Evaluating conservation auctions with limited information: the policy maker's predicament

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ABSTRACT

Buying environmental services from private landholders using tendering mechanisms are usually subject to a budget constraint. Auction theory has mostly focused on target-constrained auctions and is less well developed for this type of auction. This paper examines a theoretical model specifically developed for budget-constrained tenders and assesses its capacity to predict tendering performance under information limitations typical of those found in field applications. But this assessment cannot be done without complementing the model with controlled laboratory experiments. Subject to their external validity, we find that the model is able to make the correct policy recommendation when comparing the tender to an equivalent fixed price scheme, even when the accuracy of its prediction is far from perfect. However, the study suggests that more than a single point estimate of bidders' costs is needed for this to happen, indicating that it should be worthwhile for policy administrators to invest in some information acquisition before deciding to run a tender.

Key words: Auctions, procurement, tenders, conservation, economic experiments, model validation

JEL Classification: C91, C92, D44, Q24, Q28

I. INTRODUCTION AND BACKGROUND

Buying environmental services from private landholders using tendering mechanisms usually involves budget-constrained, procurement-type auctions. In a budget-constrained (BC) conservation auction or tender, the program's budget is predetermined; the risk lies with the number of participants or the area that might fail to come under contract, i.e. with the policy's outcome. The widespread use of the BC tender format in conservation policy poses a problem to the extent that auction theory has been well developed, since Vickrey's 1962 paper (less well-known than his much-cited 1961 paper), for target-constrained (TC) auctions, but much less so for budget-constrained (BC) auctions (Müller and Weikard, 2002). As a result, in the field of environmental policy, there is a gap between theory and practice. A better theory would allow agencies to improve tender design and perhaps decide whether such a mechanism is worth going ahead with or not, given existing alternatives.

This study investigates the predictive capacity of a model developed for BC tenders applied to land conservation programs. By predictive capacity we mean both the model's capacity to predict bids and, more importantly, to predict policy performance in the field. This model was first proposed by Latacz-Lohmann and Van der Hamsvoort (henceforth, LH) in 1997 and further refined in 1998, where policy implementation was investigated. To the best of our knowledge, this is to date the only extension of auction theory which captures the particular features of conservation tenders. It does not however conform to the standard assumptions of auction theory regarding optimal bid formulation, since in a BC tender, in contrast to the TC, bidders do not know in advance the number of winners. Müller and Weikard (2002) show that this results in multiple Nash equilibria with no dominant solution for choosing an optimal bid. LH (1997) solve this problem by introducing an exogenous parameter, the bidders' expectation of the highest acceptable bid, known the budget constraint and the number of bidders. Bidders then use this best guess of theirs to form their optimal bids. This yields a much simpler model than the more standard TC model, but at a cost, in that bidders' expectations of the highest acceptable bid cannot be observed, so that the model cannot be used by policy makers to make ex ante assessments of the value of running a tender for conservation services. No model for the *formation* of bidders' bid cap expectations is offered.

The purpose of this study is to investigate the validity and credibility of the BC *model* for assessing the performance of the BC tendering mechanism, using several performance criteria. Assessing the performance of the mechanism itself was investigated in Schilizzi and Latacz-Lohmann (2007) who compared, with repetition, the performance of the BC and TC tenders relative to an equivalent fixed-price scheme. The focus in the present study is to examine whether the BC model is capable of predicting the performance of the tendering mechanism using bids predicted from the model rather than observed experimental bids. To the extent that government agencies have, to date, almost exclusively used the BC format in environmental policy, it seems important to test any model that might serve to recommend the use of this policy instrument. In Australia, for example, the Victoria BushTender and EcoTender conservation programs were directly inspired by the BC model (Stoneham et al. 2003).

We investigate the validity and credibility of the BC model in three steps. We first study how well it can predict experimental bids. We then examine the model's capacity to predict the economic performance of a BC tender with the information set available to the experimenter. We then repeat this analysis but with an information set typically available to the policy maker. This requires implementing the model in a controlled laboratory experiment, where data on bidders' expectations of the maximum acceptable bid (the bid cap) can be acquired. The theoretical gap in the BC model's not specifying how bidders form their bid cap expectations can thus be filled in. The first two steps represent the experimenter's point of view: how does the BC model predict bids and policy performance with full knowledge of the model's input variables (costs and bid caps)? The third step mimics the situation of a policy maker who has only limited knowledge of costs and none of bid caps. The role of the experiments is twofold: besides filling in the gap left open by the non-specification of how bid cap expectations are formed, they allow us to separately evaluate the model's limitations due to poor information inputs and those that remain ever under perfect experimental information.

Submitting auction mechanisms to laboratory experimentation with a view to bridge the gap between theory and practice is not new. Kagel's review, in Kagel and Roth's (1995) *Handbook of Experimental Economics*, remains a key reference for the contributions of the experimental effort up to that date, and one finds a comprehensive update in Plott and Smith's (2008) *Handbook of Experimental Economics Results*. But it is perhaps Lust and Shogren's (2007) book, *Experimental Auctions: Methods and*

Applications in Economic and Marketing Research, which provides the most relevant material and references for the present study, in particular chapter 9.

The present study adds to the growing literature on the use of laboratory experiments to complement theory for policy purposes. Vernon L. Smith, who won the Nobel Prize in Economics for introducing experimental methods into economics, has identified three roles for economic experiments: testing a pre-existing theory, exploring new ground to suggest new theory, and test-bedding new policy mechanisms. In this study we straddle all three roles in perhaps a novel combination. In the first, we test the BC model's capacity to predict experimental bids and policy performance; in the second, we use experimental data to derive a model for the formation of bid cap expectations; and in the third, we investigate whether theory and experiment combined can help with deciding if running a tender is a desirable policy or not.

The remainder of the paper is organised as follows. Section two presents the BC tendering model. Section three describes its experimental implementation. Section four links the theoretical model and the experimental results. Section five provides and discusses the results. Section six concludes.

II. THE BUDGET-CONSTRAINED BIDDING MODEL

The sealed-bid discriminatory price budget-constrained (BC) model examined in this paper was first proposed by Latacz-Lohmann and Van der Hamsvoort (henceforth LH) in 1997. This is the first bidding model that attempts to capture the particular features of conservation tenders. They considered landholders to hold private information about their opportunity costs of participating in the government's conservation program. These costs arise when management prescriptions divert farmers' land management practices away from their current plan, assumed to be the most profitable one. The government's problem, in order to attract farmers into the scheme, is to compensate them for the lost profits without knowing the magnitude of their opportunity costs. Auctions have the property of revealing at least part of this information. In order for the landholder to participate in the scheme, the payment he or she receives must be at least equal to his or her opportunity cost of participation.

LH (1997) first assume that landholders' bidding strategies are predicated on the belief that the conservation agency (the procurer) will decide on a maximum acceptable bid, or payment level, β. This is a common practice when the agency is subjected to a constrained budget. In actual fact, this maximum bid β is determined *ex post*, after all bids have been received, as the last (highest) bid accepted within the available budget. In other words, no individual bids above β will be accepted. β represents an implicit reserve price per unit of environmental service, unknown to bidders (and also unknown to the procurer until all bids have been received). This external parameter β represents a deviation from standard target-constrained auction theory, where optimal bids are determined endogenously as a function of the number of bidders, the distribution of bidders' opportunity costs (assumed common knowledge), and the target to be achieved. In the BC auction, this target – the number of winners or hectares contracted – is unknown. A landholder will tender a bid b if the expected utility in case of participation exceeds his or her reservation utility.

The second assumption in the LH model is that bidders, not knowing the value of the bid cap β, will form expectations about it, which can be characterized by the density function $f(b)$ and by the distribution function $F(b)$. The probability that a bid is accepted can then be expressed as

$$p(b \leq \beta) = \int_{b}^{\overline{\beta}} f(b)db = 1 - F(b) \tag{1}$$

where p is probability and $\overline{\beta}$ represents the upper limit of the bidder's expectations about the bid cap, or the maximum estimate of the highest acceptable bid. The essence of the bidding problem is to balance out net payoffs and probability of acceptance. This means determining the optimal bid which maximizes the expected utility over and above the reservation utility.

Further assumptions are that there are no transaction costs in bid preparation and implementation, that payment is only a function of the bid (discriminatory price auction), and that bidders are risk-neutral[1]. A risk-neutral bidder simply maximizes expected payoff. The optimal bid, b^*, derived by LH (1997) is given by equation (2), where c represents the opportunity costs of participation:

$$b^* = c + \frac{1 - F(b)}{f(b)} \tag{2}$$

LH (1997) further assume that bidders' individual expectations about the bid cap β, unknown to them, are uniformly distributed in the range [$\underline{\beta}$, $\overline{\beta}$], where the lower and upper bounds represent the bidder's minimum and maximum expectation of the bid cap. A bidder's expectations are that any bid equal to or below $\underline{\beta}$ has a probability of 1 of being accepted, and any bid equal to or above $\overline{\beta}$ has a probability of zero of getting accepted. Then the expression for the optimal bid becomes (LH, 1997):

$$b^* = \max\,[\frac{1}{2}(c + \overline{\beta}), \underline{\beta}] \qquad \text{s.t.} \qquad b^* > c \tag{3'}$$

This is true for each of the i bidders, so that expression (3') also reads as:

$$b_i^* = \max\,[\frac{1}{2}(c_i + \overline{\beta}_i), \underline{\beta}_i] \qquad \text{s.t.} \qquad b_i^* > c_i \tag{3''}$$

Expressions (3') and (3") show that the optimal bidding strategy of a risk-neutral bidder increases linearly with both the bidder's opportunity costs c_i and his or her expectations about the bid cap, characterized by $\underline{\beta}_i$ and $\overline{\beta}_i$. Bids thus convey information about opportunity costs, which are private information unknown to the procurer; they thereby reduce the information asymmetry, but not completely: the auction's cost revelation property is blurred by the fact that bids also reflect bidders' beliefs about the bid cap. This creates room for bidders to bid above their true opportunity costs and thereby to secure for themselves an information rent.

Budget-constrained (BC) tenders differ from the target-constrained (TC) format in that the predetermination of the budget and of the outcome is reversed. As discussed by Müller and Weikard (2002), TC tenders allow endogenous expectations to form and optimal bids to be formulated without the need for exogenous bid caps. Thus, while the TC model is a Nash-equilibrium model, the BC model is a best-response model. This is because by knowing the target, bidders know the number of winners or contracts to be allocated, thereby yielding fewer degrees of freedom than the BC auction. Not surprisingly, the TC auctions were modelled much earlier, by Vickrey in 1961. Their application to multi-unit sealed-bid procurement tenders, relevant for government conservation schemes, were only modelled in 2005 by Hailu *et al*., who built on Harris and Raviv's (1981) generalization of Vickrey's approach. In a discriminative (first) price setting, both BC and TC models predict that overbidding is an optimal strategy[2].

III. EXPERIMENTAL IMPLEMENTATION

The purpose of the experiments described below was to assess the capacity of the BC model to predict the tender's economic performance. One wishes to know whether it is a credible tool for informing budget-constrained tendering design for allocating conservation contracts. We focus first on the difference between the observed experimental bids and those calculated based on equation (3”); secondly, we evaluate the performance of the tendering mechanism using bids computed with the BC model as opposed to using experimental bids. This should shed some light on whether experimental results can be used for guiding the use of BC tendering mechanisms.

Preliminary bidder surveys

Prior to holding the experiment, we surveyed our experimental subjects along two dimensions: their attitude towards environmental conservation, and towards risk. The first question was asked so as to be able, after the experiment, to relate the amount of bid shading to environmental attitudes, since the tendering experiment was set in a land conservation context. One would assume that in a real policy setting, the more environmentally concerned bidders would shade their bids less than the less concerned. Whether such a reduction in bid shading would also be observed in laboratory experiments would depend on the extent to which the context is effective in influencing participants' decisions.

Bidders' risk attitudes were measured using a certainty-equivalent method, whereby they were asked to state the minimum price they would accept from selling a lottery ticket that had been given to them. This measure was also hypothesised to explain possible differences in bid shading, whereby more risk-averse bidders would shade their bids less than the less risk-averse. As it turned out, environmental attitudes, as measured in this survey, did not appear to be related in any way to bid shading, whereas, as will be detailed later, risk attitudes, as measured, did have some impact in the expected direction. The implication of this is that contextual effects such as environmental concerns did not affect experimental outcomes – a positive feature in terms of experimental control.

Experimental setup

Experiments were first carried out at the University of K, then at the University of P.[1] The P experiment replicated the K experiment, in order to check for the robustness of results.

The K experiment was carried out with first-year students in agricultural economics. The tendering setup referred to reductions in nitrogen fertiliser (N) on a wheat crop, in order to meet EU regulations regarding limits to nitrate concentration in groundwater (50 mg/liter). This is a serious concern in rural areas of northern K, and one which students in K would be aware of and sensitive to. Participants were offered would-be contracts for committing themselves to reduce applications of nitrogen fertiliser from their *currently most profitable* level down to a predefined constrained level, equal to 80 kg per hectare. Each participant was given a different production function for nitrogen fertiliser in wheat production and thus faced a different opportunity cost resulting from the adoption of the nitrogen reduction program. Participation costs, labelled in Experimental Currency Units (ECU), were spread uniformly between 5 (the lowest-cost bidder) and 264 (the highest-cost bidder). Bidders knew their own opportunity costs but not those of rival bidders (see appendix I). Participants were told that not all of them would be able to win contracts and that they were therefore competing against each other. To keep things simple, each participant could put up just one land unit of wheat, the same area for all participants. They were told that if they won a contract, they would be paid the difference between their bid and their opportunity cost.

Since auctions are very sensitive to information structure, it was important to control for this aspect. Bidders were informed of the available budget available. The cost range (5 to 264 ECU) was not given, but bidders were told that costs were uniformly distributed. Each bidder knew his or her own opportunity cost and was given a rough estimate of where he or she stood compared to rival bidders in terms of opportunity costs. This was done by informing bidders in which cost quartile they belonged: lower quarter, second quarter, third quarter, upper quarter (see appendix I). No information regarding other bidders was given to

[1] K and P are used in lieu of actual institution and location names to preserve anonymity in the reviewing process: they will be replaced by the original names in the final version of this paper.

participants. In particular, no information about the BC model or even its existence was mentioned. There were 44 bidders in the K experiment and 27 in P.

The budget constraint announced (in ECU) was clearly distinguished from the actual payments made at the end of the session (in $ or €). Payments in hard currency would be proportional to gains in ECU terms and their gains were calculated as own bid minus participation cost. Bidders were asked two pieces of numerical information, their maximum estimate of the "highest acceptable bid" ($\overline{\beta}_i$), and their bid (b_i). We made it clear to participants that we wanted them to give us their highest possible *estimate* of what the cut-off bid might be. We did not ask for the lower bound $\underline{\beta}_i$, as initial trial sessions revealed that asking both upper and lower bounds confused many participants. Simulations later carried out with the experimental data showed however that such lower bounds would not be binding; rather, the cost constraint, $b^* > c$, turned out to be binding for some bidders. The implication for this study of not having data on the $\underline{\beta}_i$ simply means that the validity of the BC model is probably underestimated. With knowledge of both $\overline{\beta}_i$ and $\underline{\beta}_i$, its capacity to predict bids and tender performance would most likely be enhanced.

The P experiment was identical to the K experiment. Participants were mostly first-year students in K and second-year students in P, with a few third and fourth years as well as a handful of postgraduates – all in the area of agriculture or natural resource management. To reflect the different number of participants, the budget constraint was modified proportionately, so as to result in the same competition intensity (ratio of budget to bidders) in both replicates: 3900 ECU in K and 2300 ECU in P. A slight difference in the P experiment was the story told, to maintain high relevance to local conditions: rather than nutrients leaching into the groundwater, the problem was eutrophication in the P river following excess surface runoff of these nutrients – a socially and politically sensitive issue in P.

IV. LINKING THEORY AND EXPERIMENT FOR POLICY

Modelling the formation of bid cap expectations to fill in a theoretical gap

In policy applications, data on bid cap expectations (the $\overline{\beta}_i$) are not available. The BC model cannot therefore be directly used for guiding policy, since computing (optimal) bids requires knowledge of the $\overline{\beta}_i$. Two approaches are then available. One was chosen by LH in their 1997 paper: assume the $\overline{\beta}_i$ are somehow distributed around a single average cost estimate. The other approach is to implement the model experimentally and use the experimental data on bidders' costs (c_i) and bidders' stated expectations $\overline{\beta}_i$ to derive an empirical relationship between the two. One can then use this relationship to compute optimal bids and use the BC model to assess the tender's expected performance. The question then is, do the $\overline{\beta}_i$ depend on bidders' cost information? This information is twofold, the cost quartile[3] to which they belong (c_Q) and their own private cost (c_i).

Figure 1 reveals that the individual distribution of the $\overline{\beta}_i$ does depend on knowledge of one's cost quartile. On average, high-cost bidders expect the maximum bid cap to be higher than low-cost bidders: thus, the K data show the β_q increase with cost quartiles (c_Q) as 157; 162; 213; and 262. Secondly, across bidders, the $\overline{\beta}_i$ approximate a normal distribution within each cost quartile. Note that this is totally independent of the BC model's assumption of a uniform distribution on [$\underline{\beta}_i$, $\overline{\beta}_i$], which holds for an *individual* bidder. Thirdly, the variance of the $\overline{\beta}_i$ falls with higher known costs. This is simply due to the smaller margin between one's known cost (c_i) and the maximum acceptable bid $\overline{\beta}_i$ which appears most likely to the bidder: thus, in K, the quartile β_q/c_Q ratios evolve as 11.3; 1.9; 1.3; and 1.1. A similar trend obtains with the P data.

Figure 1 about here

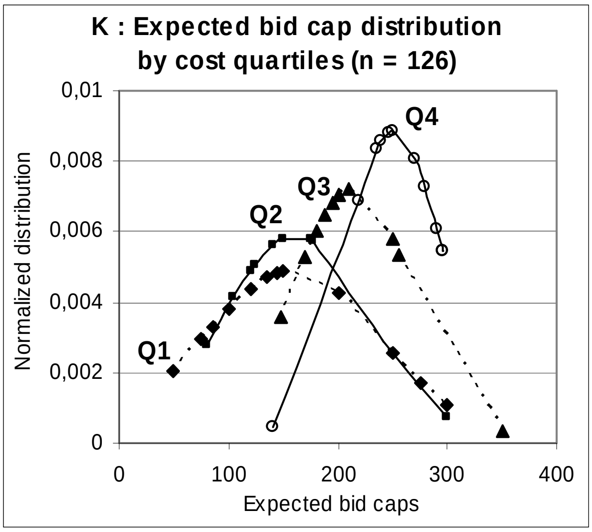

Figure 1: Influence of bidder cost information on the distribution of bid cap expectations.

The P data showed a similar pattern except that Q2 and Q3 curves (rather than Q1 and Q2) overlap.

One can further ask, how exactly the $\overline{\beta}_i$ might depend on costs. To answer this question, the relationship between individual $\overline{\beta}_i$ and the corresponding individual costs $\boldsymbol{c_i}$ was investigated. The K data yielded the following best-fit linear relationship[4]:

$$\overline{\beta} = 0.34\, \boldsymbol{c} + 159 \qquad \text{(t statistic = 5.51)}^{***} \qquad (4)$$

and the P data yielded

$$\overline{\beta} = 0.39\, \boldsymbol{c} + 171 \qquad \text{(t statistic = 3.98)}^{***} \qquad (5)$$

where the stars indicate significance at the 1% confidence level. A $\overline{\beta}$ computed using the average experimental cost of 122.5, valid for both replicates, would yield a value of 201 with the K data and 219 with the P data, a difference of 9%.

Given this difference, we may not yet have a reliable model describing the formation of bid cap expectations by bidders who have imperfect knowledge of the cost distribution. For the time being, we only have at our disposal some empirical relationships, the external validity of which is not guaranteed. More than two replicates would be needed to better understand the difference between relations (4) and (5).

We therefore focus on exploring how far the BC model could be useful to policy makers *if* these experimental relationships could be reliably extrapolated to field data[5].

Linking theory and experiment for policy assessment

With estimates of expected bid caps as obtained in the previous section, information on abatement costs can be used to compute, using equation (3”), landholders’ optimal bids. Costs being functionally linked to quantities abated, they can be considered in tandem. Estimates of quantities abated (N), costs (c) and optimal bids (b^*) together determine the tender’s performance which can thus be assessed *ex-ante*. The key issue, and the focus of the analysis, is the amount and quality of information on c and N available to the policy maker. Will the BC model be able to reliably compute optimal bids and assess tender performance *ex ante* if such information is of poor quality?

To elucidate this question, we need a benchmark that can help us disentangle the model’s intrinsic predictive potential from its sensitivity to the quality of information input. The limit case where costs and bid cap expectations are individually known can provide such a benchmark. This is the situation of the experimenter. The opposite, worst case scenario is defined by the situation where a policy maker has at his disposal only a single point average estimate of abatement and costs; for example, a regional average, with no knowledge of local variations. An intermediate case is where the policy maker has available more than one point estimate. We shall consider the case of four point estimates, which typically represent landholder ‘cost-category pools’ in the target region.

This research strategy is represented in rows 3, 4 and 5 in Table 1. The lower indices a, q and i represent, respectively, the poor, the medium and the full information scenarios, which correspond to the 1-point estimate, the 4-point estimate and the full knowledge of the experimental (N_i, c_i) set. The scenario in row 3 is of course irrelevant to the policy maker; its purpose is to evaluate the BC *model*, not the tender itself. Rows 1 and 2 in Table 1 define the theoretical and experimental benchmarks, respectively. Row 1 describes the strategy used by LH (1997) in their theoretical analysis, and row 2 describes the results of its experimental implementation. Row 1 is the theorist’s approach; rows 2 and 3 describe the experimenter’s approach; and rows 4 and 5 describe the approach adopted in this paper, linking theory and experiment for ex ante policy assessment and taking account of information deficiencies policy makers are usually confronted with.

Table 1 about here

A key issue in Table 1 is the computation of the expected bid caps $\overline{\beta}$ from which, together with estimates of bidders' costs, optimal bids (b^*) are computed. The bid caps themselves are computed from the cost estimates, as per equations (4) and (5), and are represented by the function f_e in Table 1. The difference between rows 1 and 4 or 5 is that in the latter, one evaluates how well the BC model performs relative to the 'true' performance in row 2, whereas the approach in row 1 just assumes the model is correct. As for row 3, it evaluates the BC model's capacity to predict the 'true' results of row 2 given full information on costs and abatement quantities. The effect of limited information can thus be isolated by comparing predicted policy performance in rows 4 or 5 with that in row 3. Again, the purpose of row 3 is purely to allow us to disentangle the role of limited information from the intrinsic potential of the model: it is *not* to be related to the policy maker's information.

The results of this study are organized in section V according to the rationale of Table 1. Section VI then builds on section V to examine under what information conditions the model might make the wrong policy recommendation. This is achieved by introducing an alternative but equivalent policy instrument, a fixed price scheme with the same budget constraint as the BC tender.

V. HOW WELL DOES THE BC MODEL PREDICT THE TENDER'S PERFORMANCE?

We assess the performance of the tendering mechanism by using four different criteria, namely: outlay per unit of abatement (budget cost-effectiveness); cost of abatement per unit abated (economic efficiency); outlay per unit cost (rate of information rents); and the amount abated relative to the maximum possible amount if all bidders had been contracted (policy effectiveness).

The point of view of the experimenter: the model's intrinsic predictive capacity

How well does the BC model predict individual experimental bids?

In order to assess how well the BC model predicts the tender's performance, the experimenter must first assess how well it can predict the individual experimental bids. This establishes (or not) the model's credibility. The two frames in Figure 2 plot predicted optimal bids against experimentally observed bids for the BC tender in replicates K and P. The complete experimental data is provided in Appendix II. Optimal bids were computed for each bidder using equation (3"). The 45 degree line represents perfect prediction. Two things can be observed. Firstly, prediction is less than perfect. Secondly, the model underestimates the experimental bids in K slightly but systematically, the linear fit being everywhere above the 45 degree line, whereas (except for the lowest bids) the opposite is true in the P replicate.

Figure 2 about here

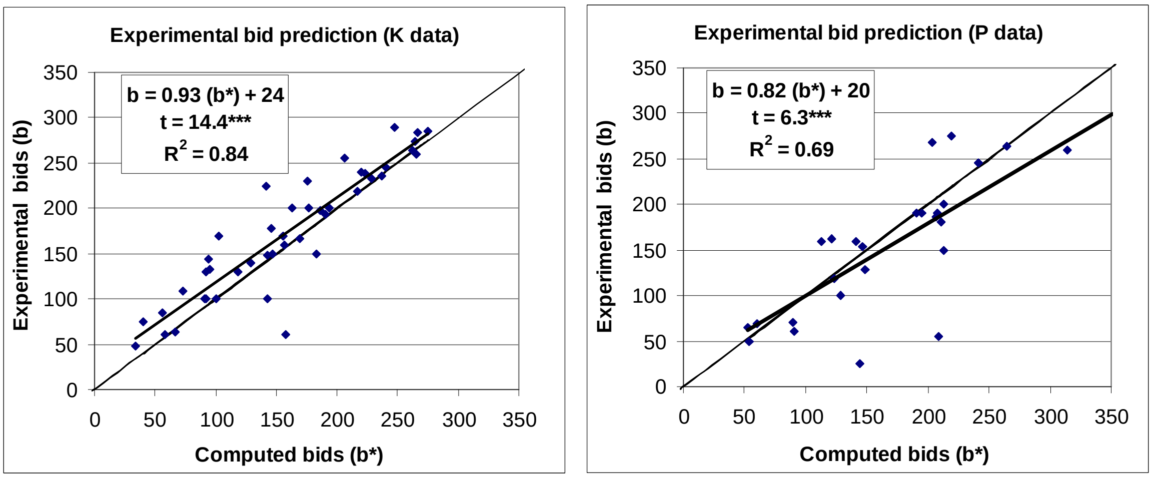

Figure 2: Model performance: Theoretically computed versus experimentally observed bids in K and P for a BC tender. The 45 degree lines of perfect fit are shown. The *** indicate significance at the 1% confidence level.

One feature of the model may explain this slight over- or under- bidding: bidders are assumed in equation (3") to be risk-neutral. The bidders in the K experiment were measured to be somewhat risk-prone, with an average certainty equivalent ratio of 108%, slightly greater than the risk neutral 100%. Participants in P were clearly risk-averse, with an average certainty equivalent ratio of 78%. The ratios of the average experimental bids to the computed bids was 1.08 in the K replicate and 0.88 in the P replicate, indicating close agreement between two completely different mechanisms, the hypothetical lottery and the experimental tender with real money. This conforms to the expectation that risk-prone bidders ask more than if they were risk-neutral and risk-averse bidders ask less.

In both K and P experiments, the linear fit has a smaller slope than the 45 degree line, with the difference more marked in P. The BC model slightly overestimates low bids higher than it does high bids. As shown in section 2, the model computes optimal bids which reflect greater bid shading for low cost bidders than for high cost bidders.

Though not perfect, the BC model seems to yield reasonable predictions of the experimental bid data. If one relates the average of the absolute differences between computed and experimental bids to the overall average bid, the relative error ratio, or the average dispersion around the 45 degree line, is 13% for K and 21% for P. The correlation coefficients between the computed and the experimental bids are 91.6% for K and 83.4% for P.

Predicting the tender's performance

With full cost information, the experimenter evaluates the capacity of the BC model to predict the performance of the tender as follows. He first evaluates it with bids computed using the BC model then compares this evaluation with the one obtained directly using the experimental data. This provides an upper limit to the model's predictive capacity. The results of this comparison can be read by comparing columns 1 and 2 of Table 2. The upper half of column 2 provides the four performance measures each in their appropriate units. The closer these measures are to the ones in column 1, the better the quality of the prediction. The lower half measures this quality in terms of percent deviation from the results in column 1. Two things can be said from this comparison. First, even in the best of all worlds, the BC model's predictive potential is not perfect. Perfection would require zero deviation on all performance criteria.

Secondly, however, the deviations remain small across all criteria and across both replicates K and P, never exceeding 6%. The BC model can thus be considered to be a credible tool to work with.

Table 2 about here

The point of view of the policy maker: the role of limited information on bidders' costs

Information scenarios and cost distribution assumptions

In contrast to the experimenter, the policy maker will only have limited information on landholders' abatement costs. As per Table 1, we examine two information scenarios, a poor quality one where only a single point (overall average) estimate is available on (N, c), and a medium quality one where four point (quartile) estimates are available. (If costs were better known than that, running a tender would be pointless.) In either case, the policy maker must make assumptions as to how the single average or the four quartile averages are distributed, since the true distribution is unknown. He then simulates bids based on that information and his knowledge of the relationship between costs and bid caps as per equations (4) or (5), for the K and P data respectively. He finally simulates the selection of bids starting from the lowest assumed bid, until the budget constraint is met. Table 3 brings together five possible distribution options which, in the absence of any other information, the policy maker might plausibly consider.

In column 1, N (indexed a and q for each information scenario, respectively) is kept constant and the cost per unit of abatement ($u=c/N$) is uniformly distributed from zero up to a maximum such that the initially known average remains unchanged; costs are then distributed accordingly. In column 2, N is also kept constant but c is now distributed independently from N. Column 3 is similar except that the distribution is triangular instead of uniform. The triangular distribution is often used by decision makers when little information is available. We assume it to be symmetric and calibrated from zero to a maximum value that allows the resulting distribution to respect the initial average point estimate. Finally, both N and c are distributed, uniformly in column 4 and triangularly in column 5, assuming perfect correlation between N and c and thus a constant cost per unit abated, u. The top half of the table provides the estimated ranges for N_a and c_a; the lower half provides quartile averages for each of the four N_q and c_q. There was not much to gain from using a triangular distribution in the four-point estimate scenario: due to the importance of estimated lower and upper bounds for each quartile[6], there were no differences with quartile uniform distributions.

Table 3 about here

How well does the BC model predict with limited information?

The abatement and cost distributions of Table 3 serve as the basis for computing expected bid caps and optimal bids, which then determine the expected performance of the tender. Columns 3 to 7 in Table 2 present results for the five abatement and cost distributions in the poor information scenario, and columns 8 to 10 do so for the medium information scenario. The upper part of the table provides the expected performance for each of the four performance criteria. The lower part measures the quality of the prediction relative to the experimental data, measured in percent deviations. We focus only on the absolute deviations.

Two things emerge. First, the BC model is able to predict tender performance very well in the medium information scenario (4-point estimates), but not in the poor information scenario (1-point estimate). However, even in the first case the model cannot be considered to be reliable, since it predicts well in the K replicate but poorly in the P replicate; it is only reliable for the criterion of economic efficiency (costs / kg N). Secondly, and rather surprisingly, cost distribution assumptions do not much affect these results. They make virtually no difference in the medium information scenario, and the results remain unreliable across all five assumptions in the poor information scenario. The difference between the K and P replicates warrants further study, however. The number of P bidders was smaller than those in K (27 compared to 44) and the variance of P bids was higher, indicating poorer bidding consistency.

VI. WOULD THE BC MODEL RECOMMEND THE RIGHT POLICY?

A model that predicts wrongly can recommend the wrong policy. In particular, it can recommend that policy A be preferred to policy B when in fact the opposite would yield better results. This section investigates this possibility by considering as an alternative to the tender an equivalent fixed price scheme. The equivalence is defined by the constraint that the total budget outlay must remain unchanged. More precisely, we are interested in the minimum *uniform* payment rate (MUP) that can respect this constraint. Of course, the number of contracts awarded will differ. They number 26 instead of 29 in the K replicate and 16 instead of 19 in the P replicate. This can be seen by comparing columns 1 in the top part of Tables 2 and 4. The top part of Table 4 is structured similarly to Table 2, except that the figures show for both replicates K and P the performance of the MUP scheme instead of the BC tender, under the same information and cost distribution assumptions.

Table 4 about here

The second horizontal section of Table 4 shows for both replicates K and P whether the BC model would recommend running the tender rather than the alternative policy, the posted price scheme with minimum uniform price (MUP). If so, a 'yes' is shown, otherwise a 'no' appears. Except for the fourth criterion, the lower the performance measure, the better. The '% max N abated' on the other hand is better the higher it is. The '?' indicates an indecisive outcome, insofar as some uncertainty is assumed to surround the MUP figures in the top part of Table 4. This uncertainty has been varied from 0 to ± 5%; results shown correspond to ± 2.5% uncertainty.

These results are only an intermediary for examining the core question: will use of the BC model to predict the performance of the tender make the wrong recommendation? 'Wrong' is defined by a recommendation that differs from that made using the experimental data, taken as a benchmark (column 1).

If the recommendation is the same (i.e., correct), a ‘1’ shows in the third (bottom) part of Table 4 and the corresponding cell is shaded; otherwise, a non-shaded ‘0’ shows.

With full information (column 2), the model always makes the correct recommendation. Except for an indecisive case (which disappears for an uncertainty of less than 2.5%), the model also makes the correct recommendation under all cost distribution assumptions in the medium information scenario (columns 8 to 10). Comparing this result for the P replicate in both tables 2 and 4 shows that the low accuracy of the model’s prediction does not prevent it from making the right recommendation. Columns 8 to 10 show that the P recommendations are as robust, if not more so, than those of K.

In the poor information scenario, cost distribution assumptions can however make a difference (columns 3 to 7 in Table 4). Except for an indecisive case (which disappears for an uncertainty of less than 2.5%), the model makes the correct recommendation in columns 3 and 4 but not in columns 5, 6 and 7. The correct recommendations correspond to average cost estimates distributed uniformly across bidders but with a non-distributed abatement quantity (*N*); that is, the cost per unit abated is also uniformly distributed around its overall average. Note that the triangular distributions do not perform well because the ‘true’ (experimental) distributions, which underlie the evaluation benchmark, are uniform. A single point average allows for a greater latitude in the choice of distribution assumptions and thereby for opportunities to ‘get it wrong’.

VI. CONCLUSIONS

The purpose of this study was twofold. First, it aimed to show how theory and experiments can be linked to improve *ex-ante* policy assessment. Second, it aimed to see whether a model used with limited information on input variables can still be useful for making policy recommendations.

The model for budget-constrained tenders developed by Latacz-Lohmann and Van der Hamsvoort in 1997 formulated optimal bids by relying on an exogenous variable, the bidders’ expectations on the maximum bid that would be acceptable to the policy maker. However, it did not model expectation formation, when such expectations are not observable. This study therefore supplemented the theory by implementing the model in a controlled laboratory experiment where bidders were asked to state their bid cap expectations along with their bids. The experiments yielded empirical relationships between bidder costs and bid cap expectations which could then be used to compute optimal bids.

Based on these optimal bids and on the available budget, it is possible to measure the performance of a tender before actually running it in the field, and thus obtain information on whether a tender would be a desirable option or not. This study focused on the fact that the performance measurement will be affected by the quality of the information input typically available in the field. Can the theoretical model, complemented by its experimental implementation, still be useful under information limitations typical of policy environments?

The results obtained from the experiments have not yet allowed us to produce a reliable model for the formation of bid cap expectations. The small but significant difference across the two experimental replicates regarding the empirical relationships linking bidder costs to bid cap expectations calls for some caution until further replicates are run. Previous experiments by Brookshire et al. (1987) and List and Shogren (1998) suggest that, if properly designed, experimental auctions tend to be externally valid. Still, the validity of our experimental relationships for use with field data in a policy context is not guaranteed.

Overall, the study suggests that LH's 1997 model of a budget-constrained tender will make the correct recommendation when comparing the tender to an equivalent fixed price scheme, provided the policy maker has several estimates of key input variables, namely averages of abatement quantities and costs. This holds even if the accuracy of the model's predicted performance is far from perfect, in this study off by up to 20% either way.

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Table 1: Use of the BC model for predicting the performance of a BC tender

	Information known by	Costs and N abatement	Bid caps β	Bids b	Evaluation of tendering performance
A	**Theoretical model** (1997 LH paper)	c_i, c_q and c_a (q = 3-pt estim) with $c = f(N)$	$\beta = f(c)$ Assumed uniformly distributed ± 40% of **average** cost c_a	$b^* = f\{c, \beta(c)\}$	BC model estimates of b^* but with no info on β or bids. <u>Assumes</u> validity of BC model.
B	**Experimental benchmark**	N_i and c_i (experimental)	β_i (experimental)	b_i (experimental)	Direct use of experimental bids (No use of BC model)
1	**Experimenter** (full information)	N_i and c_i (experimental) i = 44 or 27	Experimental β_i $\beta_i = f_e(c_i)$	$b_i^* = f(c_i, \beta_i)$	BC model estimates of b_i^* (experim. b_i serve as benchmark)
2	**Policy-maker**, with medium quality information	N_q and c_q (4-pt estimate)	$\beta_q = f_e(c_q)$	$b_q^* = f(c_q, \beta_q)$	BC model estimates of b_q^*
3	**Policy-maker**, with poor quality information	N_a and c_a (1-pt estimate)	$\beta_a = f_e(c_a)$	$b_a^* = f(c_a, \beta_a)$	BC model estimates of b_a^*

LEGEND:
c = bidders' participation costs, a function of abatement (N)
N = amount of Nutrients (fertilizer) abated
Subscript a = average, single-point estimate
Subscript q = quartile, four-point estimate (three-point in the LH 1997 paper)
Subscript i = individual costs, bids or expected bid caps (as known only to the experimenter)
b^* = computed bids, using the BC model
β = bidder's expected bid cap (highest expected cut-off bid)
f_e = empirical relationship using individual experimental data

NOTE: In the 1-point estimate scenario, the policy maker is assumed *not* to know upper and lower cost bounds. In the 4-point estimate scenario, he only knows quartile averages.

Table 2 : Estimated BC tendering performance given information on abatement and bidder costs

Column number	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
	Experimenter knowledge		**Policy maker's information scenarios and distribution assumptions**							
Information scenarios	Experimental	BC prediction	1-point estimates					4-point estimates		
Performance criteria	bid data (b_i)	using c_i and $\overline{\beta}_i$	($\underline{N}_a$, u_a)	($\underline{N}_a$, c_a)	Tr($\underline{N}_a$,c_a)	(N_a, c_a)	Tr(N_a, c_a)	($\underline{N}_q$, u_a)	($\underline{N}_q$, c_q)	(N_q, c_q)
K data	29 (*)	31	32	29	30	29	30	29	29	29
Payment / kg N	2.72	2.58	2.05	2.26	2.23	4.68	3.20	2.78	2.74	2.88
Opp Cost / kg N	1.67	1.68	1.07	1.38	1.45	2.85	2.08	1.70	1.65	1.73
Payment / costs	1.62	1.53	2.01	1.64	1.54	1.64	1.54	1.64	1.67	1.67
% max N abated	0.54	0.58	0.73	0.66	0.68	0.44	0.47	0.53	0.53	0.51
P data	19 (*)	17	17	17	16	17	16	17	17	17
Payment / kg N	2.49	2.62	2.34	2.38	2.46	3.70	3.97	3.00	2.99	3.07
Opp Cost / kg N	1.69	1.76	1.27	1.33	1.30	2.07	2.09	1.69	1.66	1.71
Payment / costs	1.47	1.49	1.84	1.79	1.90	1.79	1.90	1.78	1.79	1.79
% max N abated	0.58	0.54	0.63	0.63	0.59	0.40	0.37	0.49	0.49	0.47

Using experimental bids as benchmark

K data										
Payment / kg N	**1**	-5%	-24%	-17%	-18%	72%	18%	2%	1%	6%
Opp Cost / kg N	**1**	1%	-36%	-18%	-14%	70%	24%	1%	-2%	3%
Payment / costs	**1**	-6%	24%	1%	-5%	1%	-5%	1%	3%	3%
% max N abated	**1**	6%	34%	21%	25%	-19%	-13%	-2%	-2%	-7%
P data										
Payment / kg N	**1**	5%	-6%	-4%	-1%	49%	60%	21%	20%	24%
Opp Cost / kg N	**1**	4%	-25%	-21%	-23%	23%	24%	0%	-1%	1%
Payment / costs	**1**	1%	25%	21%	29%	21%	29%	21%	22%	22%
% max N abated	**1**	-6%	9%	9%	3%	-30%	-36%	-15%	-15%	-18%

Note: The shaded areas show predictions that deviate less than 10% from the benchmark in column 1.

Legend: N = quantity abated

$\underline{N}$ = one single, non-distributed abatement estimate used; otherwise, uniformly or triangularly distributed

u = c/N = cost per unit abated (u_a = single 1-point average estimate)

c = bidders' abatement costs

Index a = 1-point average estimate

Index q = 4-point quartile estimates

Tr(.) = triangular distribution; otherwise, uniform distribution

(*) = number of bidders selected by BC tender

Table 3 : Policy maker's distribution assumptions for both information scenarios

Poor information scenario: 1-point (average) estimate

	Distribution assumption >	Experimental data	**(1)** $(\underline{N}_a, c/N)$	**(2)** $(\underline{N}_a, c_a)$	**(3)** $Tr(\underline{N}_a, c_a)$	**(4)** (N_a, c_a)	**(5)** $Tr(N_a, c_a)$
K data (44)							
$N_a = 59$	N_a range	[13 – 93]	59	59	59	[2 – 84]	[5 – 114]
$u_a = 2.08$	u_a range	[0.38 - 2.81]	[0 - 3.03]	irrelevant	irrelevant	$u_a = 2.85$	$u_a = 2.08$
$c_a = 123$	c_a range	[5 – 261]	[0 – 176]	[5 – 241]	[11 – 236]	[5 – 241]	[11 – 236]
P data (27)							
$N_a = 59$	N_a range	[13 - 93	59	59	59	[4 – 113]	[8 – 113]
$u_a = 2.07$	u_a range	[0.38 - 2.83]	[0 - 4.30]	irrelevant	irrelevant	$u_a = 2.07$	$u_a = 2.09$
$c_a = 122$	c_a range	[5 – 264]	[0 – 243]	[9 – 235]	[17 - 237	[9 – 235]	[17 – 237]

Medium information scenario: 4-point (quartile) estimates

	Distribution assumption >	Experimental	**(1)** $(\underline{N}_q, c/N)$	**(2)** $(\underline{N}_q, c_q)$	**(3)**	**(4)** (N_q, c_q)	**(5)**
K data (44)		(N; c) data	(N; c)	(N; c)	---	(N; c)	---
	Q1 averages	28; 24	28; 36	28; 29	---	23; 29	---
	Q2 averages	54; 88	54; 96	54; 90	---	54; 90	---
	Q3 averages	71; 159	71; 153	71; 156	---	73; 156	---
	Q4 averages	86; 228	86; 213	86; 224	---	90; 224	---
P data (27)		(N; c)	(N; c)	(N; c)	---	(N; c)	
	Q1 averages	28; 24	28; 35	28; 32	---	25; 32	---
	Q2 averages	54; 88	54; 96	54; 95	---	56; 95	---
	Q3 averages	72; 160	72; 158	72; 166	---	75; 166	---
	Q4 averages	89; 240	89; 215	89; 236	---	92; 236	---

Notes: $u = c/N$: the average cost per unit of abatement
Index a = single-point overall average
Index q = four-point quartile averages
c/N refers to c_a/N_a in the upper part and to c_q/N_q in the lower part
Underlined $\underline{N}$ refers to a non-distributed N
Tr(.) refers to a triangular distribution; the others are assumed uniformly distributed

Table 4 : Decision to run the BC tender rather than a fixed-rate minimum uniform price (MUP) scheme

Column number	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Experimenter knowledge		**Policy maker's information scenarios and distribution assumptions**							
Information scenarios	Known abatement costs		**1-point estimates**					**4-point estimates**		
Performance criteria	(same here for both)		$(\underline{N}_a, u_a)$	$(\underline{N}_a, c_a)$	$Tr(\underline{N}_a, c_a)$	(N_a, c_a)	$Tr(N_a, c_a)$	$(\underline{N}_q, u_q)$	$(\underline{N}_q, c_q)$	(N_q, c_q)
MUP performance results										
K data	26 (*)		31(*)	26	26	26	26	26	26	26
Payment / kg N	3.41		2.12	2.49	2.52	5.71	4.14	3.30	3.35	3.48
Opp Cost / kg N	1.49		1.03	1.24	1.27	2.85	2.08	1.65	1.59	1.65
Payment / costs	2.29		2.05	2.00	1.99	2.00	1.99	2.00	2.11	2.11
% max N abated	0.44		0.70	0.59	0.59	0.26	0.36	0.45	0.45	0.43
P data	16 (*)		16(*)	16	16	16	16	16	15	15
Payment / kg N	3.36		2.45	2.45	2.44	4.03	3.94	3.18	3.34	3.46
Opp Cost / kg N	1.36		1.19	1.26	1.29	2.07	2.09	1.65	1.57	1.62
Payment / costs	2.47		2.05	1.94	1.89	1.94	1.89	1.93	2.13	2.13
% max N abated	0.43		0.59	0.59	0.59	0.36	0.37	0.46	0.41	0.40
Comparing BC tender to MUP results (± 2.5% uncertainty to above figures) : see corresponding columns in Table 2										
K data										
Payment / kg N	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Opp Cost / kg N	No	No	No	No	No	?	?	No	No	No
Payment / costs	Yes	Yes	?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
% max N abated	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
P data										
Payment / kg N	Yes	Yes	Yes	Yes	?	Yes	?	Yes	Yes	Yes
Opp Cost / kg N	No	No	No	No	?	?	?	?	No	No
Payment / costs	Yes	Yes	Yes	Yes	?	Yes	?	Yes	Yes	Yes
% max N abated	Yes	Yes	Yes	Yes	?	Yes	?	Yes	Yes	Yes
Using experimental bids as benchmark: Will the BC model recommend the right policy?										
K data										
Payment / kg N	Benchmark	1	1	1	1	1	1	1	1	1
Opp Cost / kg N	Benchmark	1	1	1	1	0	0	1	1	1
Payment / costs	Benchmark	1	0	1	1	1	1	1	1	1
% max N abated	Benchmark	1	1	1	1	1	1	1	1	1
P data										
Payment / kg N	Benchmark	1	1	1	0	1	0	1	1	1

Opp Cost / kg N	Benchmark	1	1	1	0	0	0	0	1	1
Payment / costs	Benchmark	1	1	1	0	1	0	1	1	1
% max N abated	Benchmark	1	1	1	0	1	0	1	1	1

Note: (*) = Number of participants willing to accept a contract, when the MUP paid out is greater than their abatement costs.
The '**?**' above mean differences between BC tender and MUP results are less than ± 2.5% and are thus indecisive
The shaded '1' above mean the same (correct) prediction as obtained with experimental data; '0' means 'wrong' or indecisive prediction.

APPENDIX I

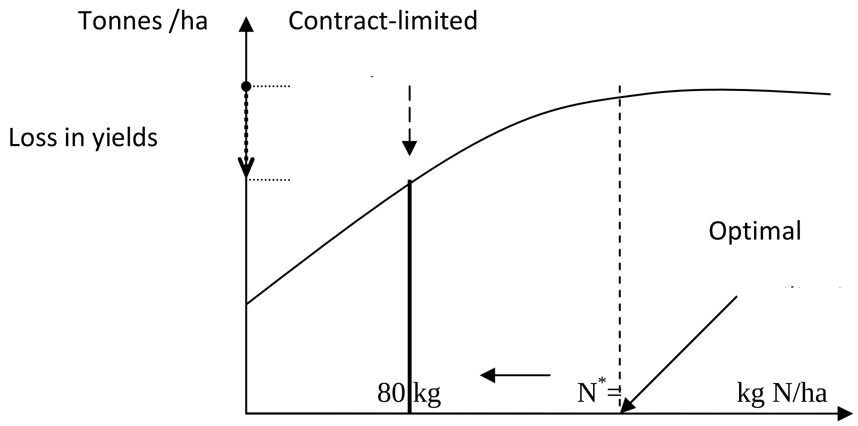
Pages 2 and 4 of the Budget-Constrained Tender in P

(*Page 1 provided the 'story' and the motivation.*)

Individual farm data (page 2)

to work out the costs of your participation in our P River protection program.

Suppose you are a horticulturalist and producing vegetables for P. Output as a function of N fertiliser use is given by the following graph:



The optimal fertiliser amount maximises value of output minus cost of inputs (N fertilisers).

This results in the following:

	With N = 80	With N^*	Difference
Net revenue (ECU/ha) *Experimental Currency Units*			

My costs of participation are ………………… ECU/ha (= the income difference)

Important:

- Your costs of participation are known only to you and your private adviser; they are not known by the environmental authority, or anyone else.
- Your competitors all have different participation costs. So that you may have a better idea of how you compare relative to your competitors, we give you the following information: you are in one of the following four quartiles:

lower quarter	second quarter	third quarter	upper quarter

(*Page 3 provided "some advice from your private consultant"*)

Bidding sheet (page 4)

Now it is time you put in your bid. Please first write in your full name. We shall need it to pay you your gains if you are among the winners.

Name: …………………………………………………………………………

1) First please write down the highest possible bid you believe will be accepted. This must be your best guess:

Highest acceptable bid (best guess): .... ECU/ha

ECU = Experimental Currency Units

2) Now please write in the amount we must pay you so that you accept to participate in our P River protection program:

Your bid: .... ECU/ha

The selection of participants will be made on the ground of their bid in ECU/ha. The lowest bid will be selected first, then the second lowest, then the third lowest, and so on until the available budget of 2300 ECU is exhausted.

For paying the winners in **real money ($)**, the following rules hold:

- The successful bidders will be paid, not their bid, but the gains from their participation in the program, that is: bid <u>minus</u> participation costs.
- Unfortunately, because of limited research funds, we cannot pay out the full value of the gains, but only a fixed percentage of the gains. This percentage will be calculated after the end of the bidding session. Of course, the higher your gains, the higher your proportional payment. For this session the funds we have available for payment to this group total an amount of approx. <u>$300</u>.

APPENDIX II : Raw experimental data from both replicates (c_i, $\overline{\beta}_i$ and b_i)
Data are ordered by bids (b_i), with indication of selection cut-off line.

	K			P		
#	c_i	$\overline{\beta}_i$	b_i	c_i	$\overline{\beta}_i$	b_i
1	18	50	48	13	275	25
2	15	300	60	9	100	50
3	31	85	61	18	400	55
4	54	80	63	33	148	60
5	5	75	75	5	100	65
6	11	100	85	39	80	69
7	77	105	100	49	130	70
8	35	250	100	56	200	100
9	59	125	100	87	160	119
10	81	120	100	108	190	128
11	27	120	109	27	400	150
12	49	135	130	137	155	154
13	98	140	130	65	160	160
14	39	150	133	103	180	160
15	108	150	140	157	85	162
16	44	145	144	171	250	180
17	137	148	148	164	250	186
18	65	300	150	116	300	190
19	119	175	150	186	195	191
20	144	170	160	179	210	191.01
21	150	188	166	125	300	200
22	6	200	170	237	245	245
23	131	180	170	203	500	253
24	114	178	177	229	400	260
25	186	195	194	249	280	264
26	171	200	198	258	150	268
27	103	250	200	264	175	275
28	125	200	200			
29	177	210	200			
30	216	219	219			
31	9	275	225			
32	210	140	230			
33	221	235	233			
34	224	250	235			
35	205	240	239			
36	191	250	240			
37	234	246	245			
38	157	256	255			
39	182	350	260			
40	255	270	264			
41	249	279	274			
42	237	295	283			
43	261	290	285			
44	200	295	290			

Note: The post-marginal bid in P of 191.01 was indeed put in as such by the participant.
The $\overline{\beta}_i$ refer to the highest acceptable bids estimated by the participants.

[1] This is not an essential assumption and could be relaxed to include risk aversion, as done by LH (1997). However, it would not add much to the present argument and might confuse matters unnecessarily.

[2] By contrast, uniform (second-price) sealed-bid auctions should in theory lead to bidding one's true opportunity costs, both in TC and BC tenders; but they have rarely been used in conservation contracting programs, mainly because of the potential for the policy maker to *ex post* manipulate bids.

[3] This notation c_Q differs from the one used later (c_q), in that the former represents the bidder's information whereas the latter represents the policy maker's information. c_Q represents the knowledge a bidder has of his belonging to one of the four cost quartiles; c_q will represent the quartile pool's average cost as estimated by the policy maker.

[4] For this purpose, the complete data set of three repetitions in both replicates was used, as there was no visible trend across them. The data from the second and third repetition were not otherwise used, as they had been generated for a purpose different from the one focused on in this paper.

[5] This hinges on how well the experiment is calibrated to the policy context, namely w.r.t. to key parameters defining auction design (budget-to-bidders ratio, cost spread, etc.). We do not elaborate any further here on external validity and experimental calibration in policy test-bedding, an area that, in spite of Brookshire *et al*.'s (1987) and List and Shogren's (1998) early work, has only seriously begun to be investigated in recent years. See e.g. Schramm (2005), Garcia & Wantchekon (2009), Boly (2009), Bardsley (2010) and, for an overview, Lusk & Shogren (2007), in particular chapter 9.

[6] It is always possible, given quantile averages, to compute lower and upper bounds around each average, once a distribution has been chosen.