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**Can a simple model predict complex bidding behaviour?
Repeated multi-unit conservation auctions.**

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ABSTRACT

Buying environmental services from private landholders using auction mechanisms often involves repeated multi-unit procurement-type auctions. These can either be target-constrained or budget-constrained. Most of the theoretical literature has focused on the former, whereas government agencies have, for conservation purposes, mainly implemented the latter. This paper examines the predictive power of a simple model previously developed for budget-constrained auctions, in comparison to that of the more standard and more complex target-constrained auction model. Experiments carried out in Germany and Australia lend credibility to the non-standard and simpler budget-constrained model.

Key words: Auctions, procurement, conservation, learning, economic experiments

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

I. INTRODUCTION

With the increasing importance of environmental values and policy, the lack of markets for pricing and allocating environmental goods and services has become a serious concern. At the same time, traditional command-and-control regulation has shown its limits, particularly when government policy creates constraints on economic agents and these then use their energies to resist such policies. Governments increasingly need to be able to obtain such goods and services from private economic agents. Hence the recent interest in market-based instruments. These rely on economic incentives to modify the private agents' cost-benefit balance.

One particularly important instance of such policies is where public environmental agencies wish to purchase from landowners services such as land and water conservation, biodiversity and wildlife enhancement, or reduction in pollution emissions from agricultural activities. There has been growing interest by governments in contracting with landowners to that effect. Such contracts typically

specify the conservation-oriented tasks to be done, but not the price to be paid the landowner. This is because it is not easy for the procurement agency to identify what the appropriate price is. Fixed price schemes run the risk of setting it either too high or too low. A solution to this problem is the use of auctions as a way to ask landowners to fix their prices, and the agency can then use this information to allocate contracts to those offering best value for money. In this way, auctions can help allocate public funds in the most efficient way.

In the procurement case, where the auctioneer (the government in this case) buys rather than sells the goods, there is the choice of carrying out the auction with a fixed target or, alternatively, with a fixed budget. In the first case, the number of contracts or hectares of land to come under contract is decided upon and known; the risk is with what it might end up costing. In the second case, it is the reverse: the budget is decided upon and is known; the risk is with the number of contracts or hectares that might not come under contract, that is, with the degree of effectiveness of the policy. It seems that target constrained auctions are used where government cannot fall short of its objectives, as is typically the case with military procurement programs. In the field of environmental policy, governments' use of the budget constrained auction probably reflects their general political priorities. As a result, budgets are usually given for environmental procurement programs.

This poses a problem to the extent that economic theory has been well developed, since Vickrey's 1962 paper, for target constrained (TC) auctions, but much less so for budget constrained (BC) auctions (Müller and Weikard, 2002). In the field of environmental policy, there is a gap between theory and practice. A better theory would allow agencies to improve auction design and also, when necessary, decide which of the two auction formats is more appropriate.

This study sets out to investigate this issue. It considers a new model developed for BC multiunit procurement auctions by Latacz-Lohmann and van der Hamsvoort in 1997. As shown by Müller and Weikard (2002), applying the same assumptions to the BC auction model as for the TC model leads to a complex situation with multiple Nash equilibria. Latacz-Lohmann and van der Hamsvoort solve this problem by introducing an exogenous parameter, the bidders' expectation of what the highest acceptable bid might be. Bidders then use this best guess of theirs to form their bid. The result is a very simple model, much simpler than the more standard TC model. In this model, as described below, the highest expected

participation cost plays an analogous, though different role to that of the highest acceptable bid. The fact that it is endogenous to the model makes the model more complicated, as will appear below.

The purpose of this study is to investigate the validity and credibility of this new BC auction model. This appears as a prerequisite before asking questions about its allocative efficiency compared to the TC model. As a result, the problem investigated here relates to the comparative performance of two models, not to the comparative performance of two auction institutions. The latter question cannot be investigated before the first one. Given the lack of theoretical backdrop, the comparison was made with the use of controlled economic experiments. In addition, since agri-environmental contracts are often renewed, we extended the problem to repeated auctions under both formats. With repetition, bidders learn to bid more efficiently, and, as shown in Hailu and Schilizzi (2004), extract increasing information rents at the expense of contract allocation efficiency.

The remainder of the paper is organized as follows. Section two presents the two auction models. Section three describes the economic experiments, and section four provides and discusses the results. Section five concludes. It is shown that the Latacz-Lohmann – van der Hamsvoort (1997) model for multiunit procurement auctions is a credible tool for auction design and environmental policy analysis.

II. THE TWO AUCTION MODELS

The budget constrained (BC) model

We follow the rationale set out in Latacz-Lohmann and van der Hamsvoort (1997) and summarize the essentials of their model for the reader's convenience. Let us consider that landowners or farmers hold private information about their own farm income, and let π_0 be the associated profits. Let π_1 be the profit remaining after a landowner has given up a proportion of his land, exclusive of any compensation payments by government. More precisely:

π_0 = profits from business-as-usual land management or farming

π_1 = profits with a new, conservation-oriented land management

Note that π_l may include income from employment outside farming. $\pi_l = 0$ if the farmer gives up all of his land and has no alternative employment prospects.

In order for the landowner or farmer to participate in the scheme, the payment he receives must be at least equal to $(\pi_0 - \pi_l)$, his or her opportunity cost of participation. If he or she submits a bid b that is accepted, utility will be $U(\pi_l + b)$, where $U(\cdot)$ is a monotonically increasing, twice differentiable von Neumann-Morgenstern utility function. If the bid is rejected, the bidder's utility is $U(\pi_0)$, the reservation utility.

Now let us consider that landowners' bidding strategies are predicated on the belief that the government agency will decide on a maximum acceptable bid, or payment level, β , a common practice when the agency is subject to a constrained budget. This maximum bid 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 a reserve price per unit of decommissioning service, unknown to potential bidders. A landowner will tender a bid b if the expected utility in case of participation exceeds his or her reservation utility, as shown in equation (12), where p stands for probability:

$$U(\pi_l + b) \cdot p(b \leq \beta) + U(\pi_0) \cdot [1 - p(b \leq \beta)] > U(\pi_0) \quad (1)$$

Bidders do not know the value of the bid cap β , but they 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

$$p(b \leq \beta) = \int_b^{\bar{\beta}} f(b) db = 1 - F(b) \quad (2)$$

where $\bar{\beta}$ represents the upper limit of the bidder's expectations about the bid cap, or the maximum expected bid cap. Substituting (2) in (1) yields

$$U(\pi_1 + b) \cdot [1 - F(b)] + U(\pi_0) \cdot F(b) > U(\pi_0) \quad (3)$$

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 (on the left hand side of (3)) over and above the reservation utility (on the right hand side of (3)). Let us assume that there are no costs in bid preparation and implementation, and that payment is only a function of the bid. We also assume that bidders are risk neutralⁱ.

A risk-neutral bidder simply maximizes expected payoff, so that (3) can be rewritten as

$$(\pi_1 + b - \pi_0) \cdot [1 - F(b)] > 0 \quad (4)$$

The optimal bid b^* is then obtained by maximizing (4) through the choice of b :

$$b^* = \pi_0 - \pi_1 + \frac{1 - F(b)}{f(b)} \quad (5)$$

To gain further insights, one must specify the distribution function $F(b)$. The simplest case is where bidders' expectations about the bid cap β are uniformly distributedⁱⁱ in the range $[\underline{\beta}, \bar{\beta}]$, where the lower and upper bounds represent the bidder's minimum and maximum expected bid cap. For example, if a landowner believes that the cut-off point will lie somewhere between \$X and \$Y per hectare, then $\underline{\beta} = X$ and $\bar{\beta} = Y$. Note that these bidder's expectations are exogenous to the model.

The density and distribution functions of a uniform (rectangular) distribution are:

$$f(b) = \begin{cases} 0 & \text{if } b < \underline{\beta} \\ \frac{1}{\overline{\beta} - \underline{\beta}} & \text{if } \underline{\beta} \leq b \leq \overline{\beta} \\ 0 & \text{if } b > \overline{\beta} \end{cases} \quad (6)$$

$$F(b) = \begin{cases} 0 & \text{if } b < \underline{\beta} \\ \frac{b - \underline{\beta}}{\overline{\beta} - \underline{\beta}} & \text{if } \underline{\beta} \leq b \leq \overline{\beta} \\ 1 & \text{if } b > \overline{\beta} \end{cases}$$

Of course, there is no sense in the bidder bidding below $\underline{\beta}$ (this would not increase the acceptance probability) or above $\overline{\beta}$ (his chances of winning would be nil).

With this specification of $f(b)$ and $F(b)$, one obtains an explicit optimal bid formula for a risk-neutral bidder:

$$b^* = \max \left[\frac{1}{2}(\pi_0 - \pi_1 + \overline{\beta}), \underline{\beta} \right] \quad \text{s.t. } b^* > \pi_0 - \pi_1 \quad (7)$$

Expression (7) shows that the optimal bidding strategy of a risk-neutral bidder increases linearly with both the bidder's opportunity costs $(\pi_0 - \pi_1)$ and his or her expectations about the bid cap, $\underline{\beta}$ and $\overline{\beta}$. Thus, a bidder's bid conveys information about his or her opportunity costs, which are private information unknown to government. The information asymmetry is thus reduced, but not completely: indeed, the auction's cost revelation property is blurred by the fact that the bid also reflects the bidder's beliefs about the bid cap chosen by the agency. This creates room for

bidders to bid above their true opportunity costs and thereby to secure themselves an information rent – area CBDG in Figure 1.

Figure 1 about here

The target constrained (TC) model

Vickrey (1962) formulated a Nash equilibrium bidding model in the case of single-unit sealed-bid discriminative price auctions (when agents bid only for one unit) and demonstrated that the Revenue Equivalence Theorem holds for risk-neutral bidders with individual values for the auctioned objects drawn from a uniform distribution. Harris and Raviv (1981) generalized the Vickrey model for bidders' valuations drawn from general distribution functions and when all bidders have identical concave utility functions. All subsequent extensions (Milgrom and Weber, 1982; Cox et al, 1984) have focused on “selling” auctions. In the literature, optimal bid formulas have been explicitly given for direct or selling auctions (e.g. Cox et al. 1984) but not for procurement or reverse auctions. We use the Vickrey-Harris-Raviv approach, as customised in Hailu, Schilizzi and Thoyer (2004), to model the Nash equilibrium risk neutral bid functions in a procurement multiple unit auction, relevant for government conservation schemes. We first do the calculation for a single unit auction then extend it to a multiple unit action.

Nash equilibrium bidding strategy for a single-unit procurement auction in a discriminative sealed bid setting

Let n risk-neutral bidders compete to sell one unit of a good to the auctioneer: let v_i be the monetary value of this good to bidder i . Assume that each v_i is drawn (with

replacement) from a distribution with density $f(\cdot)$ and probability distribution function $F(\cdot)$ whose support is the interval $[0, v^{\text{sup}}]$. Suppose bidder 1 with value v bids b , and all $(n-1)$ rival bidders k bid according to the strictly monotonous increasing equilibrium strategy $B(v_k)$.

The expected gain of bidder 1 is:

$$E(v, b) = (b - v) \Pr[B(v_k) > b] \quad \forall k \neq 1, \text{ or}$$

$$E(v, b) = (b - v) [1 - F(B^{-1}(b))]^{n-1} \quad (8)$$

Maximizing (8) with respect to b yields the following first-order conditions:

$$[1 - F(B^{-1}(b))]^{n-1} - (b - v)(n-1)[1 - F(B^{-1}(b))]^{n-2} \frac{f(B^{-1}(b))}{B'(v)} = 0 \quad (9)$$

At equilibrium, $b = B(v)$

$$[1 - F(v)]^{n-1} - (B(v) - v)(n-1)f(v) \frac{(1 - F(v))^{n-2}}{B'(v)} = 0$$

$$B'(v) = (n-1)(B(v) - v) \frac{f}{1 - F}(v) \quad (10)$$

For a uniform distribution between 0 and 1, $F(v) = v$, $f(v) = 1$ and (3) simplifies to:

$$B'(v) = (n-1) \frac{B(v) - v}{1 - v} \quad (11)$$

Therefore, the optimal bidding strategy is given by:

$$B(v) = \frac{n-1}{n}v + \frac{1}{n} \quad (12)$$

The optimal bidding strategy is one of overbidding ($b > v$). This overbidding declines when the number of bidders (n) increases.

As a comparison, the optimal bidding strategy for a “selling” (or direct) sealed bid auction is:

$$B(v) = \frac{n-1}{n} v \quad (\text{Wolfstetter, 1996})$$

Contrary to what one might have expected, the optimal bid formulae for direct and procurement auctions are not symmetrical.

Generalization to multiple unit procurement auctions

Consider a multiple unit reverse auction with n bidders and m units demanded by the auctioneer, each bidder wanting to sell *at most* one unit. Each bidder submits a bid for a single unit with the understanding that each of the m^{th} lowest bidders will sell a unit of the good at a price equal to his own bid (discriminative sealed bid auction).

The probability that a bid b by bidder 1 will win is the probability $G(B^{-1}(b))$ that at least $(n-m)$ of the values drawn by the rivals are greater than $B^{-1}(b)$. This probability is given by $1 - H(F)$ where $H(F)$ is the distribution function of the m^{th} order statistics for a $(n-1)$ sample from distribution F :

$$G(B^{-1}(b)) = \frac{(n-1)!}{(m-1)!(n-1-m)!} \int_{B^{-1}(b)}^{v^{\text{sup}}} F(v)^{m-1} (1-F(v))^{n-1-m} f(v) dv \quad (13)$$

The expected gain of bidder 1 of value v and bid b is:

$$E(v,b) = (b-v)G(B^{-1}(b)) \quad (14)$$

The first-order conditions for the maximization problem in (14) are:

$$G(B^{-1}(b)) + (b-v) \frac{G'(B^{-1}(b))}{B'(v)} = 0$$

At equilibrium, $b=B(v)$

$$B'(v) \cdot G(v) + B(v) \cdot G'(v) = v \cdot G'(v)$$

$$B(v) = - \frac{\int_v^{v^{\text{sup}}} u G'(u) du}{G(v)} \quad (15)$$

Therefore, the optimal bid is:

$$B(v) = \frac{\int_v^{v^{\text{sup}}} u G'(u) du}{\int_v^{v^{\text{sup}}} G'(u) du} \quad (16)$$

For a uniform distribution between 0 and 1, we have:

$$G(v) = \frac{(n-1)!}{(m-1)!(n-1-m)!} \int_v^1 u^{m-1} (1-u)^{n-m-1} f(u) du \quad (17)$$

$$b(v) = \frac{\int_v^1 u^m (1-u)^{n-m-1} du}{\int_v^1 u^{m-1} (1-u)^{n-m-1} du} \quad (18)$$

An important feature of the optimal bid as determined in (18) is that the level of overbidding is high for low value bidders. Overbidding decreases as the value increases, with the bids from high value bidders asymptotically approaching their respective values. For example, in an auction involving 100 bidders with values uniformly distributed between 0 and 1 competing for the sale of 30 units, the level of overbidding is 300% for a value of 0.075 and only 11.70% for a value of 0.305.

III. THE EXPERIMENTAL SETUP

The question now is, how well does the BC model perform? This is not such a trivial question, since we lack standard benchmarks to measure its performance. One solution is to benchmark it relative to a fixed price mechanism, as was done in Schilizzi & Latacz-Lohmann (forthcoming). Perhaps a better solution is to

benchmark it relative to the other auction format, the TC auction, for which a well established theory exists. The purpose of the experiments described below was to compare the performance of the two auction models.

Setup common to both auction formats

Both auction formats were submitted to a common experimental setup. They were first carried out at the Christian Albrechts University in Kiel, Germany, in January of 2004, then, in October, at the University of Western Australia in Perth. The Perth experiment was meant to replicate the Kiel experiment, in order to check for the stability of results. One slight change was introduced, however, as described below.

The Kiel experiment was carried out with first year students in agricultural economics. The total number of students was about 88 (the number varied slightly across sessions). They were divided into two groups, one for each of the two auction formats. A pre-session had controlled for key environmental and risk aversion attitudes, in terms of certainty equivalents. Table 1 shows that the two groups were nearly identical in terms of risk aversion; they were also tested to be very similar in environmental attitudes, with the TC group being slightly “greener” than the BC groupⁱⁱⁱ.

Table 1: Risk attitudes – Kiel

	AUCTION TYPE	
	BC	TC
Risk loving	39%	30%
Risk neutral	49%	46%
Risk averse	12%	24%
CE ratio	108	107

CE = Certainty Equivalent ratio (100 = risk neutral)

The auction setup referred to reductions in nitrogen fertiliser on a wheat crop, in order to meet EU regulations regarding limits to nitrate concentration in groundwater (50 mg/litre). This is a serious concern in the agricultural areas of northern Germany, and one which students in Kiel would be aware of and sensitive to. Participants were offered would-be contracts for committing themselves to reduce applications of nitrogen fertiliser from their optimal level down to a predefined constrained level, equal to 80 kg per hectare. Each participant had a different opportunity cost resulting from the adoption of the nitrogen reduction program. Thus

participation cost a different amount for everyone. Participation costs were spread uniformly between €4 (the lowest-cost farmer) and €64 (the highest-cost farmer). Students 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 very 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 compensated for the environmental service they were providing to society – reduced groundwater pollution – by getting paid the difference between their bid and their opportunity cost. They were therefore not to bid an amount lower than their opportunity cost. On the other hand, they were to think carefully about how much they could bid above their opportunity cost, as the higher they bid the lower their chances of winning a contract. It was up to each bidder to strike the balance and decide on the trade-off.

For both groups, three rounds were held, with a few days interval between each. The purpose of this was to investigate the performance of the models with potential bidder learning. That is, which of the two auction models was better able to maintain the quality of outcome predictions as bidders learn to bid closer to the marginal cost bidder? This would provide some insight as to the dynamic performance of the two models. In rounds two and three, exactly the same setup was used, except that bidders knew of their own result in the previous round(s), and successful bidders had been paid their net gains at the end of each session.

Auction specific setup

The two auction formats differed mainly with respect to the information given to, and asked of, the bidders. Since auctions are very sensitive to information structure, it was important to perfectly control for this aspect.

- BC auction specifics

For the first round, the group playing the BC auction was given the following information: the available budget for the current session (€900) and a rough estimate of where the bidder stood compared to his or her competitors in terms of participation cost. It was assumed that bidders could look around and estimate the number of competitors in his or her group: between 40 and 44 depending on sessions.

The budget constraint announced was clearly distinguished from the actual payments made at the end of the session. These reflected the further budget constraint

weighing on the experiment, which amounted to €300. Bidder payments would be proportional to their gains calculated as bid minus participation cost. The cost positioning information was given by indicating to which quartile the bidder belonged to: lower quarter, lower half, upper half, or upper quarter. The cost range (€4 to €264) was not given, but bidders were told that costs were uniformly distributed.

Bidders were asked two pieces of numerical information, their upper beta value ($\bar{\beta}$), and their bid (b). They were asked their $\bar{\beta}$ value as follows: “Please write down the highest bid you believe will be accepted. This must be your best guess”.

In the following rounds (2 and 3), bidders also knew whether they had previously been successful or not, and if so, what their net gains were. No information regarding other bidders was given, as e.g. the number of winners. However, it was assumed that students could and would communicate between rounds and gain a better idea of what the values involved were, just as in real auction settings.

- TC auction specifics

To the TC auction group, instead of a budget constraint, the number of contracts to be allocated was announced. This number had to be worked out immediately after the BC auction had been held, for the target was set equal to the number of contracts allocated with the €900 budget constraint. In the first round, this was 30 contracts. Thus the number 30 was announced to the TC auction group. Similarly to BC group participants, a bidder was shown to which cost quartile he or she belonged. Importantly, during the first session, the two groups were not allowed to communicate. The TC group entered the experimental venue as the BC group exited by an opposite door. Tutors were present to make sure no communication happened.

Two pieces of quantitative information were also asked of the TC group. Besides the amount bid for a contract, a bidder was also asked the value v_{sup} , that is, his best guess of what the highest participation cost in his or her group was. The value v_{sup} appears as the upper bound of the integral in equation (16), normalised to 1 in equation (18). Bidders were asked their v_{sup} value as follows: “Please write in your best guess of the highest participation cost in your bidding group. That is, how high do you believe is the participation cost of your “most expensive” competitor in your group? Please write in your *best guess* here below”.

The Perth replicate

The Perth experiment was in all points identical to the Kiel experiment, save for the following practical details and for the implementation of the TC auction. Participants were mostly second year students, with a few third and fourth years as well as a handful of post-graduates – all in the area of agriculture or natural resource management. They totaled about 50 in number, with a variation of one or two between sessions, split about evenly between the BC and TC groups. Whereas in Kiel participants were paid at the end of every session, in Perth they were not. Instead, for logistical reasons, participants were privately informed of their gains (if any), in individual envelopes, at the start of the following session (i.e. of sessions 2 and 3). They were also informed from the very beginning that actual payments would be made after the final session, provided they had attended all three sessions. This was to avoid inconsistencies across sessions with variable bidders and numbers. (The method proved quite effective!)

The first round of the TC auction was an exact replicate of the Kiel one, but a slight change was introduced in the two following sessions. Instead of informing bidders of their relative opportunity costs by showing them in which cost quartile they belonged, no such information was given them. Instead, the lower and upper bound of the range within which costs had been uniformly drawn was shown. The range given was \$0 to \$300. The question regarding their guess of the highest cost bidder was then framed as follows: “What is your best guess of the highest cost bidder knowing it has been randomly drawn from the interval \$0-\$300?” Participants could estimate the number of draws (about 25) by looking around for the numbers in their group.

The reason for making this change reflects the interpretation of the TC model, and more precisely, the bounds of the integrals in equation (16). In the model, bidders are assumed to be rational and play a Nash equilibrium strategy. The value v -sup is drawn for each bidder from a uniformly random distribution, and it is assumed that, on average, the values drawn using this procedure would be the same as those chosen by the bidders themselves, provided they played the Nash equilibrium strategy. Furthermore, bidders are told that participation costs are uniformly distributed between 0 and 300, but not that the highest cost is 264.

The experiment had to make a compromise between reproducing, for comparative purposes, the information structure of the BC model, and the exact

implementation of the TC model. The information structure of the two models differs because of the parallel but different role played, in the BC model, by the highest acceptable bid $\bar{\beta}$, and, in the TC model, by v-sup. At the same time, combining the Kiel and Perth experiments would allow us to assess whether such a change produced any substantial consequences or not. Though the statistical strength of the results would suffer, the expected gain in qualitative information was deemed to yield better value for the limited money available, at least as a first go. The resulting setup can be represented as follows:

Table 2 – Information structure for TC auction

TC auction	KIEL	PERTH
Session 1	A	A
Session 2	A	B
Session 3	A	B

In Kiel, session repetitions would provide information on how the auction performed under repetition in one format. The first sessions in Kiel and Perth would provide information on any structural differences between the two replicates. Comparing sessions 2 and 3 would provide information on whether the change in auction format produced any noticeable effects under repetition.

Another slight difference in the Perth experiment was the twist given to the story. Rather than nitrogen leaching into the groundwater, the government agency was buying back from horticulturalists in the Swan catchment area a composite good made of nitrogen and phosphorus, and the problem was eutrophication in the Swan river following excess runoff of these two nutrients – a socially and politically sensitive issue in Perth.

IV. RESULTS AND DISCUSSION

How well does the BC model predict the one-shot auction?

We focus here on the comparative performance of the two models, not on the performance of the two auction institutions. Figure 2 plots optimal predicted bids against experimental bids. The 45 degree line represents perfect prediction, if all data

points were situated on it. Two things can be observed. Firstly, prediction is less than perfect. The R^2 is 0.83 in Kiel and 0.78 in Perth (top graphs). Secondly, the model underestimates the experimental bids in Kiel slightly but systematically, the linear fit being everywhere above the 45 degree line. There are two features of the model that may explain this less than perfect prediction: the distribution of expected bid caps is assumed to be uniform, which may or may not be an accurate assumption; and bidders are assumed to be risk neutral.

It is not possible to check for the first assumption, but bidders' risk aversion in Kiel was roughly measured previous to holding the auction, and was found to be slightly negative. That is, experimental subjects were found to be slightly risk-prone, with an average certainty equivalent ratio of 107% (where 100% indicates risk neutrality). This may partly explain the underestimation of the model, since risk-prone bidders can be shown to optimally over-bid relative to risk neutral bidders.

The Perth data confirm this. Perth participants were slightly risk-averse, with an average certainty equivalent ratio of 88%, and the model no longer underestimates the bids. However, in both Kiel and Perth experiments, the linear fit has a smaller slope than the 45 degree line, with the difference more marked in Perth. The model slightly predicts low bids higher than it does high bids. Alternatively, low-cost bidders tend to bid higher than their optimal bid than high cost bidders. This effect is consistent throughout most of the rounds.

These imperfections notwithstanding, the model seems to be predicting the data rather well. This is a first response to the title of this paper: can a simple model predict bidding behaviour in multi-unit procurement auctions? However, we need a better measure of how good is 'rather well'. To gain some insight into this question, we compare these model results with those of the more standard TC model.

Does the BC model predict better than the TC model?

Figure 2 allows for a first comparison of the two models. Let us first consider the Kiel data (the two graphs on the left). It seems that on all accounts, the BC model does at least as well as the TC model, and indeed does better. In terms of statistical fit, the BC model's R^2 is 0.83 whereas the TC model's R^2 is only 0.37, for a similar number of observations (respectively 44 and 43). The difference is even more dramatic when considering the Perth data (the two graphs on the right).

However, one must ask whether this is due to model performance or to different behaviour of experimental subjects in the two groups. In Kiel, the coefficient of variation in actual bid dispersion is remarkably similar for the BC and TC groups (resp. 40% and 41%), indicating no behavioural difference in bid dispersion (Table 3). The difference in data fit must therefore come from the model: the CV of optimal (predicted) BC bids is 43% compared to 40% for observed bids, and for the TC model it is 32% compared to 41%, clearly not as good a predictor. If one considers the average difference between predicted and observed bids (in absolute terms), the BC model yields €14 compared to TC €17 (where in both cases, as noted earlier, predicted values are lower than observed ones). This is reflected by the slope of the two linear fits, where the BC model reads 0.93 and the TC model 0.84. The corresponding differences in standard deviations are €29 and €60. Both the average and the dispersion of the difference between predicted and observed bids are lower for the BC than for the TC model.

With the Perth data, one might expect such differences to reflect marked differences in behaviour, in contrast with the Kiel participants. However, such does not appear to be the case. The coefficient of variation in bid dispersion is 43% for the BC group and 41% for the TC group – remarkably similar to the ones in Kiel. The CVs of optimal and actual bids are 45% and 43% in the BC group and 22% and 41% in the TC group, reproducing the pattern observed in Kiel, even more marked. The average differences between predicted and observed bids are BC: \$27 and TC: \$63, and the differences in the standard deviations are BC: \$25 and TC: \$68, again quite similar to the results obtained in Kiel. Such similarity between the Kiel and Perth experiments is quite remarkable.

Table 3 – Comparison of model performance for first round

Round 1 only	KIEL		PERTH	
	BC	TC	BC	TC
CV (actual bids)	40%	41%	43%	41%
CV (optimal bids)	43%	32%	45%	22%
mean (opt – act)	€14	€17	\$ 27	\$63
SD (opt – act)	€29	€60	\$ 25	\$68

Legend: CV = coefficient of variation SD = standard deviation
 Opt = optimal bids act = actual bids

On the basis of this preliminary analysis, the BC model seems to predict observed data better than the more standard TC model. The fact that this holds across the Kiel and Perth experiments lends some credence to this conclusion. Does this performance hold up when the auction is repeated and bidders have the opportunity to learn about other bidders' values as well as about the marginal bid price?

How robust is the BC model to repetition and bidder learning?

Recall that we are not evaluating the auction's performance as an institution, but that of the model describing the auction. In particular, we are comparing the predictive power of the two models, not the allocative efficiency of the two auctions. We first analyse the Kiel experiment, which has a homogenous implementation of the TC auction, then the Perth experiment, where the implementation was slightly changed for rounds 2 and 3, as explained earlier.

The graphs in Figure 3 show the series of three repetitions for both auction formats in Kiel. At first sight, it is not clear by looking at these graphs how the two models compare. In addition, both models appear not to have a monotonic trend, whether towards improvement or deterioration of predictive power. The issue here is complicated by the fact that bidders learn differently in the two settings. In the TC setting, bids end up clustering around the maximum accepted bid, corresponding to the marginal bid price, which is \$200 in the third round. In the BC auction, no such clustering is visible. This suggests that, as an institution, the BC auction is in these experiments more robust to bidder learning than the TC. However, our focus here is on the model, not the institution.

Considering the sequence of the three rounds in Kiel^{iv}, the comparison of the average differences between the optimal and actual bids shows a smaller difference

for the TC model than for the BC (Table 4a). In round 3, the average difference in the BC auction was € 31 but only € 14 in the TC auction. Analysis of the standard deviations of the differences between optimal and actual bids showed smaller variation in round 1 for the BC model, but this difference disappears after two repetitions. The Kiel data do not allow us to draw any definite conclusions. Whence the value of the Perth replication.

The Perth experiment is more “well behaved”, in that we do not observe an anomaly in round 2 (Figure 4). The trends are monotonic, which is what one would expect as bidders learn with repetitions. Let us observe the progression of the mean and standard deviation of the difference between optimal and actual bids (Table 4b). Initially, in round 1, the BC model clearly predicts better than the TC model in relative terms, but with repetition and differential bidder learning, the TC predictions clearly converge towards actual bids. No such convergence is manifest in the BC auction, where predictions, though initially better than those of the TC model, hardly improve. As a result, in round 3, the TC model performs better, in both relative and absolute terms, than the BC model. The average deviation is only \$15 compared to an average bid (both optimal and actual) of around \$200 – an 8% discrepancy. This result warrants an explanation.

As noted earlier, the TC auction institution allows bidders to infer more quickly the marginal bid price, and their bids quickly converge and cluster around it, as auction theory predicts. Accordingly, the model improves its predictions. In the limit, as the number of repetitions increase, all else being equal, one would expect that optimal bids and actual bids would coincide very closely, as they would all be very close to the marginal bid price. In the TC setting, bidders quickly learn to bid their Nash equilibria by aligning themselves on the marginal bidder. This has also been shown in simulations using an agent-based model (Hailu and Schilizzi, 2004; Hailu et al., 2004), and was observed in the early years of the US Conservation Reserve Program. In the BC model, by contrast, bidders are prevented from inferring the implicit cut-off price, and they continue bidding mostly as a function of their individual opportunity costs, as shown in Figure 4. However, the BC model maintains fairly good predictive performance throughout, with a discrepancy of 12 to 15%.

A closer examination of the discrepancy between the relative dispersion of actual and optimal bids, as measured by their coefficients of variation, confirms these conclusions. The BC model also tends, however slightly, to overestimate the

dispersion of the bids, whereas the TC model tends, however slightly, to underestimate the dispersion (Tables 5a and 5b). This holds across all rounds and across both Kiel and Perth experiments. Finer analysis is needed to decide whether this effect is statistically significant. Better still, further repetitions will be able to tell if there is something here worth pursuing. At this stage, the reasons why this should happen are not clear.

Table 4a - Kiel experiment

Average of difference between actual minus optimal bids (€)			
All bidders	Round 1	Round 2	Round 3
BC	14	36	31
TC	17	16	14
SD of difference between actual minus optimal bids (€)			
All bidders	Round 1	Round 2	Round 3
BC	29	35	25
TC	60	20	26

SD = standard deviation

Table 4b - Perth experiment

Average of difference between actual minus optimal bids (\$)			
All bidders	Round 1	Round 2	Round 3
BC	28	21	25
TC	63	35	15
SD of difference between actual minus optimal bids (\$)			
All bidders	Round 1	Round 2	Round 3
BC	25	22	21
TC	68	38	14

SD = standard deviation

Table 5a – Kiel experiment

KIEL	CV of BC bids		
	Round 1	Round 2	Round 3
Actual	0.40	0.29	0.26
Optimal	0.43	0.35	0.36
Difference	0.03	0.06	0.10

	CV of TC bids		
	Round 1	Round 2	Round 3
Actual	0.41	0.19	0.15
Optimal	0.32	0.17	0.15
Difference	-0.09	-0.02	0.00

Table 5b – Perth experiment

PERTH	CV of BC bids		
	Round 1	Round 2	Round 3
Actual	0.43	0.32	0.36
Optimal	0.44	0.35	0.38
Difference	0.01	0.03	0.02

	CV of TC bids		
	Round 1	Round 2	Round 3
Actual	0.41	0.34	0.17
Optimal	0.22	0.12	0.12
Difference	-0.19	-0.22	-0.05

Implementing the information structure of the TC auction

As discussed earlier, implementing the TC auction required a compromise between exact comparability with the BC auction, and exact implementation of the TC model. The BC model provided bidders with information about the distribution of participation costs by showing them in which quartile they belonged. Implementing the TC theoretical model required bidders to be given a lower and upper bound between which costs were drawn with a uniform distribution. The highest cost bidder was somewhat close to the upper bound, though how close was not known to other bidders, nor did the highest cost bidder know he was the highest. As shown in Table 2, in Kiel perfect comparability between the two auction formats was chosen, whereas in Perth rounds 2 and 3 were implemented in a theoretically rigorous way. Round 1 replicated the Kiel implementation to allow comparison between the two experiments.

Tables 4 a,b and 5 a,b seem to indicate there is no qualitative difference in the results observed in Kiel and Perth. The structural consistency of the other aspects seen above lends credence to the overall consistency of the results obtained. This can be further checked by examining Figure 5, where the expected highest costs have been shown together with actual bids for the TC auction in Kiel and Perth. The vertical dotted line in round 2 and 3 of the Perth experiment represent the upper bound (\$300) to the participation costs, information given to participants. A comparison between round 2 and 3 in Kiel and Perth shows that, except for two points in Kiel round 3, bidders' behaviour appears very similar. This indicates that the difference in the implementation of the TC information structure has had no noticeable impact on the results. The learning effects in Kiel and in Perth are therefore comparable, and the results analysed above do not need qualification on these grounds.

V. CONCLUSIONS

This study addresses the repeated purchase by a government agency of public environmental goods from private landowners by means of auctioned contracts. Such auctions are characterized as repeated multiunit procurement auctions. Farmer provision of biodiversity, land and water conservation, or landscape management are examples of such public goods. In this context, the government agency has the choice between setting itself a target and setting itself a budget. An example of a target constrained (TC) auction is the decision to sign contracts with landowners to manage at least N hectares, and to pay whatever cost the auction will entail. A budget constrained (BC) auction fixes the budget, but accepts the risk of seeing less than N hectares under contract. A practical question for a government agency is, which auction format is best?

Auction theory is well developed for TC, but not for BC auctions. By contrast, nearly all environment-oriented procurement auctions implemented by government agencies are BC auctions. As a result, there is a gap between what is understood by economic theory and what is common practice. It turns out that the analytical study of BC auctions is very difficult if undertaken from the same theoretical standpoint as for TC auctions. Instead, an auxiliary assumption must be made, by introducing an

exogenous 'bid cap' in the formation of bidders' bids. This assumption results in a very simple model, much simpler than the more standard TC model. Before asking which of the two auction institutions might be preferable in this context, it was deemed necessary to assess the validity and credibility of this model. Doing otherwise would not allow it to be used to predict auction outcomes and provide guidance to policy makers.

This study focused on assessing the validity and credibility of the BC model. To do so, the model was submitted to two repeated experiments, in two different countries (Germany and Australia), and it was compared with the repeated multiunit TC procurement auction, which was also investigated experimentally. Comparability across the two auction types and across the two experiments was controlled for. Particular attention was given to the information structure of the two auctions.

The experimental results clearly show that the BC model predicts not only as well as the TC model, but, especially in the first round, better. It also performs well in absolute terms. The model is able to predict actual bids in both experiments in a more consistent way than the TC model. The conclusion may therefore be drawn from this study that the BC model is credible and can be used to address the second question, of more direct interest to policy makers: which of the two auction institutions performs best? In particular, how robust is each to repetition and bidder learning? How do they compare in terms of bidders' information rents and efficiency in resource allocation?

These questions will be addressed in a publication to follow.

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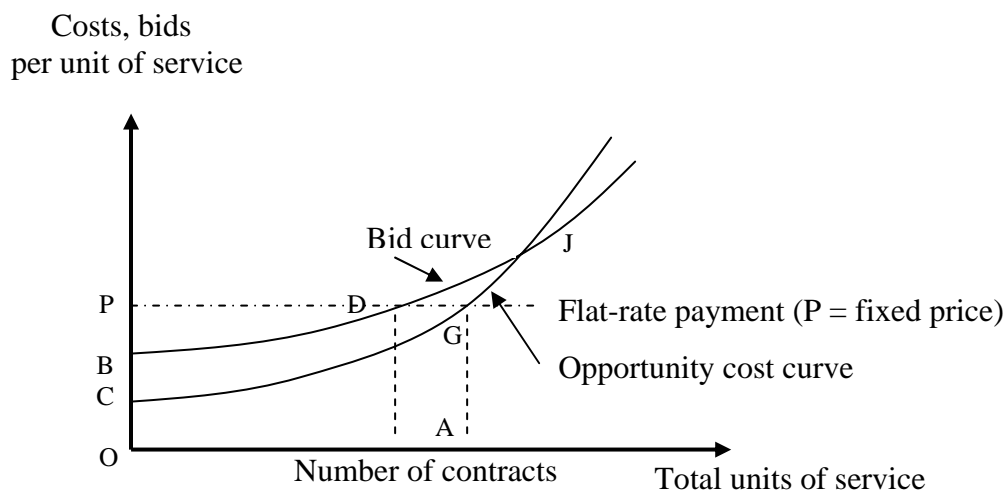


Figure 1 - Bid and opportunity cost curves

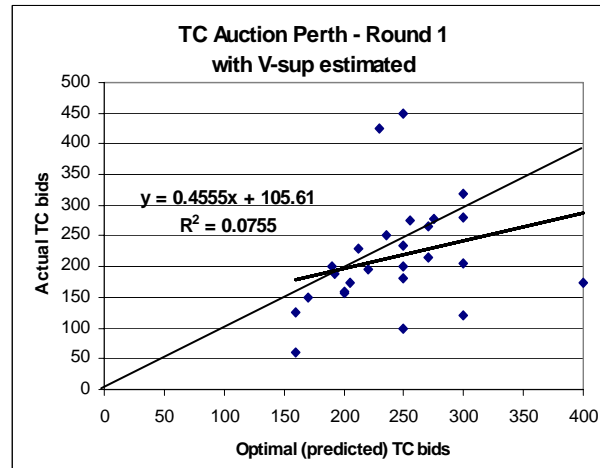
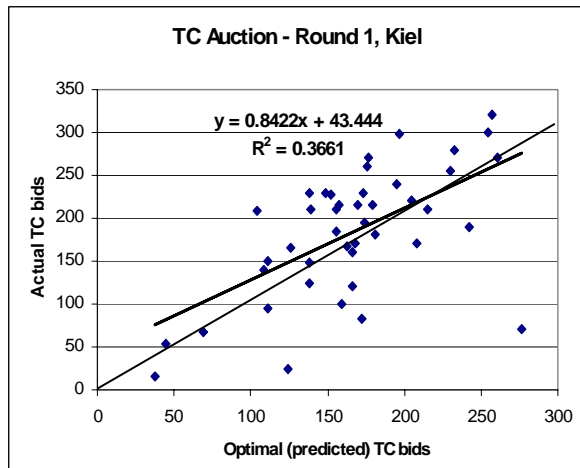
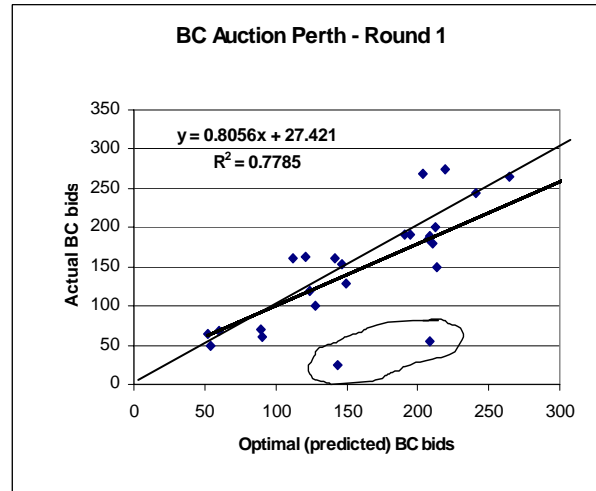
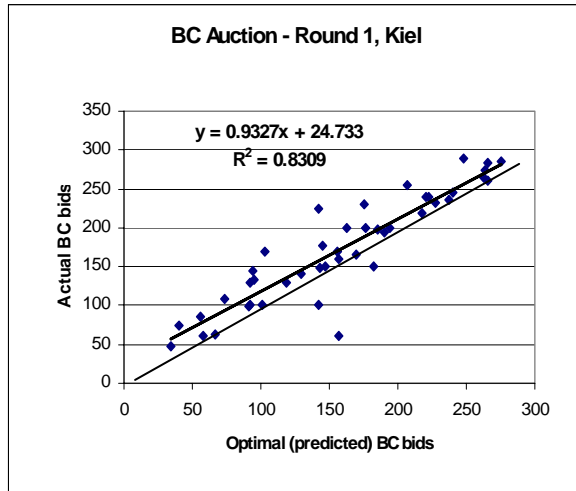


Figure 2: First rounds in Kiel and Perth, BC and TC auctions

The 45 degree lines of perfect fit are shown. The two circled points in the Perth BC auction correspond to participants who had not understood the rules of the game. They were left out of the analysis.

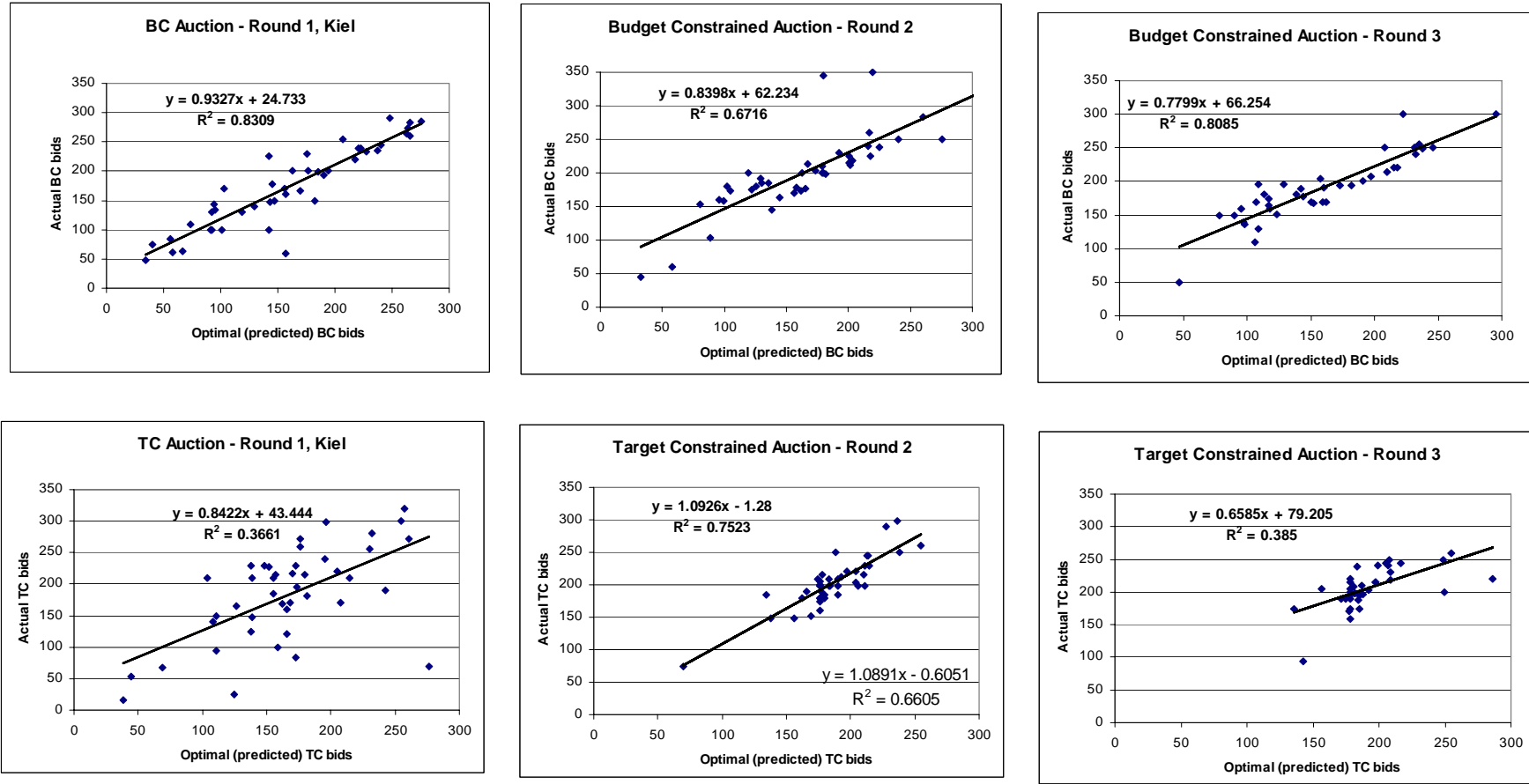


Figure 3 – The Kiel experiment

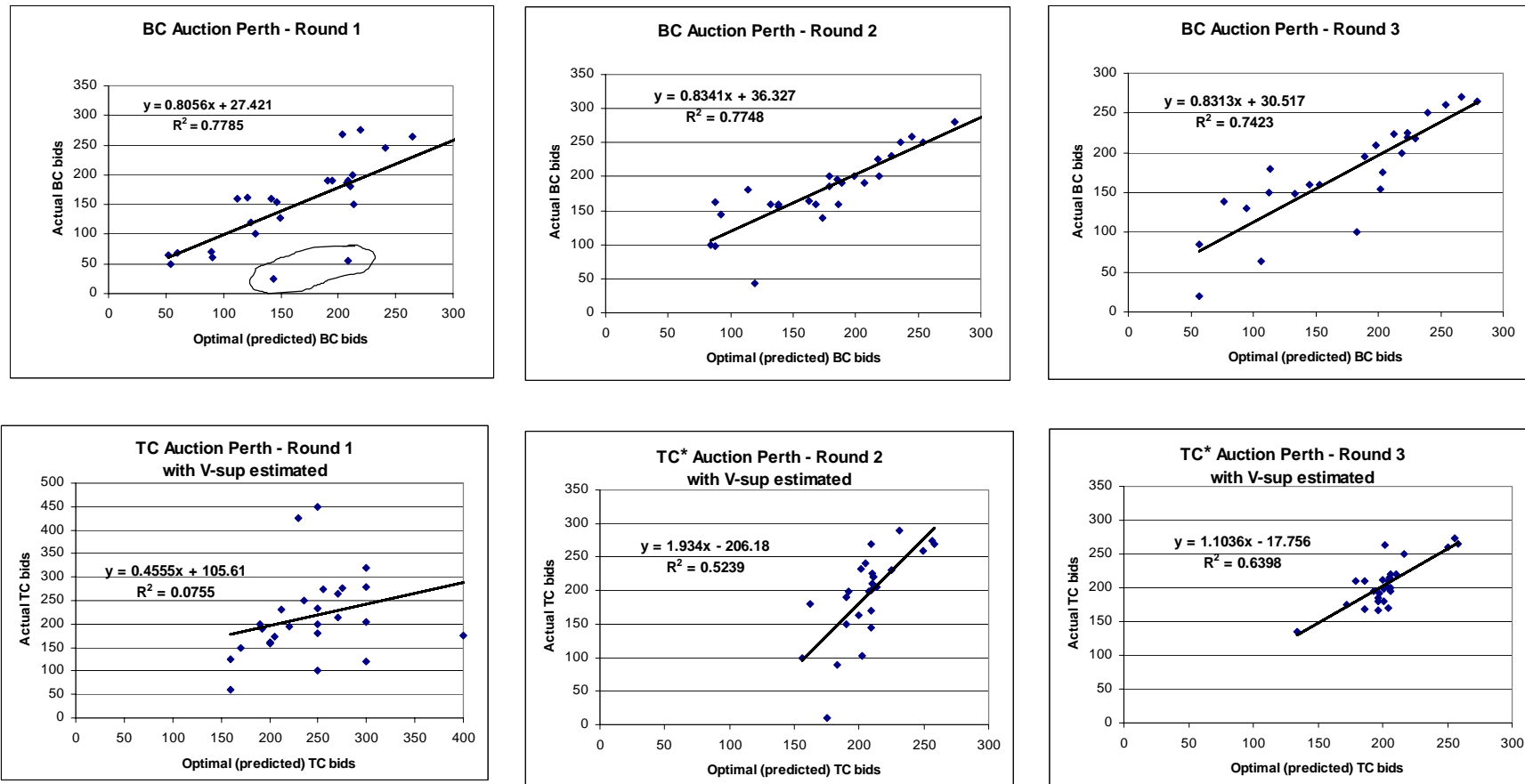


Figure 4 – The Perth experiment (The two outliers in the first graph are explained under Figure 2).

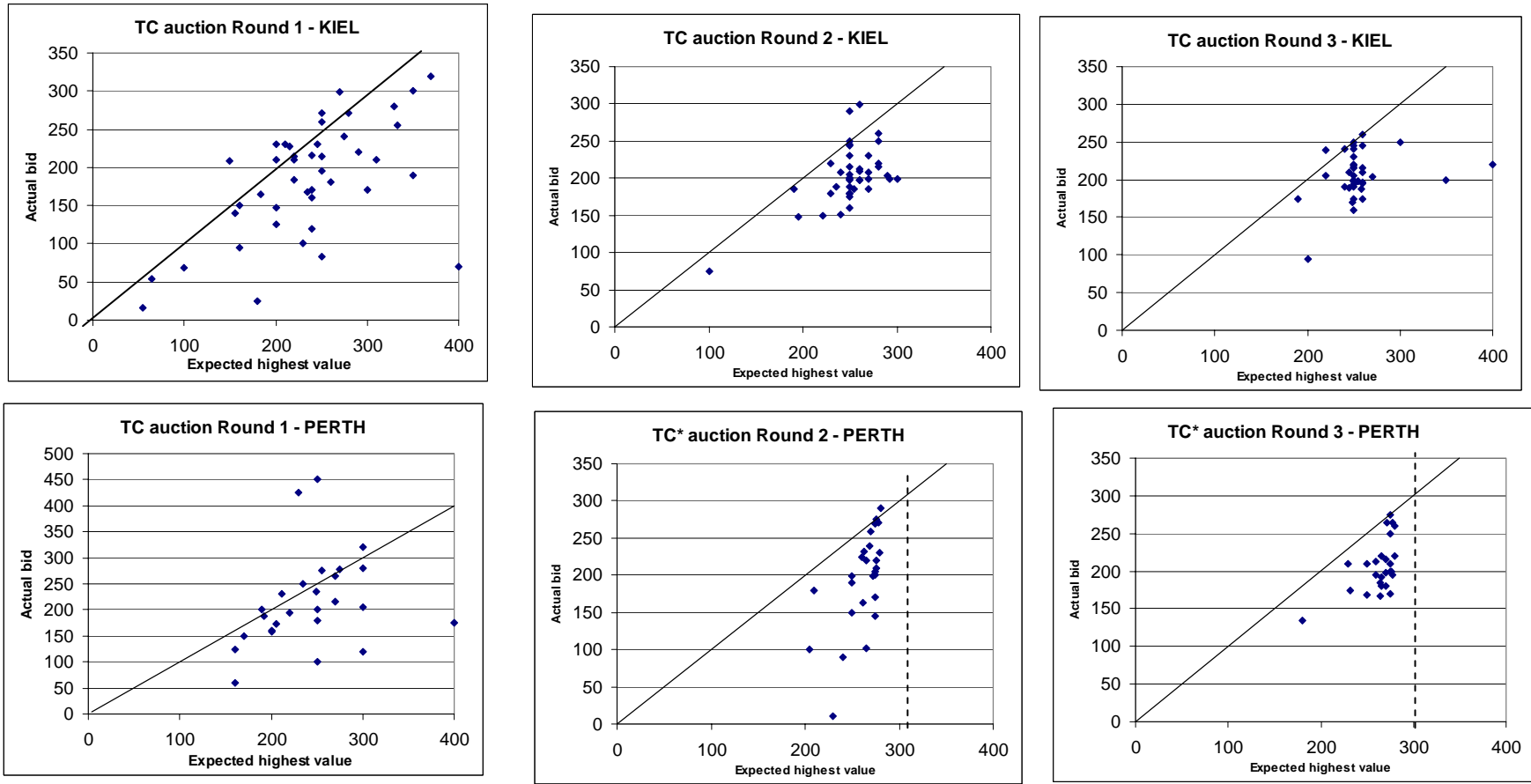


Figure 5 – TC auction in Kiel and Perth, expected highest participation cost and actual bids

ENDNOTES

ⁱ This is not an essential assumption and could be relaxed to include risk aversion. However, it would not add much to the argument and might confuse matters unnecessarily.

ⁱⁱ The results are not very sensitive to different assumptions about the type of distribution.

ⁱⁱⁱ The following three statements were put to participants: (1) Agriculture contributes more to the destruction than to the conservation of the land; (2) Larger farms harm the environment more than smaller farms do; (3) Organic agriculture is more environmentally friendly than conventional agriculture. Participants were asked to indicate their degree of agreement or disagreement on a 5-point scale, with the middle point indicating “don’t know” or hesitation.

^{iv} As will appear in comparing with the Perth experiment, round 2 in Kiel appears to contain an anomaly – one which we have not been able to explain.