Auctioning conservation contracts in Indonesia — Participant learning in multiple trial rounds

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Abstract

This paper examines bid adjustments across multiple trial rounds to identify learning by participants in a procurement auction for conservation contracts in Indonesia. Outcomes from previous rounds show an effect on adjustment in subsequent rounds, which is significantly different from predictions under simulated random bidding. This pattern indicates systematic incorporation of information into bid formation, consistent with learning. Individual bidding variability decreases with repetition, consistent with the discovery of a common value component to the auctioned conservation contract. Implications for future implementation of conservation auctions in developing countries and directions for future research are discussed.

Keywords: conservation contract, auction, learning, developing country, non-market goods

JEL subject codes: Q15, Q21, D44, D82, D83

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The Sustainability Science Program at Harvard's Center for International Development seeks to advance basic understanding of the dynamics of human-environment systems; to facilitate the design, implementation, and evaluation of practical interventions that promote sustainability in particular places and contexts; and to improve linkages between relevant research and innovation communities on the one hand, and relevant policy and management communities on the other. See http://www.cid.harvard.edu/sustsci.

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I. Introduction

Market-based mechanisms are becoming more popular in developing countries, extending beyond the firm to target household- and individual-level decision making. Market-based approaches are particularly advantageous in the presence of asymmetric information between the regulator and the regulated agent. A market-based regulatory structure induces revelation of private information, leading to more cost effective regulatory outcomes (Stavins 2001). Concerns surrounding the extension of market-based policies to developing countries often center on the monitoring and enforcement capacity of regulatory bodies (Blackman and Harrington 2000). Complex market-based instruments, such as auctions, may also fail to transfer smoothly from developed to developing country contexts if the targeted individuals or entities do not understand the instrument. This paper explores both the appropriateness of a market-based approach and design choice in a developing country setting.

Environmental policy goals that depend on conservation investments on private lands have recognized the advantages of auctions as mechanisms for both least cost allocation and revelation of private information. Prior to the application discussed here, the implementation of conservation auctions has been restricted to developed country contexts, where they have been used primarily to purchase environmental services from private landholders (Latacz-Lohmann and Van der Hamsvoort 1997; Cummings, Holt et al. 2004; Hailu and Schilizzi 2004; Eigenraam, Beverly et al. 2005; Latacz-Lohmann and Schilizzi 2005). This paper discusses a procurement auction for conservation outcomes on private lands, which was implemented in October 2006 in Sumberjaya Sub-District on the island of Sumatra.[1] Coffee farmers in two villages bid over contracts for soil erosion control investments in an auction designed to facilitate learning — seven trial rounds of the auction were run prior to the final implementation round. The bid data generated across rounds contains features of both lab and field auctions. On the one hand, more data is available than in typical empirical auction studies, where only the winning bid or bids are observed. On the other hand, the data from the trial rounds lack the control available in experimental auction studies, where private values are observed. While existing learning models from the experimental literature do not directly apply, insights from standard auction theory, applied to the Sumberjaya data, provide suggestive evidence that participants understood the mechanism.

The paper is organized as follows. Section II describes the auction setting and implementation. Section III provides a conceptual framework and outlines hypotheses. Section IV reviews relevant research in auction theory and the learning literature. Section V contains the empirical analysis, including tests both for random bidding and for the content of learning across rounds. The conclusion discusses policy implications of the findings and presents suggestions for future research.

II. Context and implementation

The Sumberjaya auction followed a reverse, sealed bid, uniform price auction format with a fixed budget and multiple "learning" rounds preceding a final allocation round. The design features (Table 1) were selected for truthful revelation of value and to allow for learning about both the auction mechanism and common value components of the contract during the first seven rounds.

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[1] The implementing organization is an international agricultural research organization: ICRAF – The World Agroforestry Center.

Table 1. Auction characteristics.	
Auction characteristic	Description
Auction type	One-sided, sealed bid, reverse
Bidding units	Total willingness to pay, single unit
Budget limit	Pre-determined, concealed
Number of rounds	Multiple, announced in advance
Announcement of provisional winners	By ID number
Bid timing	Simultaneous
Pricing rule	Uniform, first rejected price
Tie rule	Random
Bidder number	Known, fixed
Activities contracted	Determined in advance

The budget was set exogenously according to available funds and remained the same across rounds. Bids were ranked on a per hectare basis and accepted, beginning with the lowest bid, until the budget was exhausted by setting the uniform price equal to the first rejected bid. Individuals were not informed of the budget or the cutoff price between rounds. The identification numbers of provisional winners were announced between rounds, which were run in quick succession, with pauses in between for questions and clarifications. Eighty-two coffee farmers, all with secure land tenure, participated in the auction, which was run in two sessions at different locations. Participants were instructed to bid the amount they would require to be willing to implement the described contract, which consisted of three specific soil conservation investments that do not directly affect farm productivity.[2]

A household survey conducted prior to the auction provided data on plot characteristics, household measures, and behavioral variables. Individual heterogeneities in these characteristics are likely to drive variation in private implementation costs. For example, the conservation contract investments require more labor on more steeply sloped plots and hence are more costly to implement on steep plots, holding other factors constant. Some of the variance in survey measures is described in Table 2.

Table 2. Summary statistics for selected household survey responses.		
Survey measures	Descriptive statistics	
Assets (10,000 Rp.)	Mean: 7803	Std. Dev.: 18892
Education (yrs)	Mean: 5.756	Std. Dev.: 3.176
Plot size (ha)	Mean: 0.832	Std. Dev.: 0.530
Distance from plot to road	Mean: 25.96	Std. Dev.: 18.63
Current soil conservation	Winners: 79%	Losers: 66%
Slope	46% of participants on slope>25%	
Assistance from ICRAF	82.9% receive assistance from ICRAF	

Information search costs should not have been a major component in bid price formation. All of the participants responded that they knew someone who had implemented all of the contracted soil conservation techniques, however, none of the farmers had engaged in all three of the techniques themselves. Most had implemented at least one activity aimed at on-farm soil conservation in the past. Based on these survey measures, information about implementation was accessible to all participants. However, heterogeneities may have existed among the farmers with regard to the accuracy of their cost estimates or, more importantly, their confidence in their estimates.

[2] Plots were treated as homogenous in their contribution to erosion control in this application. A scoring rule that prioritizes more erosion-prone plots would improve the cost effectiveness of the auction (see Jack et al. 2009).

III. Conceptual framework

An auction approach to the allocation of conservation contracts is more cost effective than a fixed price approach if the bidders have private information about implementation costs that is revealed through the auction mechanism (Ferraro 2008).[3] This result relies upon two assumptions: first, that participants understand the mechanism, and second, that there exists a private value component to the contract. The failure of either of these assumptions undermines the benefits of an auction approach to contract allocation. The multiple round format of the Sumberjaya auction provided participants with the opportunity to learn both about the mechanism and about any common value component to the contract. The hypotheses tested in this paper seek to provide evidence on two central questions: 1) do the assumptions necessary for an auction to be advantageous hold in this context (Part 1), and 2) does the multiple round format improve auction outcomes (Parts 2 and 3)?

Part 1	H_0: Random bidding	
Part 2	H_1: Private value	$H_{1\text{-}1}$: Pure private value $H_{1\text{-}2}$: Mixed private/common value
Part 3	H_2: Learning	$H_{2\text{-}1}$: Learning common value $H_{2\text{-}2}$: Other learning

Figure 1. Conceptual framework and outline of hypotheses.

Part 1 of the empirical investigation tests the assumptions that contracts have a private value component (H_1) and that participants understand the mechanism (H_2) by comparing sample data to a null hypothesis of random bidding. Rejection of the null provides support for the assumptions of understanding and private value, and implies that the auction was successful in revealing private information. I simulate random bidding and compare the random data with the sample data in a dynamic panel data regression of bid formation across rounds to test Part 1. Part 2 extends the alternative hypothesis of a private value component to the contracts (H_1), looking for evidence of pure private value ($H_{1\text{-}1}$), which, if rejected, supports the hypothesis of a mixed private and common value to the contract ($H_{1\text{-}2}$). Since the explanatory power of survey measures should increase with experience in a pure private framework, as participant understanding of the mechanism improves, I compare model fit for a regression of bids on survey characteristics for each round. If the R-squared measures do not improve with time, it indicates a mixed private and common value framework ($H_{1\text{-}2}$). Part 3 further investigates the learning content supported in H_2, testing whether participants learn about the common value component of the contract ($H_{2\text{-}1}$), which is conditional on a conclusion in the second stage of a mixed private and common value ($H_{1\text{-}2}$). If participants learn about the common value component to the contract, their bids should converge over time. A comparison of mean adjustments across rounds provides straightforward evidence on

[3] Under a fixed price scheme, the contract price is determined by the implementing agency and is uniform for all participants.

convergence. If no convergence is observed, then another type of learning is present (H_{2-2}). Other learning models are not directly testable with the current data; however, rejection of the common value learning hypothesis (H_{2-1}) in combination with rejections in the first two parts indicates that the participants are learning something over the trial rounds, though the precise nature of the learning is unclear.

The hypotheses in Parts 2 and 3 build on models of the value content of the conservation contracts in the Sumberjaya auction. The model for a mixed private and common value is developed in detail here and extended for the pure private value case. In the mixed value setting, the private value content of contract implementation cost includes heterogeneities in plot characteristics and individual opportunity cost. The common value component is likely to relate to the labor requirements of the contract that do not vary across individuals, and to the general value of entering into a formal contract with an international organization, which may also vary with trust and other behavioral characteristics. A general model capturing both private and common value elements can be represented by a value that is a function of both private signals and all other auction participants' signals:

$$v_{i,t} = s_{i,t} + \theta_{i,t} \sum_i s_{-i,t} \text{ , where } s_{i,t} = s_{i,t-1} + \theta_{i,t-1} \sum_i s_{-i,t-1} = s_{i,1} + \sum_t (\theta_{i,t-1} \sum_{-i} s_{-i,t-1})$$

$v_{i,t}$ is the value placed on the contract by individual *i* at time *t*

$s_{i,t}$ is the updated private signal of value held by individual *i* at time *t*, where $s_{i,1}$ is the initial private signal which is adjusted to reflect information obtained across rounds

$s_{-i,t}$ are the private signals held by all individuals ≠ *i* at time *t*, which represents the common value element of the contract

$\theta_{i,t}$ is the weight placed on the common value element by individual *i* at time *t*, which represents the degree of updating due to learned information about common value

Updating revises bids according to the information acquired about common value: $adj_{t-1} = E(v_t - v_{t-1} | \theta_{i,t-1} \sum s_{-i,t-1})$, which, after canceling terms, can be expressed as $v_{i,t} - v_{i,t-1} = \theta_{i,t} \sum s_{-i,t}$, indicating that adjustment depends solely on the $\theta_{i,t}$ parameter, taking other bidders signals as fixed. It is straightforward to show the expected direction of adjustment is increasing in the aggregate signals: $\frac{\partial v_{i,t}}{\partial \sum s_{-i,t}} > 0$, such that bidders that learn that the distribution of others' bids is higher should adjust upward.

If $\theta_{i,t}$ is rationally updated across rounds, then it should be decreasing in *t* as previous aggregate signals are incorporated into bidders' private signals. Thus, $\theta_{i,t} = \sum \theta_{i,t} - \sum \theta_{i,t-1} = \sum \theta_{i,t} (1 - \frac{\sum \theta_{i,t-1}}{\sum \theta_{i,t}})$, such that $\theta_{i,t} \to 0$ and $v_{i,t} \to v_i$ as $t \to \infty$. If convergence does not occur, then the data is inconsistent with rational learning about the common value component and the hypothesis in Part 3 (H_{2-1}) may be rejected. If instead, the contract is of pure private value (H_{1-1}), bidders may still face uncertainty around their own private value, represented by an independent error terms surrounding each bidder's private signal, then $v_{i,t} = s_i + \varepsilon_{i,t}$, and predictions for updating are unclear without additional assumptions surrounding correlations in values, signals, and disturbances across rounds.

IV. Related literature

In theory, the auction structure induces revelation of private information by creating a competitive bidding environment where setting bids equal to private value is the best response for all participants. If the costs of engaging in land use practices that provide environmental services are unknown and have a common value structure, then landholder costs are homogenous and an auction will not reveal private information. In practice, many auctions include a mix of private and common value, resulting in heterogeneous values across bidders. Generally, and in the specific case of the Sumberjaya auction, a second price auction with a common value component should not create a winner's curse (Klemperer 2004).

In a repeated auction, bidders may learn from one another based on provisional announcements of winners or prices in laboratory settings, or from previous auction outcomes in field settings. In most applications, auction rules are adapted across repetitions to eliminate learning, which may lead to strategic bidding and the accrual of rents to bidders (Reichelderfer and Boggess 1988; Latacz-Lohmann and Schilizzi 2005). In the Sumberjaya application, where bidders were intentionally allowed to learn, learning may relate to both the contract value and to the mechanism itself. In the case where bidders are learning about a common value component to the contract, bidders would be expected to incorporate information from previous rounds into bids in future rounds, updating prior private values with information about the common value. Value estimates improve with time, leading to a decline in adjustment as the auction progresses, consistent with a convergence in $\theta_{i,t}$ as predicted in the hypothesis of learning about the common value component to the contract (H_{2-1}).

Alternatively, individuals may face uncertainty surrounding their own private valuations, which can only be updated through experience with the unfamiliar good or under an assumption of affiliated private values (Shogren, List et al. 2000). Rasmusen (2006) explores uncertain private values and information acquisition during the auction, building on several prior theoretical investigations of costly information acquisition (e.g., Guzman, Kolstad et al. 1999; Compte and Jehiel 2004; Compte and Jehiel 2007). The Sumberjaya auction participants were not provided with any information that would reduce uncertainty around private values as long as error terms on private signals are uncorrelated. Concerns surrounding spurious affiliation of values among participants in repeated auctions are diminished when prices are not announced between rounds (List and Shogren 1999; Bernard 2005). Prices were not announced in the Sumberjaya auction, so that participants were unable to anchor on irrelevant price information. As a result, affiliation in values indicates either a common value component to the contract or an affiliation in values associated with, for example, costs of information acquisition.[4]

If the market mechanism itself, and not valuation, is the source of uncertainty, then learning of a different type may occur (List and Shogren 1999). In early rounds, individuals may adjust their bids in order to learn about the mechanism. Where a budget cap is used to endogenously determine the cutoff price, then bidders may use early auction rounds to acquire information about the size of the budget. Between rounds, participants in the Sumberjaya auction learned only whether they won or lost. Thus the information available to update bids between periods was restricted to the outcome from the previous round and the cumulative outcomes up to that point. More generally, in repeated strategic interactions under uncertainty, individuals use the information obtained from previous interactions to adjust behavior in future rounds (Fudenberg and Levine 1995). Models of this learning process have emerged in both the

[4] An affiliation of values in the costs of implementation would be present if, for example, the opportunity cost of contract implementation is directly affected by the contracting outcomes of other auction participants. Information search costs might be one source of affiliation; the greater number of villagers holding contracts, the greater the available knowledge on implementation and the lower the costs of acquiring information on implementation.

theoretical and empirical literature.[5] However, testing any of these learning models requires information that is not available for the Sumberjaya auction participants.

Studies, primarily in experimental economics, have examined learning behavior in auction contexts. Shogren et al. (1994) describe a Bayes Nash equilibrium bidding strategy in a second price auction where bidders incorporate information from previous non-binding trials, however, they do not solve for the updating between rounds. In a different study, Shogren et al. (2000) explore preference learning in a repeated auction, in which winners gain experience with unfamiliar goods before proceeding to the next round. While substantial discussion in the experimental economics literature focuses on behavior across auction trials, the observed behavior is rarely modeled. Using an agent based modeling approach in a conservation auction context, Hailu and Schilizzi (2003) assume that winners adjust bids upward while losers adjust bids downward across auction rounds, however, no learning model is developed to support these assumptions. In a common value setting, Dyer et al. (1989) compare learning behavior across rounds between "naïve" student bidders and experienced corporate bidders and find little difference between participant types, which they conclude as an indication that experience does not readily transfer between auction settings. List and Shogren (1999) also compare naïve and experienced bidders across rounds in repeated second-price auctions and find that naïve bidders are overly responsive to price information, though repetition allows for mechanism learning that improves bidding behavior over time. Possible heterogeneities in learning across individuals may detract from findings in Part 3 of the empirical investigation of the Sumberjaya auction.

V. Empirical analysis

In the Sumberjaya auction, the distribution of contract prices captured by the final round bids mimics a fairly standard cost curve, with greater variance in costs at the higher end of the cost curve (Figure 2).

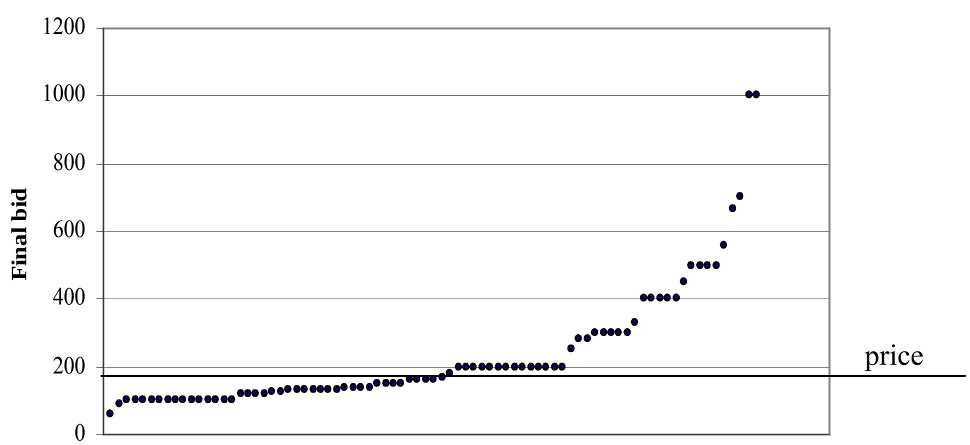

Figure 2. Distribution of final round bids.

[5] Much of the empirical work has been laboratory based. Prominent models of learning include a rational or Bayesian approach, in which individuals update their beliefs given new information in statistically accurate ways (Fudenberg 1998). Naïve or cognitive models of learning, such as fictitious play, rely on mental models of the game space to determine play, which are updated to incorporate new information (Fudenberg and Levine 1995; Fudenberg 1998). Another popular learning model, reinforcement learning emerged from laboratory studies of strategic games with a pre-determined Nash equilibrium (Erev and Roth 1998). All of these models involve convergence to equilibrium strategies and analyze the convergence process. The eight rounds of data from the Sumberjaya auction lack an observed or predicted convergence value, such that these learning models may not be readily applied.

Winners of the contracts fall below the price cutoff line, which is determined by the budget, and contain relatively little of the total variance in costs, as described by final round bids. As an initial investigation of the relationship between the individual characteristics and the final contract values from the allocation round, I regressed the logarithm of final round bids on twenty survey measures of plot, household, and behavioral characteristics thought to capture important determinants of opportunity cost. The fitted values from the regression reveal poor explanatory power from the survey measures (Figure 3).

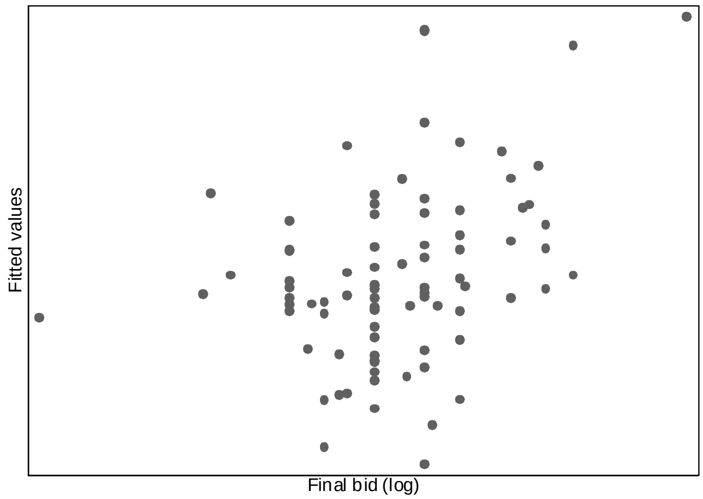

Figure 3. Fitted values from OLS regression of (log) final bids on 20 survey measures.

The poor predictive power of the survey measures could be attributed to a variety of factors. First, unobservable characteristics may be driving the costs represented by final bids. Second, measurement error could increase the standard errors and decrease the overall fit of the model, but would still produce unbiased estimation as long as the measurement error is uncorrelated with any omitted variables (Wooldridge 2002). Third, bids may not contain information about opportunity cost, either because of a lack of understanding about the mechanism or because of a pure common value to the auctioned contract as perceived by the bidders. Either of the first two explanations could exist simultaneously with truthful revelation of private information under the auction mechanism. The third of these explanations is investigated in Part 1, below. Additional analysis of the relationship between survey measures and bidding behavior is carried out in Parts 2 and 3.

Part 1

A general empirical model that captures the dynamic aspects of the trial rounds sets adjustment equal to a linear combination of adjustment from the previous round and the information acquired from lagged outcomes, with an individual specific fixed effect. The empirical model is not constrained by any of the models of contract value described in Section III and can therefore be used to test hypotheses about value structure, participant understanding, and learning behavior.

$$adj_{i,t} = \alpha * adj_{i,t-1} + \beta_1 * win_{i,t} + \beta_2 * \sum win_{i,t-1} + \eta_i + v_{i,t}$$

where $adj_{i,t} = bid_{i,t+1} - bid_{i,t}$

The dependent variable represents the forward adjustment in bids, and winning outcomes are contemporaneous with the base round for the dependent adjustment variable. The cumulative number of wins is lagged to avoid double counting the winning outcome. An individual fixed effect is included in the regression, to capture individual heterogeneities in adjustment, which may reflect confidence in the private signal, and thus either the weight on the common value component or the error around the private signal.

Beginning with straightforward summary statistics that compare bids across means for winners and losers of the auction (Table 3) shows that winners adjust bids upward between each round. Losers, on the other hand, adjust bids downward, with adjustments significantly different than those of winners. Between the next to last and the final round, loser strategies change, and bids are adjust upward.

Table 3. Mean bid adjustments between rounds for winning and losing bidders.

	Mean lose	Mean win	p-value
bid(2) – bid(1)	-.1603	.2087	0.0412*
bid(3) – bid(2)	-.1871	.2014	0.0126*
bid(4) – bid(3)	-.3124	.1626	0.0027**
bid(5) – bid(4)	-.1010	.2653	0.0489*
bid(6) – bid(5)	-.2806	.2094	0.0064**
bid(7) – bid(6)	-.1755	.4368	0.0002***
bid(8) – bid(7)[†]	.0600	.1785	0.2533

[†] Allocation round; binding.
*p<.10, **p<.05, ***p<.01 based on a t-test with unequal variance.

The effects described in Table 3 can be better analyzed through a panel data regression that includes individual-level controls. The parameter $\theta_{i,t}$, introduced in Section III, represents the weight that individuals place on the signals of other auction participants, which may vary over time. As an inverse measure of the strength of the private signal, $\theta_{i,t}$ is unobserved and would be expected to bias the estimates on lagged winning outcomes under a pooled ordinary least squares specification. A stronger private value signal, associated with a lower $\theta_{i,t}$, should increase the magnitude of the coefficient on lagged win. The fixed effects estimation eliminates individual effects that would affect bidding adjustment and addresses the omitted variable problem for $\theta_{i,t}$ only if $\theta_{i,t}$ is time invariant. The estimates presented in columns (2) and (3) of Table 4, use a random effects specification and add the assumption that the individual specific effect is orthogonal to the error term. An individual fixed effects estimate is shown in column (1). Comparing the estimates in the fixed effects model with a random effects model in a Hausman test rejects the null that the individual effects are exogenous, and thus the random effects model is inconsistent. In Table 4, the outcome variables (adjustment) are in differences of logarithm bids, so the coefficients can be interpreted approximately as percentage changes in the dependent variable. The mean adjustment (constant) is significantly different from zero under all specifications, though the sign on the coefficient changes directions when household covariates are included.

Table 4. Static specifications for learning rounds only.			
Adjustment	(1) Fixed Effects	(2) Random Effects with plot covariates	(3) Random Effects with plot and household covariates
Win (lag)	0.865***	0.493***	0.508***
	(0.11)	(0.08)	(0.09)
Sum wins (lag)	0.095***	-0.024	-0.021
	(0.03)	(0.02)	(0.02)
Constant	0.412***	0.307***	-0.497**
	(0.05)	(0.11)	(0.25)
R-squared	0.0933	0.1150	0.1185

N: 82 individuals, 492 observations
Standard errors (in parentheses) clustered at the individual level for all specifications
(2) includes 10 plot level measures
(3) includes 16 plot and household measures, including those in (2)
*p<.10, **p<.05, ***p<.01

The static specifications presented in Table 4 ignore the relationship between the lagged values of the dependent variables and their future values. Updating behavior in previous rounds is likely to affect future updating decisions. Imposing an assumption of sequential exogeneity relaxes the strict exogeneity assumption that would be required to introduce a lagged value of adjustment into the specifications defined in Table 4. Under the assumption of sequential exogeneity, error terms from previous periods may be correlated with future observations of the independent variables but must be uncorrelated with past observations (Arellano 2003). Within the adjustment model, the assumption of sequential exogeneity is reasonable if bidders do not anticipate future bids in determining bid submissions in any given round.

Three models were run using dynamic panel data techniques from Arellano and Bond (1991) with lagged independent variables as instruments for explanatory variables. In the first specification (1), all adjustment periods were estimated, with no distinction between learning and allocation rounds. In the second specification (2), two controls for changes in the market over time were added: the standard deviation in bids to control for convergence and a learning round dummy. The third specification (3) is only applied to the first seven rounds and so concentrates exclusively on learning behavior. In all three specifications, the previous round win outcome and the lagged cumulative number of wins were treated as predetermined and endogenous, and thus lagged levels rather than lagged differences were used as instruments (Arellano and Honore 2001).

In all three specifications in Table 5, the signs of the coefficients on the explanatory variables are consistent. Winning in a previous round corresponds to a significant upward adjustment, with a greater magnitude under specification (3). The learning rounds in specification (3) show a 98 percent increase over the mean adjustment of negative sixteen percent for a move from lose to win. The lagged adjustment predicts around a twenty percent adjustment downward for one point, or ten percent, increase in the lagged value. For specifications (1) and (3), the constant is not significantly different from zero, so the direction of adjustment is negatively related to the previous round adjustment for all rounds, including the allocation round, when controlling for winning outcomes. Finally, the cumulative number of wins is significant only for the learning round specification (3), with an additional previous win corresponding to approximately a 45 percent increase over the mean adjustment. As in Table 4, the dependent variable is measured in the difference in logarithm values of large numbers (millions of Indonesian Rupiah), so the percentage interpretation around the mean is approximate. Controlling for the lagged adjustment makes the mean adjustment (constant) insignificant for specifications (1) and (2) and reverses the sign in specification (3) from the fixed effects static estimate (Table 4).

Table 5. Arellano-Bond (1991) estimates of previous outcome on adjustment.

	Dynamic panel estimate		
	(1)	(2)	(3)
Adjustment		With round controls	Learning rounds only
Win†	1.177***	1.126***	1.983***
	(0.38)	(0.38)	(0.50)
Adjustment (lag)	-0.210***	-0.208***	-0.222***
	(0.06)	(0.06)	(0.07)
Cumulative wins (lag)†	0.157	0.104	0.450***
	(0.10)	(0.10)	(0.16)
Constant	-0.042	0.003	-0.162**
	(0.05)	(0.05)	(0.07)

N: 82 individuals, (1) and (2) 410 observations, (3) 328 observations
† win and cumulative wins assumed to be predetermined and endogenous
(2) controls for standard deviation of bids across rounds and includes and learning round dummy
*p<.10, **p<.05, ***p<.01

The significance measures in Table 5 pertain to a null hypothesis of no effect. To test the first null hypothesis that bids do not contain private cost information (H_{01}: random bidding) from Section III, I simulated observations for 82 sets of random draws from a normal distribution with a mean of 14.5 and a standard deviation of 0.7, such that the simulated distribution parameters matched those in the sample. A "winning" price was set using the average winning price from the auction rounds, instead of an endogenous rule determined by the budget. Two thousand iterations of the regression used in column (3) in Table 5 were run to generate estimates on the explanatory variables from random bidding behavior for the learning rounds only. I tested the linear hypotheses that the sample coefficients are equal to the mean of the simulated coefficients. The p-values for the null hypotheses, adjusted for multiple inference using Bonferroni's method, are reported in Table 6.

Table 6. Simulated bidding effects and test of null hypothesis that observed bids are random.

	Mean	Std. Dev.	Min	Max	p-value†
Win	0.8941	0.5360	-1.0261	2.7376	0.0926*
Adjustment (lag)	-0.0157	0.0619	-0.2299	0.2593	0.0086***
Cumulative wins (lag)	-0.3309	0.5665	-2.6198	1.7487	0.0000***

† Bonferroni adjusted p-values.
*p<.10, **p<.05, ***p<.01

The adjusted p-values allow me to reject the null hypothesis of random bids (H_{01}) at the 10 percent confidence level for all three hypotheses, and with p<0.000 for all three hypotheses jointly. The simulated data suggest that some share of the effect of win on adjustment reported in Table 5 can be attributed to mean reversion. The direction of the effect for random bids and for the sample are the same for lagged adjustment and winning, though the signs are reversed for the coefficient on the effect of cumulative wins on adjustment. The data thus indicate non-random bidding, which provides support for the alternative hypotheses of a private value component to the contract (H_1) and participant learning (H2) and indicates that the auction revealed private information.

Part 2

Having rejected the null hypothesis of random bidding, I move on to the first of the alternative hypotheses, that the contracts contain a private value component (H_1). Further defining whether the contracts are of a pure private value ($H_{1\text{-}1}$) or of mixed private and common value ($H_{1\text{-}2}$) has implications both for auction design and for investigation of learning behavior.

If the contracts are of a pure private value ($H_{1\text{-}1}$), then survey measures should explain the variation in bid price. Specifically, the explanatory power of the survey measures should improve across rounds, as participants gain experience with the mechanism.

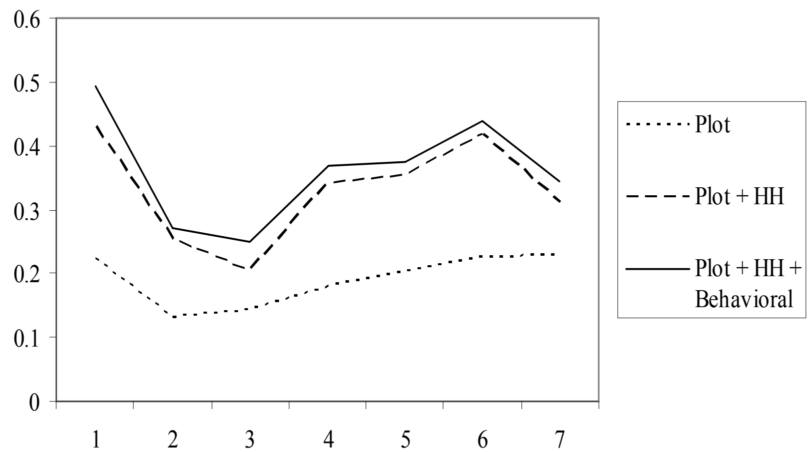

Figure 4. R-squared values for OLS regression log bid on survey characteristics, across learning rounds.

For each learning round, I regressed the logarithm bids on a combination of survey measures. The R-squared values for the regressions in each of the learning rounds are plotted in Figure 4. The best fit of survey measures and bid levels appears in the first round, which potentially suggests a movement away from private value based bids. The pattern in model fit may also be consistent with some experimentation in early rounds of the auction, as bid levels move away from and then return to a better fit with private value predictors. The R-squared values clearly demonstrate no improvement in explanatory power of the survey measures across rounds, indicating that the contract is not of pure private value ($H_{1\text{-}1}$). As long as the survey measures accurately reflect private values of the private value component to the contract, these results indicate that the contract is of mixed pure and common value, which allows me to move on to the third stage of the analysis and explore the learning behavior in the auction.

Part 3

Having concluded that the contracts are of mixed common and private value, I test a potential refinement to the learning hypothesis (H_2). If participants use early auction rounds to learn about the common value component from previous outcomes (H_{2-1}), then bidders should incorporate new information on the common value component of the contract into their bids and $\theta_{i,t}$ should converge to zero. However, if $\theta_{i,t}$ does not converge to zero as $t \to \infty$, then $v_{i,t}$ also does not converge, and individuals do not improve their private signals by learning about the common value component. The mean of the absolute value of bid adjustments across rounds is presented in Figure 5.

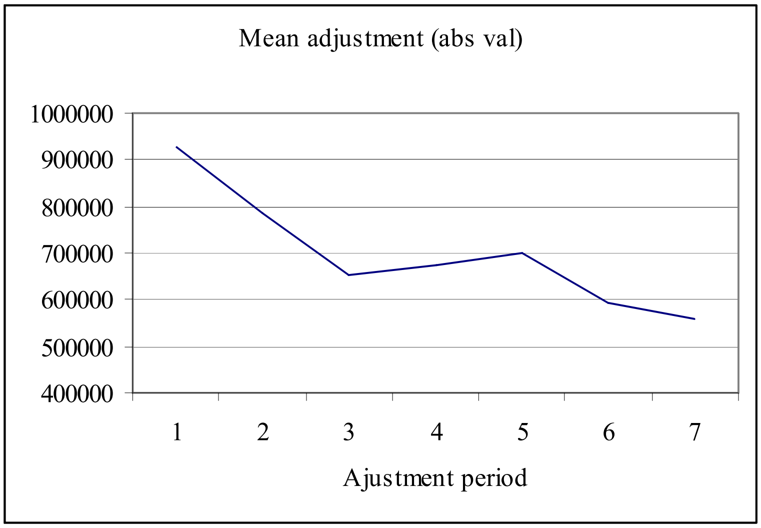

Figure 5. Bid adjustment (absolute value) across learning rounds.

The mean adjustment level exhibits a clear declining, but non-monotonic trend across rounds, and specifically, decreases over time as predicted by learning about the common value component of the contract. Thus, the hypothesis of aggregate common value learning (H_{2-1}) cannot be rejected. The alternative hypothesis at this stage in the investigation supports the outcomes from Parts 1 and 2, of a mixed private and common value to the contract, and of learning about the common value component of the contract across rounds.

The third part of the empirical analysis offers suggestive evidence about the nature of learning by auction participants in Sumerjaya. The hypothesis of learning is supported in Part 1 and the mixed private and common value nature of the contract is supported in Part 2. Part 3 further suggests that individuals are learning about the common value component of the contract through repetition.

VI. Discussion and conclusion

Analysis of bidding adjustment across rounds suggests that the participants in the soil conservation auction in Sumberjaya were responding to the information revealed to them in previous rounds. However, the results of this investigation remain tentative. Bidding is statistically different from the patterns observed under random bidding, the explanatory value of survey measures, including plot-level characteristics, do a poor job of predicting bids, and bid variability decreases with repetition, as predicted for learning in a mixed private and common value auction. The conclusion from Part 1 demonstrate an understanding of the mechanism and a mixed private and common value to the contract, which indicates that an auction approach to implementation was more cost effective than a fixed price implementation scheme. These conclusions rely on certain assumptions, including sequential exogeneity and the correlation of survey measures with private opportunity costs. Thus, conclusions about observed behavior are tentative.

While the data analyzed here support the value of an auction in this context, they would be strengthened with further investigation of the implications of an implementation design that includes multiple learning rounds prior to the allocation round. An alternative evaluation of the value of multiple trial rounds compares the efficiency of the hypothetical outcomes in the first round with the quantity of hectares of conservation investment purchased in the final allocation round. Twenty-five hectares were purchased under the budget in the final allocation round. If the first round bids had been used instead, only 21.85 hectares or 12.6 percent fewer hectares would have been purchased for the same budget. The multiple auction rounds were successful in decreasing bids, allowing for conservation on a greater number of hectares, assuming contract compliance. From a pure efficiency standpoint, this outcome is useful, though welfare implications should be further explored, together with obvious implications of non-compliance. An alternative approach might consist of a single shot auction with participant training prior to the implementation.

The findings from this paper can be extended and improved in several directions. First, a theoretical model of learning in a repeated auction context that generates testable predictions in the current data environment would be useful for further investigation of the type of learning that occurred across rounds. Such a model would clearly require assumptions about bidder behavior and preferences. Second, additional data from the survey participants, both about their experiences in the auction itself and about contract implementation costs, would shed additional light on bid formation across rounds and the nature of the contract value. Finally, compliance data will confirm whether participants were accurate in their assessment of costs, which should predict contract compliance rates, and whether this accuracy improved with repetition.

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