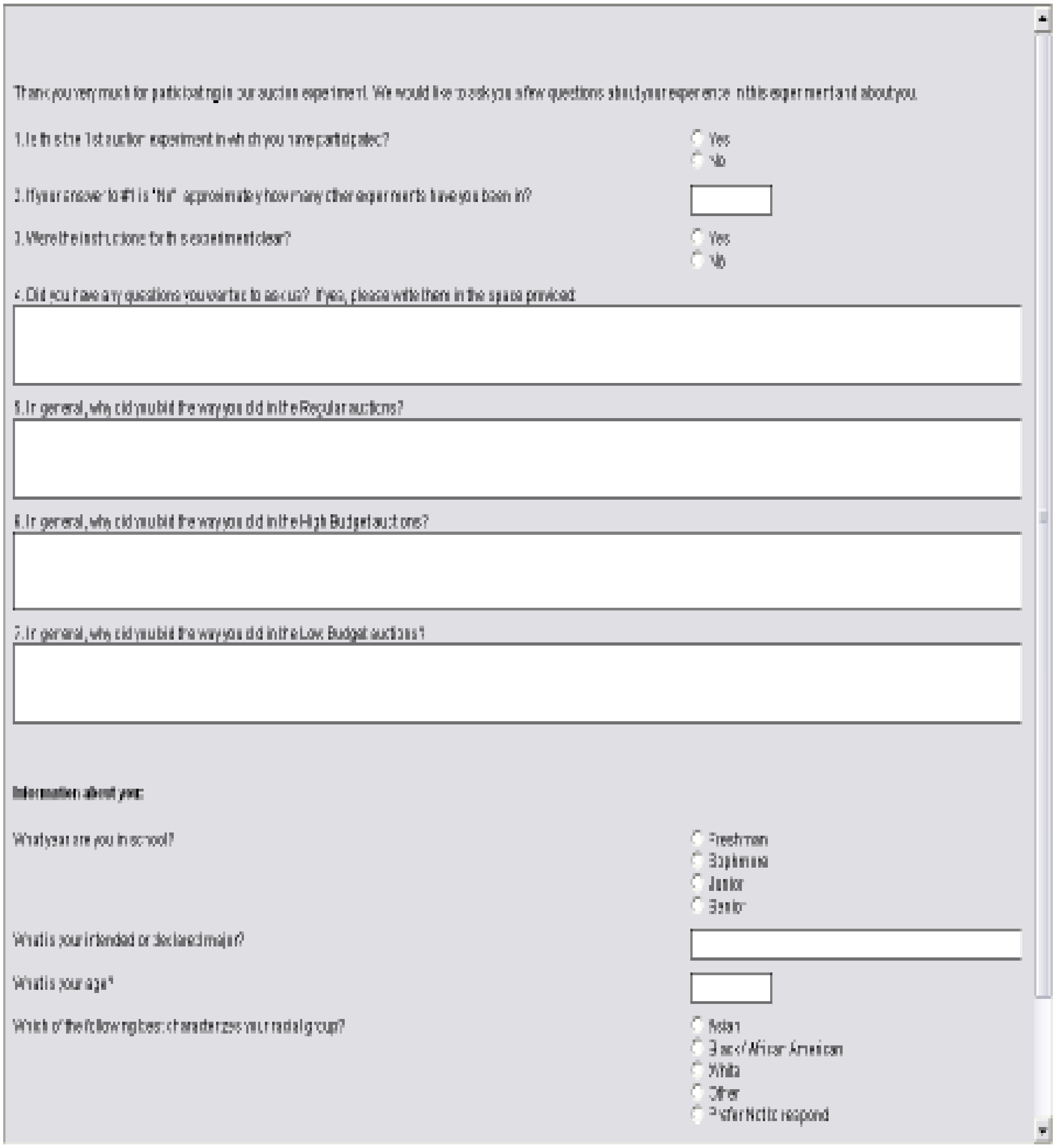
Please submit a bid between 1 and 20 to sell your commodity.

OK

Results from the previous auctions.

Period	Type of auction	Your Value	Your Bid	Lowest bid	Highest bid	Did you sell?	Intervention	Points earned
1	Regular	7	13	9	13	Y	No	13
2	Regular	4	5	5	9	Y	No	5
3	Regular	5	16	11	16	Y	No	16
4	Regular	5	8	8	10	Y	No	8
5	Regular	7	15	8	15	Y	No	15
6	Regular	10	16	7	16	Y	No	16
7	Regular	4	11	7	11	Y	No	11

Figure 21. High Budget Treatment Bidding Screen



Thank you very much for participating in our auction experiment. We would like to ask you a few questions about your experience in this experiment and about you.

1. Is this the 1st auction experiment in which you have participated? ○ Yes ○ No

2. If your answer to #1 is "No" approximately how many other experiments have you been in?

3. Were the instructions for this experiment clear? ○ Yes ○ No

4. Did you have any questions you wanted to ask us? If yes, please write them in the space provided.

5. In general, why did you bid the way you did in the Regular auctions?

6. In general, why did you bid the way you did in the High Budget auctions?

7. In general, why did you bid the way you did in the Low Budget auctions?

Information about you:

What year are you in school? ○ Freshman ○ Sophomore ○ Junior ○ Senior

What is your intended or declared major?

What is your age?

Which of the following best characterizes your racial group? ○ Asian ○ Black/African American ○ White ○ Other ○ Prefer Not to respond

Figure 22. Subject Questionnaire Screenshot

Appendix B: Instructions for the Regulatory Threat Experiment

This Appendix contains complete written subject instructions for the Regulatory Threat experiment. Subjects were able to keep the relevant instructions at their computer for the duration of each treatment. Additionally, there were summaries of key points from the instructions on the computer screen during the experiment and the experimenter discussed the instructions aloud before each bidding session. Except for details of pagination, the instructions are presented below are the same as those seen by actual subjects.

General Background

Welcome. Thank you for participating in today's experiment.

It is important that you remain silent until you are told it is ok to ask questions.

In this experiment each of you are going to be sellers of a fictitious commodity in a sequence of auctions. **There are 11 sellers in each auction.**

In addition to earning $3 for showing up and participating, you will have the potential to earn more money based on the results of the auctions. There are three types of auctions. The rules of each type of auction will be explained in detail later. Each type of auction will be repeated more than once. At the end of the experiment, one period for **each** of the three auction types will be chosen at random for final payout. These selections will be made in plain view at the front of the laboratory using a bingo cage. **You will be paid $1.00 for each point that you earn in those 3 auctions.** How points are earned in each auction period will be explained in detail later.

To summarize, your earnings today will consist of $3 for participating plus $1.00 for each point you earn in three randomly selected auction periods.

Regular (R) Auction Instructions

In each period, you will play the role of seller in an auction and will be given a randomly drawn value for your commodity. Your value will be between 3 and 10. You and the other 10 sellers in the auction will each have an equal chance of having a value of 3, 4, 5, 6, 7, 8, 9, or 10. Values are drawn randomly for every seller, so it will be possible for two or more sellers to have the same value. There will be a new value draw in each period.

Your task in each period is to enter a bid between 1 and 20 to try to sell your commodity.

- If your bid is accepted, then you will earn points for the period equal to your bid.
- If your bid is rejected, then you will earn points for the period equal to your commodity value.

Recall that each point you earn is worth $1.00 if the period in which it is earned is chosen for final payoff at the end of the experiment.

Acceptance Rules:

The computer's role is to order all bids from lowest to highest and to accept only the lowest six bids in every period. **Again, the computer will only accept the *lowest* six bids in each period**. If there is a tie for the 6th lowest bid, then the computer will randomly choose to accept one of the tied bids.

Therefore, there are two possible scenarios that may occur in the Regular auction:

Scenario 1: You submit a bid between 1 and 20 to sell your commodity and your bid is accepted (because it was one of the lowest six bids). When your bid is accepted, you will earn the number of points equal to your bid for the period.

Scenario 2: You submit a bid between 1 and 20 to sell your commodity and your bid is rejected (because it was not one of the lowest six bids). When your bid is rejected, you will earn the number of points equal to your commodity value for the period.

This is the end of the written instructions for the Regular auction. If you have a question at this time, please raise your hand and the experimenter will come to give you an answer.

You will see a brief summary of the instructions during the auction periods.

If you have a question during the auctions, please raise your hand and the experimenter will come to give you an answer.

High Budget (H) Auction Instructions

The High Budget auctions will be similar to the previous Regular auctions except for one very important difference.

- **In the High Budget auction, there is a possibility of an intervention. If an intervention occurs, then everyone will earn zero points for the period.**

In each period, you will play the role of seller in an auction and will be given a randomly drawn value for your commodity. Your value will be between 3 and 10. You and the other 10 sellers in the auction will each have an equal chance of having a value of 3, 4, 5, 6, 7, 8, 9, or 10. Values are drawn randomly for every seller, so it will be possible for two or more sellers to have the same value. There will be a new value draw in each period.

Your task in each period is to enter a bid between 1 and 20 to try to sell your commodity.

- If your bid is accepted, then you will earn points for the period equal to your bid.
- If your bid is rejected, then you will earn points for the period equal to your commodity value, **unless an intervention occurs, in which case all bids are rejected and everyone will earn zero points for the period.**

Recall that each point you earn is worth $1.00 if the period in which it is earned is chosen for final payoff at the end of the experiment.

Acceptance Rules:

The computer's roles are to order all bids from lowest to highest and to determine whether or not an intervention occurs.

- **Intervention will occur if the lowest six bids add up to a number greater than the High Budget.**

- **The High Budget is a randomly drawn number between 36 and 40. This means that there is an equal chance that the High Budget is 36, 37, 38, 39, or 40.**

- **Important: When intervention occurs, all bids are rejected and everyone earns zero points for the period.**

If no intervention occurs, then point earnings are awarded in the same way they were in Regular (R) auctions. Recall from earlier that when your bid was one of the six lowest, then it was accepted and you earned points for the period equal to your bid. When your bid was not one of the six lowest, then it was rejected and you earned points for the period equal to your commodity value.

Therefore, there are three possible scenarios that may occur in the High Budget auction.

Scenario 1: You submit a bid between 1 and 20 to sell your commodity and your bid is accepted (because it was one of the six lowest and there is no intervention). When your bid is accepted, you will earn the number of points equal to your bid for the period.

Scenario 2: You submit a bid between 1 and 20 to sell your commodity and your bid is rejected (because it was not one of the six lowest). When your bid is rejected **and there is no intervention**, you will earn the number of points equal to your commodity value for the period.

Scenario 3: You submit a bid between 1 and 20 to sell your commodity and your bid is rejected (because the six lowest bids added up to a number greater than the High Budget and there was an intervention). **When intervention occurs, everyone's bid is rejected and everyone will earn zero points for the period.**

For illustration purposes only, consider the following examples:

Example 1

The six lowest bids in a period turn out to be 20, 20, 20, 20, 20, and 20. In this case, the sum of the lowest six bids 20+20+20+20+20+20 = 120 is greater than the High Budget, since the High Budget is a randomly chosen number between 36 and 40. There would be an intervention and all bidders would earn zero points for the period.

Example 2

The six lowest bids in a period turn out to be 1, 1, 1, 1, 1, and 1. In this case, the sum of the lowest six bids 1+1+1+1+1+1 = 6 is less than the High Budget, since the High Budget is a randomly chosen number between 36 and 40. There would not be an intervention. If your bid was accepted, then you would earn points for the period equal to your bid (here, all six low bidders would earn 1 point for the period). If your bid was rejected, then you would earn points for the period equal to your commodity value.

This is the end of the written instructions for the High Budget auction. If you have a question at this time, please raise your hand and the experimenter will come to give you an answer.

You will also see a brief summary of the instructions during the auction periods.

If you have a question during the auctions, please raise your hand and the experimenter will come to give you an answer.

Low Budget (L) Auction Instructions

The Low Budget auctions will be similar to the previous High Budget auctions except for one very important difference.

- **The Low Budget is smaller than the High Budget.**
  The Low Budget is a randomly drawn number between 26 and 30.

In each period, you will play the role of seller in an auction and will be given a randomly drawn value for your commodity. Your value will be between 3 and 10. You and the other 10 sellers in the auction will each have an equal chance of having a value of 3, 4, 5, 6, 7, 8, 9, or 10. Values are drawn randomly for every seller, so it will be possible for two or more sellers to have the same value. There will be a new value draw in each period.

Your task in each period is to enter a bid between 1 and 20 to try to sell your commodity.

- If your bid is accepted, then you will earn points for the period equal to your bid.
- If your bid is rejected, then you will earn points for the period equal to your commodity value, **unless an intervention occurs, in which case all bids are rejected and everyone will earn zero points for the period.**

Recall that each point you earn is worth $1.00 if the period in which it is earned is chosen for final payoff at the end of the experiment.

Acceptance Rules:

The computer's roles are to order all bids from lowest to highest and to determine whether or not an intervention occurs.

- **Intervention will occur if the lowest six bids add up to a number greater than the Low budget.**

- **The Low Budget is a randomly drawn number between 26 and 30. This means that there is an equal chance that the Low Budget is 26, 27, 28, 29, or 30.**

- **Important: When intervention occurs, all bids are rejected and everyone earns zero points for the period.**

If no intervention occurs, then point earnings are awarded in the same way they were in Regular (R) auctions. Recall from earlier that when your bid was one of the six lowest, then it was accepted and you earned points for the period equal to your bid. When your

bid was not one of the six lowest, then it was rejected and you earned points for the period equal to your commodity value.

Therefore, there are three possible scenarios that may occur in the Low Budget auction.

Scenario 1: You submit a bid between 1 and 20 to sell your commodity and your bid is accepted (because it was one of the six lowest and there is no intervention). When your bid is accepted, you will earn the number of points equal to your bid for the period.

Scenario 2: You submit a bid between 1 and 20 to sell your commodity and your bid is rejected (because it was not one of the six lowest). When your bid is rejected **and there is no intervention**, you will earn the number of points equal to your commodity value for the period.

Scenario 3: You submit a bid between 1 and 20 to sell your commodity and your bid is rejected (because the six lowest bids added up to a number greater than the Low Budget and there was an intervention). **When intervention occurs, everyone's bid is rejected and everyone will earn zero points for the period.**

For illustration purposes only, consider the following examples:

<u>Example 1</u>

The six lowest bids in a period turn out to be 20, 20, 20, 20, 20, and 20. In this case, the sum of the lowest six bids 20+20+20+20+20+20 = 120 is greater than the Low Budget, since the Low Budget is a randomly chosen number between 26 and 30. There would be an intervention and all bidders would earn zero points for the period.

<u>Example 2</u>

The six lowest bids in a period turn out to be 1, 1, 1, 1, 1, and 1. In this case, the sum of the lowest six bids 1+1+1+1+1+1 = 6 is less than the Low Budget, since the Low Budget is a randomly chosen number between 26 and 30. There would not be an intervention. If your bid was accepted, then you would earn points for the period equal to your bid (here, all six low bidders would earn 1 point for the period). If your bid was rejected, then you would earn points for the period equal to your commodity value.

This is the end of the written instructions for the Low Budget auction. If you have a question at this time, please raise your hand and the experimenter will come to give you an answer.

You will also see a brief summary of the instructions during the auction periods.

If you have a question during the auctions, please raise your hand and the experimenter will come to give you an answer.

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Vita

William Bruton Holmes, son of Dr. John Parham and Mrs. Pamela (Easman) Holmes, was born in Auburn, Alabama in 1974. After graduating from Auburn High School, he went on to earn a Baccalaureate degree in Economics from Auburn University. He then worked for Regions Financial Corporation as a trading assistant on the foreign exchange desk in the company's headquarters in Birmingham, Alabama. During his time at Regions, he was promoted to the position of Assistant Foreign Exchange Trader, second to the Chief Dealer in responsibility on the trading desk. He also began earning an M.B.A. degree in Management from Samford University in Birmingham, Alabama while working at Regions, finishing in June of 2003. In 2004, William married Anne Locklin Bowling, daughter of Mr. Robert Anderson and Mrs. Barbara Anne (Locklin) Bowling. The couple then moved to Atlanta and William began his PhD in Economics at the Andrew Young School of Policy Studies of Georgia State University. In addition to working as a research assistant to Dr. James C. Cox at Georgia State, William has also served as an Adjunct Instructor at Gwinnett Technical College in Atlanta, Georgia, teaching Introductory Macroeconomics. Upon completion of his PhD, the couple will move to Lawrenceville, Georgia where William will be employed at Georgia Gwinnett College as an Assistant Professor of Economics. William and Anne are the proud parents of their son William Bruton Holmes, Jr. (Bru) who was born in 2007.