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Abstract

Conservation auctions are reverse auctions designed to allocate payments for environmental services to voluntary farmers. In such reverse auctions, the maximum number of contracts to be allocated can be announced to the bidders (target constraint auction). In practice, it is often the maximum budget dedicated to the program that is announced (budget constraint auction). Coiffard et al. (2023) compare the two formats when constraints are equivalent. Here, we perform an online decontextualized experiment with the strategy method to study the cost-effectiveness of the double constraint auction, in which both constraints are announced to the bidders. Our main result is that the double constraint auction provides, on average, better cost-effectiveness than auctions where only a target constraint or a budget constraint is announced. However, the cost-effectiveness of the double constraint auction decreases as the announced budget increases.

Keywords— Reverse auctions, Conservation auctions, Double constraint.

1 Introduction

Conservation auctions are a widely studied tool used to allocate agri-environmental payments to farmers (Schilizzi, 2017; Whitten et al., 2017; Bingham et al., 2021).

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The farmers' costs of complying with the agri-environmental contract are private information. Because of this asymmetry of information, auctions are theoretically more cost-effective than fixed payment schemes in allocating contracts (Ferraro, 2008; Viaggi et al., 2010). The Conservation Reserve Program (CRP) (Hellerstein, 2017) in the US and ecoTender in Australia (Stoneham et al., 2012) are well-known examples of large scale conservation auction applications. Competitive bidding is also encouraged by the European Common Agricultural Policy (CAP) to allocate agri-environmental contracts, yet the implementation of conservation auctions in Europe is not much widespread (e.g Ulber et al., 2011). Conservation auctions are reverse auctions because the auctioneer is the buyer (of environmental services) and the bidders are the sellers (providers of environmental services), typically farmers. Conservation auctions are multi-unit auctions, as the auctioneer commonly establishes agri-environmental contracts with several farmers, resulting in multiple winning bidders. In such reverse auctions, the maximum number of contracts to be allocated can be announced to the bidders (hereafter Target auctions). Nevertheless, in practice, the auctioneer generally announces his available budget as a constraint (hereafter Budget auctions). To our knowledge, auction theory, which takes into account bidders interactions, does not consider the case of budget-constrained reverse auctions.[1] Therefore, it is difficult to predict how farmers bid in such situations. The performance of Target and Budget reverse auctions has been compared in few experimental papers (Schilizzi and Latacz-Lohmann, 2007; Boxall et al., 2017; Coiffard et al., 2023).

In this paper, we experimentally study the multi-unit reverse auction format where both the target constraint and the budget constraint are announced (hereafter Double constraint auction). In a Double Constraint auction, units are ranked by the auctioneer in ascending order of price and purchased from the cheapest bid until either the target or the budget constraint is exhausted. We consider only the discriminatory payment rule, i.e., winning bidders receive the price they bid. Our main research question is how the Double Constraint auction performs compared to the auctions in which only one of the two constraints is announced (Target or Budget).

For simplicity, we assume that each farmer can only offer a single contract and that each contract has the same value for the auctioneer. In other words, we assume that each farmer's contract provides the same value of environmental services. This is a strong assumption as many aspects of agri-environmental contracts can influence the level of environmental services provided (number of hectares covered by the contract, location of the farm, etc.). In practice, the auctioneer usually needs to compute an environmental benefit index to weight price offers submitted by farmers (see Glebe, 2008). This aspect of conservation auctions is not considered in this paper, which allows us to consider a much simpler auction format where

[1]Latacz-Lohmann and Van der Hamsvoort (1997) propose a budget-constrained auction model, but within the framework of decision theory (as opposed to game theory), i.e., they do not consider strategic interactions of bidders.

farmers compete only on price, and where the auctioneer simply selects the lowest bids. In conservation auctions, the target is the amount of environmental services to be purchased. In our simplified context, where each farmer provides the same amount of environmental services, the target is the number of contracts or units, i.e., the number of winning farmers. The budget spent in such Target auctions can be very high (depending on the bid offers) and may exceed the maximum budget available for the purchase of contracts (Viaggi et al., 2010). Indeed, in practice, any auctioneer's budget is limited. To avoid exceeding his budget in Target auctions, the auctioneer can announce a reserve price beyond which offers cannot be accepted (Boxall et al., 2017). This reserve price may be kept secret (see Schilizzi, 2017). Here we propose an alternative auction design, the Double Constraint auction, in which a budget constraint is announced in addition to the target constraint.

To measure auction performance, we do not consider a specific demand function for the auctioneer, but only assume that the marginal utility of environmental services is strictly positive. Additionally, the auctioneer is assumed not to have any strong constraint: neither to meet the announced environmental target nor the announced budget. This is generally the case as the environmental benefits are complex to define and the auctioneer usually has some leeway in setting the budget for the environmental program.

We use the experimental data obtained in Coiffard et al. (2023), and we propose new treatments using the same methodology. As in Coiffard et al. (2023) we first consider two equivalent constraints to make treatment results comparable. To set equivalent constraints, we first run the Target auction treatment. Then, we use the average budget spent in the Target treatment to set the budget constraint in the Budget treatment. The new Double Constraint auction treatment allows us to study the impact of adding a second equivalent constraint in either the Target or the Budget auction. We also run two other new treatments to better understand the impact of announcing a higher budget constraint in the Budget auction and the Double Constraint auction.

The experiment is conducted online and monetarily incentivized, but is not contextualized to the case of conservation auctions. Indeed, our subjects are not farmers, so giving them instructions related to farmers and environment services may cause confusion. The instructions given to subjects only state that each of them has a single unit to sell. Our experiment relies on the strategy method to obtain the subjects' bidding function: we ask subjects to fill out a decision table in which they indicate the amount of their bid corresponding to every possible cost. Auction outcomes can be simulated ex post from these functions, for any set of costs. By simulating the auction outcomes for all the possible cost sets for a given group of bidders, we generate a very rich data set. Considering the average of the auction outcomes on exhaustive costs arrangements avoids using arbitrary bidders' cost draws. In the data analysis, the participants are randomly attributed to a single auction group, so that the average outcomes at the group level are independent observations. Therefore, the combination of the strategy method with auction outcome simulations is very useful and allows us to obtain a large sample of independent auction data.

The paper is organized as follows. A literature review on conservation auctions is presented in Section 2. Next, the auction game and experimental design are presented in Section 3 along with the criterion we use to compare the different auction formats and information about the online implementation of the experiment and data. In Section 4, we present the results of the treatments. Finally, we discuss our results and conclude in Section 5.

2 Literature on conservation auctions

Conservation auctions are among the main areas of application of reverse auctions and are covered by an extensive literature. In practice, conservation auctions deviate significantly from theoretical auction models, and most research on conservation auctions is empirical, often using an experimental approach.

A significant body of literature on conservation auctions has compared discriminatory and uniform payment rules using laboratory experiments (Cason and Gangadharan, 2005; Liu, 2021), numerical simulations (Hailu and Thoyer, 2010; Iftekhar and Latacz-Lohmann, 2017) or observational data (Windle and Rolfe, 2008; Deng and Xu, 2015). In a discriminatory auction, winning bidders receive their bid, whereas in a uniform price auction, all winning bidders receive the same price (generally the highest winning bid). Overall, these studies have shown that discriminatory-price auctions are more cost-effective than uniform price auctions (Cason and Gangadharan, 2005; Windle and Rolfe, 2008; Deng and Xu, 2015; Duke et al., 2017; Liu, 2021), although this result may be sensitive to the level of competition (Hailu and Thoyer, 2010; Iftekhar and Latacz-Lohmann, 2017) and the interval of bidders' costs (Iftekhar and Latacz-Lohmann, 2017). Low participation and anti-competitive behaviors (collusion) are also major issues in auctions (Klemperer, 2002) and are equally important when implementing conservation auctions. Indeed, studies show that the cost-effectiveness of conservation auctions may be drastically reduced in the case of low participation (Palm-Forster et al., 2016; Rolfe et al., 2022). Collusion between bidders is typically overlooked in laboratory or online experiments, as subjects usually do not know the other bidders, which reduces collusion risk. Yet in practice, farmers are not monitored during the bidding process and may easily collude in some cases (Packman and Boxall, 2010).

However, what interests us more here is the impact of the auctioneer's announced constraint. Once the units are ranked, a stopping rule must be defined to indicate when the buyer stops purchasing the highest ranked units. In conservation auctions, typically the auctioneer has a limited budget available and tries to achieve the highest possible environmental target. Thus, in practice, the auctioneer usually purchases units in ascending order of price until this budget constraint is exhausted. Note that the level of the budget constraint may or may not be announced to the bidders (Messer et al., 2017). Nevertheless, when no constraint is announced, it is particularly difficult for bidders to define their bid. As explained in the introduction, an alternative to this budget constraint auction is to announce a target constraint, which means that the cheapest units are purchased until the environmental target (i.e., the targeted number of units) is met.

To our knowledge, three experimental studies have compared Target and Budget reverse auctions (Schilizzi and Latacz-Lohmann, 2007; Boxall et al., 2017; Coiffard et al., 2023). Schilizzi and Latacz-Lohmann (2007) and Boxall et al. (2017) conducted laboratory experiments set in an agri-environmental context. They use a between-subject design in which student subjects submit bids in several auction periods to generate more observations. In contrast, Coiffard et al. (2023) uses the strategy method, which allows to obtain the complete bidding strategy of all subjects and to carry out the experiment online. Furthermore, the experimental protocol is completely decontextualized. Schilizzi and Latacz-Lohmann (2007) and Boxall et al. (2017) found mixed results: Target auctions performed equally or slightly better than Budget auctions in the early stages, but the auction performance deteriorates more slowly in Budget than in Target auctions after several auction periods. In a one-shot setting, Coiffard et al. (2023) found that for the same average budget spent, the Budget auction allows the auctioneer to buy significantly more units on average than does the Target auction. The issue (Target vs. Budget) is not only addressed in experiments but also with multi-agent models (Hailu et al., 2005; Lan et al., 2021). Hailu et al. (2005) found that both formats performed similarly, whereas Lan et al. (2021) found that the auction performance was equal or higher in Budget than in Target auctions. However, announcing a Target auction only is not completely credible in practice, because farmers know that the buyer's budget is generally quite limited. In conservation auctions, the auctioneer usually has an implicit reserve price (Schilizzi, 2017). Announcing the reserve price increases the auction's efficiency according to Holmes (2010) (based on observational data) and Boxall et al. (2017) (in an experimental study).

In this paper, instead of a reserve price, we study the impact of announcing both a target and a budget constraint to bidders, which to our knowledge has never been considered in the literature on reverse auctions. We also investigate the impact of increasing the size of the budget announced in a Budget auction. Howard et al. (2023) showed that the performance of conservation auctions decreases with the budget size. Their objective was to elicit farmers' home-grown values for different types of conservation contracts (different agricultural practices) and considering different types of policy interventions, including reverse auctions, using a choice experiment. However, note that in their study, the budget constraint is not announced to the farmers, whereas in our experiment it is, and subjects might adjust their bids according to the announced budget constraint.

3 The experiment

The experiment was conducted online with subjects from the general population. For better control (e.g., heterogeneity of subjects' perceptions regarding the agri-environmental context), the protocol is completely decontextualized. In section 3.1, we describe the auction game and the different auction formats. In our between-subject design, subjects are randomly assigned to a single treatment: either Target, a Budget, or a Double Constraint auction. Section 3.2 explains how we obtain the complete bidding strategy of all the bidders using the strategy method. Section 3.3 details how we calculate the outcomes (number of units sold and budget spent) of an auction in each treatment, and then how we simulate a large number of auctions at the group level to finally derive the average outcomes at the treatment level. The synthetic criterion used to compare the auction treatments is presented in section 3.4, and finally, we present the online implementation of the experiment and the data in section 3.5.

3.1 The auction game and the different auction formats

The auction game considered is the same as the one presented in Coiffard et al. (2023). Subjects are the bidders who want to win conservation contract payments. Conservation contracts are assimilated to units of a homogeneous good, which are assumed to be perfectly divisible for the auctioneer (the experimenter). Each bidder i proposes a bid b_i to sell his unit. The provision cost of the bidder's unit is identically and independently drawn from a uniform distribution in the interval $[\underline{c},\overline{c}]$, which is common knowledge. The number of bidders N who participate in the auction is exogenous and common knowledge. The auctioneer ranks the N bids b_i in ascending order of price. Let $(r) = 1, ..., N$ denote the rank of ranked bids.

$$b_{(1)} \leq b_{(2)} \leq ... \leq b_{(N)}$$

The auctioneer purchases the cheapest units first. The payment rule considered is the discriminatory payment, i.e., winning bidders are paid their bid. The number of winning bids is defined by the announced constraint(s) and the constraint(s) is(are) announced to the bidders before they submit their bid.

Three auction formats are considered. In the Target auction, the auctioneer announces the number of units to be purchased (M) and accepts the cheapest bids until this target is achieved. As bidders only bid for one unit, the target constraint is also the number of winning bidders. In the Budget auction, the auctioneer accepts the cheapest bids until the predetermined fixed budget (B) is entirely spent. In a Double Constraint auction, the buyer announces both the target (M) and the budget constraint (B) and stops purchasing units as soon as one constraint is reached. In case of a tie, the buyer purchases the same fraction from each tied unit.[2] In Budget and Double Constraint auctions, the auctioneer may split up the last unit to fill the budget constraint.

3.2 The strategy method

Your cost	Your selling price
0 €	€
5 €	€
10 €	€
15 €	€
20 €	€
25 €	€
30 €	€
35 €	€
40 €	€
45 €	€
50 €	€
55 €	€
60 €	€
65 €	€
70 €	€
75 €	€
80 €	€
85 €	€
90 €	€
95 €	€
100 €	€

Figure 1: Decision table

As in Coiffard et al. (2023), we use the strategy method of Selten (1967). This method allows us to obtain the entire bidding function of the subjects and to conduct the experiment online without requiring the subjects to be connected simultaneously. Subjects are told that groups of N bidders will be randomly made ex-post and that the cost used for their payment will also be randomly drawn ex-post for each of them from a uniform distribution (single one-shot auction). More precisely, costs are multiples of five between 0 and €100 (21 possible cost values). The principle of the strategy method is to ask each subject what he would bid for every possible cost draw (see Figure 1). By collecting the entire bidding strategy of each subject, the strategy method subsequently allows to simulate a large number of one-shot auctions. This is an advantage over most auction experiments, which typically involve a few auction groups per treatment and several periods with

[2]In practice this tie rule is probably not the most pertinent, but it is easy to implement in the experiment and is the same as drawing a winner among the ties.

different cost draws in order to generate more (non-independent) observations. Indeed, in such multi-period experiments, bidders do not play a one-shot auction but repeated or sequential auctions.

3.3 Computation of auction outcomes (M and B)

To fully take advantage of having the entire bidding strategy of all the subjects, the auction results are computed for all possible cost configurations. In other words, for each possible cost arrangement $k = 1, ...K$ within an auction group g, we identify corresponding bids and compute auction outcomes: the budget spent in the Target auctions (B_{gk}^{TC}), the number of units purchased in the Budget auctions (M_{gk}^{BC}) and both outcomes in the Double Constraint auction treatments (M_{gk}^{DC} and B_{gk}^{DC}).

So let first define auction results at the level of one auction.

• **The number of units purchased:** In a Target auction, the number of units purchased is always equal to the announced constraint (M). We assume that M is an integer with $0 < M < N$. M_{gk}^{BC}, the quantity purchased in a Budget auction for a group g and a costs draw k, is given by

$$M_{gk}^{BC} = \begin{cases} N & \text{if } B \geq \sum_{r=1}^{N} b_{(r)gk} \\ t + \frac{B - \sum_{r=1}^{t} b_{(r)gk}}{b_{k(t+1)}} & \text{if } \sum_{r=1}^{t} b_{(r)gk} \leq B < \sum_{r=1}^{t+1} b_{(r)gk} \end{cases} \tag{1}$$

where t is a positive integer such as $0 < t < N$ and B is the announced budget constraint.

Similarly, M_{gk}^{DC}, the quantity purchased in a Double Constraint auction for a group g and a costs draw k, is given by

$$M_{gk}^{DC} = \begin{cases} M & \text{if } \sum_{r=1}^{M} b_{(r)gk} \leq B \\ t + \frac{B - \sum_{r=1}^{t} b_{(r)gk}}{b_{k(t+1)}} & \text{if } \sum_{r=1}^{t} b_{(r)gk} \leq B < \sum_{r=1}^{t+1} b_{(r)gk} \end{cases} \tag{2}$$

where t is a positive integer such as $0 < t < M$ and B is the announced budget constraint.

• **The budget spent:** The budget spent in a Target auction for a group g and a costs draw k is $B_{gk}^{TC} = \sum_{r=1}^{M} b_{(r)gk}$.
In a Budget auction, the budget spent is usually the announced constraint B. However, if B allows the auctioneer to buy all the units offered by the N bidders (i.e., no constraint is exhausted), there may be an excess budget E_{gk}

$$E_{gk} = \begin{cases} 0 & \text{if } B \leq \sum_{r=1}^{N} b_{(r)gk} \\ B - \sum_{r=1}^{N} b_{(r)gk} & \text{if } B > \sum_{r=1}^{N} b_{(r)gk} \end{cases}. \tag{3}$$

Thus, the budget spent in the Budget auction is $B_{gk}^{BC} = B - E_{gk}$.
The budget spent in a Double Constraint auction is computed as

$$B_{gk}^{DC} = \begin{cases} \sum_{r=1}^{M} b_{(r)gk} & \text{if } \sum_{r=1}^{M} b_{(r)gk} \leq B \\ B & \text{else} \end{cases}. \tag{4}$$

To calculate the average outcomes for any auction treatment X ($X = TC$, BC, or DC), we first average the auction outcomes (the number of units sold and the budget spent) over all cost draws k at the level of each group g (M_g^X and B_g^X). This provides an exact mean for each group in the different treatments that takes into account the entire bidding functions of the N bidders of each group since all the bidders' costs are used.

We constitute random groups of N bidders in each treatment (between-subject design experiment) such that each subject belongs to a single group. Therefore, group-level means are independent observations. The number of auction groups (G) in each treatment is the number of independent observations.

Finally, in each treatment X, group-level values are averaged again over all groups ($g = 1, ..., G$) to provide treatment-level outcomes (M^X and B^X). As group-level means are independent observations, we can compute standard deviations and test statistics to compare auction outcomes at the treatment level.

3.4 Computation of the performance criterion

As explained in Coiffard et al. (2023), constraints in Target and Budget treatments (M and B respectively) are defined as equivalent constraints. The Budget constraint is the average budget spent in Target, so the budget spent in both treatments is about the same. Budget is found better than Target because the Budget treatment allows purchasing significantly more units on average than the Target treatment.

Here, we use these two equivalent constraints simultaneously in our Double Constraint treatment. So no more than M units can be purchased and the budget spent is at most B. Each constraint is likely to be saturated in a certain number of cases, which would lead on average at the treatment level to $M^{DC} < M$ and $B^{DC} < B$. In this case, no conclusion could be drawn about a difference in performance using M and/or B as performance criteria.

The objective of the auctioneer is both to maximize the environmental benefits (the number of units purchased) and to minimize the budget spent. Therefore, to take into account both average outcomes of the treatment, the synthetic criterion we use is the average unit cost (hereafter UC^X), defined at the treatment level as the ratio B^X/M^X. We assume that the auctioneer prefers to use the auction format that minimizes UC^X.

Table 1: Sample description

Sample description	**Value**
Number of subjects	705
Age (mean, SD)	39.81 (12.8)
Income (proportion of €1,900 or more)	0.40
Gender (proportion of female)	0.51
Education (proportion of bachelor's degree or beyond)	0.47
Student (proportion of students)	0.09

3.5 Online implementation and experimental data

Anonymous subjects are from the Foule Factory panel.[3] They are not only students, as in most lab experiments, and so they are more representative of the general population. A description of the subject sample is made in Table 1. Auction groups of four bidders ($N = 4$) are formed ex-post anonymously. Subjects received a lump sum payment of €2.5 based on an announced duration of 15 minutes to answer the survey. To compute the auction payoffs, we randomly drew one cost for each bidder among the 21 possible costs. The bid corresponding to that cost was used to determine whether a bidder succeeded in selling his unit according to the bids offered by the three other bidders of his group. Every winning bidder received an extra payment defined as his bid minus his cost (discriminatory payment). The subjects who did not succeed in selling their unit received no extra payment. They received only the lump sum participation payment. The average auction payoff was €2.88 per subject (including subjects who did not win the auction game, about 50% of the sample).

We use data from five experimental treatments, whose parameters are presented in Table 2. We use the Target and Budget treatments presented in Coiffard et al. (2023), here denoted as TC1 and BC1, respectively. In addition, we consider three new treatments: BC2 (where the announced budget is increased), DC1 (with constraints from TC1 and BC1) and DC2 (with constraints from TC1 and BC2). The budget announced in BC1 (€72) is the average budget obtained in TC1, see Coiffard et al. (2023). To study the impact of the budget size, a larger budget is used in BC2 (€120), which corresponds to the theoretical budget obtained on average in a group of four bidders when they all bid, as in the equilibrium strategy in Hailu et al. (2005). Instructions for the DC1 treatment can be found in Appendix A.1. Some comprehension questions were also submitted to subjects before the experiment (see Appendix A.2).

[3]Participants are paid to complete surveys. See https://www.wirk.io/en/50k-freelancers-in-france/ (former web address: https://www.foulefactory.com/en/)

Table 2: Experimental treatments

Treatment	Number of subjects*	Nb auction group	Target constraint	Budget constraint
TC1	131	32	2 units	-
BC1	198	49	-	€72
BC2	128	32	-	€120
DC1	120	30	2 units	€72
DC2	128	32	2 units	€120

* Some subjects were removed randomly in TC1 and BC1 to create groups of four subjects.

4 Results

The results in this section are based on a single set of randomly selected independent groups for each treatment. However, we conducted additional simulations with alternative group sets in each treatment and found that all the results are robust.

4.1 Announcing both a target and a budget constraint

In the DC1 treatment, subjects face the target constraint $M = 2$ and the budget constraint $B = 72$. Results given in Table 3 show that the average unit cost UC is significantly lower in DC1 than in BC1 and TC1. Therefore, the Double Constraint auction is found to be more cost-effective than both Target and Budget constraint auctions. If the auctioneers' main objective is to maximize cost-effectiveness, using both equivalent constraints simultaneously in a Double Constraint auction appears to be a reasonable thing to do.

As expected, the average number of units purchased (outcome M) and the average budget spent (outcome B) are lower in DC1 than in TC1 and BC1 (see Section 3.4). Table 3 shows that these differences are significant. Consequently, if the auctioneer has a strong constraint, either meet the target or spend the entire budget, he should only announce this constraint.

Among all simulated auctions for the treatment DC1, we observe that the target constraint is reached first 51.65% of the time; in these cases, a part of the budget is not spent. Conversely, in 47.18% of the cases, the budget constraint is reached first, so the targeted number of units is not met. Finally, in 1.17% of the cases, both constraints are simultaneously exhausted. These proportions, close to 50/50, are not surprising, since both constraints are defined in Coiffard et al. (2023) to obtain a kind of equivalence between TC1 and BC1.

Table 3: Comparison of treatments with equivalent constraints

Outcome	**TC1** (1)	**DC1** (2)	***Diff.*** (2)-(1)	**BC1** (3)	**DC1** (4)	***Diff.*** (4)-(3)
M	2	1.78	-0.22***	2.14	1.78	-0.36***
	(.)	(0.05)		(0.10)	(0.05)	
B	72.32	58.01	-14.31***	71.91	58.01	-13.9***
	(6.56)	(3.33)		(0.04)	(3.33)	
UC	36.16	32.53	-3.63***	33.68	32.53	-1.15**
	(3.28)	(2.33)		(1.68)	(2.33)	

Standard deviations in parentheses.

Wilcoxon rank-sum tests.

* p<0.1, ** p<0.05, *** p<0.01

4.2 Announcing the same target but a larger budget constraint

In the DC1 treatment, the budget spent on average is only €58.01. In this section, we consider another Double Constraint treatment (DC2) with the same target constraint, but with a higher budget constraint, in order to have an ex-post average spent budget closer to €72. This new budget constraint $B = 120€$ is the average budget spent when all subjects adopt the theoretical equilibrium bidding function in TC1.[4] Indeed, we have no insights, other than the value predicted by the theory, to help us set a higher value for B in the DC2 treatment. Here we compare DC2 with TC1 and with a new budget treatment (BC2), where the constraint is set to $B = 120$ as in DC2.

Results presented in Table 4 shows that UC is significantly lower in DC2 than in BC2, but, it is significantly higher in DC2 than in TC1 at the ten percent significance level. To provide additional evidence on the latter result, we can rely on M to compare TC1 and DC2 as, by chance, the average budget spent in DC2 (€73.92) is not significantly different from the €72.32 spent on average in TC1 (*Wilcoxon rank-sum test*, p-value = 0.11). We find M to be significantly lower in DC2 than in TC1, but the difference is very small, only 0.04 units.

Thus, if the auctioneer's budget constraint is relatively high (€120), our results suggest that it is on average more cost-efficient to announce both the target and the budget constraints (DC2) instead of only announcing a budget constraint (BC2). However, compared with announcing both constraints (DC2), it is on average more

[4]This can be done, as the closed formula for the optimal bid is known in the Target auction (Hailu et al., 2005; Liu, 2021).

Table 4: Comparison of treatments with a higher budget

Outcome	TC1 (1)	DC2 (2)	***Diff.*** (2)-(1)	BC2 (3)	DC2 (4)	***Diff.*** (4)-(3)
M	2	1.96	-0.04***	2.74	1.96	-0.78***
	(.)	(0.01)		(0.13)	(0.01)	
B	72.32	73.92	1.60	119.08	73.92	-45.16***
	(6.56)	(6.22)		(0.47)	(6.22)	
UC	36.16	37.64	1.48*	43.52	37.64	-5.88***
	(3.28)	(3.38)		(2.33)	(3.38)	

Standard deviations in parentheses.

Wilcoxon rank-sum tests

* p<0.1, ** p<0.05, *** p<0.01

interesting to only announce the target constraint (TC1).

Out of all simulated auctions for the DC2 treatment, it is very often the target constraint that is reached first (85.53% of auctions), whereas it is the budget in only 13.70% of cases, and both constraints are met simultaneously in 0.77% of the cases. Therefore, it is worth considering that the Double Constraint auction eliminates the risk of overspending for the buyer, compared to the Target auction TC1.[5]

4.3 Increasing the budget constraint

This section analyzes how cost-effectiveness is affected, within the same auction format, by an increase of the announced budget constraint from €72 (BC1 and DC1) to €120 (BC2 and DC2).

The results presented in Table 5 indicate a significant increase in UC (i.e, a decrease in cost-effectiveness) when the size of the announced budget is increased for both auction formats (Budget and Double Constraint). Although increasing the budget allows for the purchase of more units on average ($M^{BC1} < M^{BC2}$ and $M^{DC1} < M^{DC2}$), the increase in M does not compensate for the higher budget spent.

[5]The budget spent is over €120 in 12.57% of all simulated auctions in TC1.

Table 5: Comparison of treatments when the budget increases

Outcome	**BC1** (1)	**BC2** (2)	***Diff.*** (2)-(1)	**DC1** (3)	**DC2** (4)	***Diff.*** (4)-(3)
M	2.14	2.74	0.60***	1.78	1.96	0.18***
	(0.10)	(0.13)		(0.05)	(0.01)	
B	71.91	119.08	47.17***	58.00	73.92	15.92***
	(0.04)	(0.47)		(3.33)	(6.22)	
UC	33.76	43.52	9.84***	32.53	37.64	5.11***
	(1.68)	(2.33)		(2.33)	(3.38)	

Standard deviations in parentheses.

Wilcoxon rank-sum tests

* p<0.1, ** p<0.05, *** p<0.01

5 Discussion and conclusion

We propose an auction format that combines a budget constraint and a target constraint, i.e., a Double Constraint auction. To study the impact of announcing both the target and the maximum available budget in conservation auctions, we conducted an online decontextualized experiment with 705 subjects. Thanks to the strategy method and auction outcome simulations, we compared the performance of the different auction formats at the treatment level according to a criterion that combines both average auction outcomes: the average number of units purchased and the average budget spent. More precisely, we assume that the objective of the auctioneer is to minimize a synthetic criterion defined at the treatment level as the average unit cost of conservation contracts, i.e., the ratio of the average budget spent over the average number of purchased units.

Our results show that with equivalent target and budget constraints (each constraint has about a 50% chance of being the binding constraint), the Double Constraint auction (DC1) outperforms the Target auction (TC1) in terms of cost-effectiveness. However, a Double Constraint auction may not be advisable if the budget constraint is relatively large, and may not be saturated in most cases. Indeed, with the same target but an increased budget, the cost-effectiveness becomes lower in DC2 than in TC1. Therefore, our second main conclusion is that it is better to announce only the target when the budget available (to reach this target) is relatively high. This is in line with results from Boxall et al. (2017). Nevertheless, other experiments with more restrictive budget constraints need to be performed in order to reinforce these results.

The Double Constraint auction thus seems particularly beneficial when the funds dedicated to a conservation program are scarce and the auctioneer's objective is to get the highest environmental benefit for each euro spent. However, in practice, it is not always easy to determine ex-ante which constraint (target or budget) is the most binding.

Our last finding is that increasing the budget in Budget and Double Constraint auctions allows the auctioneer to purchase more units, on average, but at the cost of a (much) lower cost-effectiveness. This result is consistent with what Howard et al. (2023) found regarding the impact of a higher budget.

However, it is worth noting that, as in most auction experiments and models, we have considered a game in which the number of bidders is exogenous and common knowledge. The number of bidders is also the same in all our treatments, whereas in practice, it is endogenous and may depend on the auction format. On the one hand, a higher budget may increase participation by attracting more farmers. This could in turn increase the auction cost-effectiveness (Rolfe et al., 2022). On the other hand, presenting a target constraint as a collective environmental objective may encourage more farmers to participate in conservation auctions. Indeed, the procedure may appear more rewarding to farmers than competing to win the largest share of an announced budget. Considering that endogenous participation goes beyond the scope of this paper, it should be kept in mind when implementing conservation auctions, as should the question of the appropriate spatial scale of the conservation auction.

A Content of the experiment

A.1 Instructional video for DC1 treatment (Translated slides from French to English)

Welcome !

This **experiment** is being conducted by researchers as part of a public research project to study decision making.

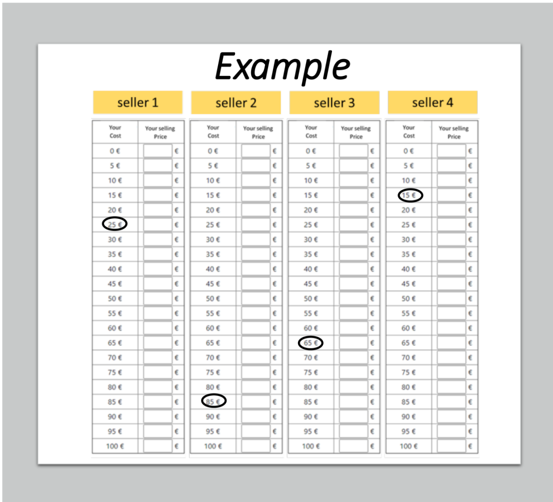
In this experiment you will have the **opportunity to earn money** in addition to the fixed participation payment.

The additional ***gain*** will depend on <u>your decisions,</u> as well as the <u>decisions of other participants</u> involved in this experiment.

We ask you to pay close attention to the instructions provided.
They should allow you to understand your role in the experiment.

Once all sellers have completed their table,

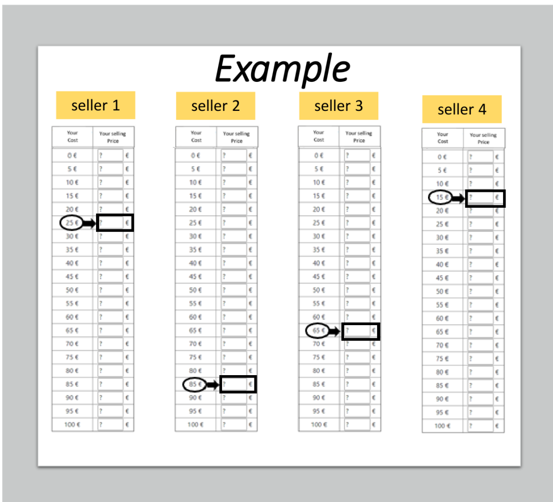
a production ***cost*** will be drawn randomly for each seller.



Once all sellers have completed their table,

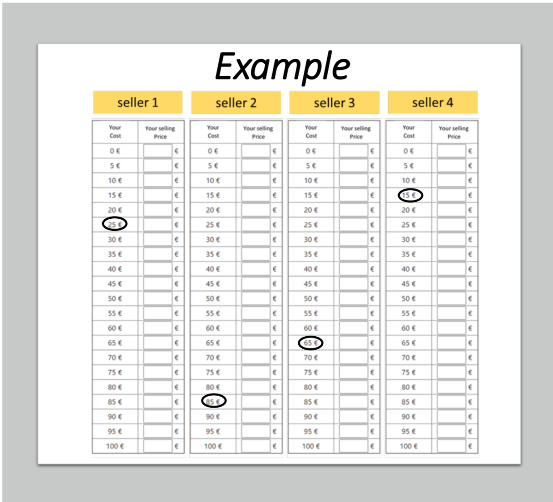
a production ***cost*** will be drawn randomly for each seller.

Then each seller's corresponding bid ***price*** for this ***cost*** will be looked up in their table.



Once all sellers have completed their table,

a production ***cost*** will be drawn randomly for each seller.



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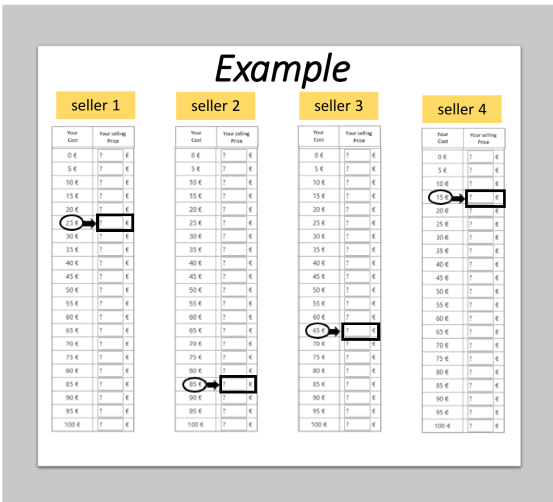

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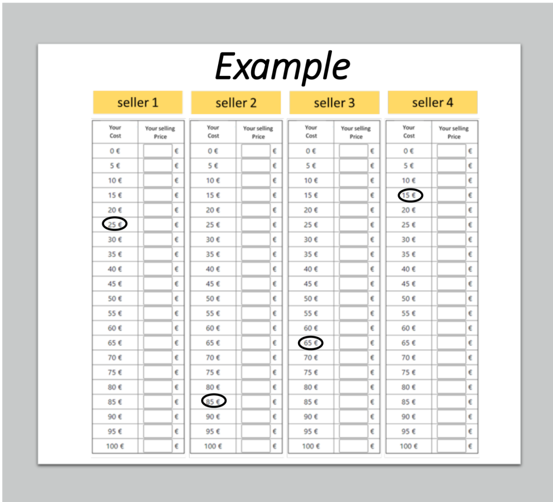

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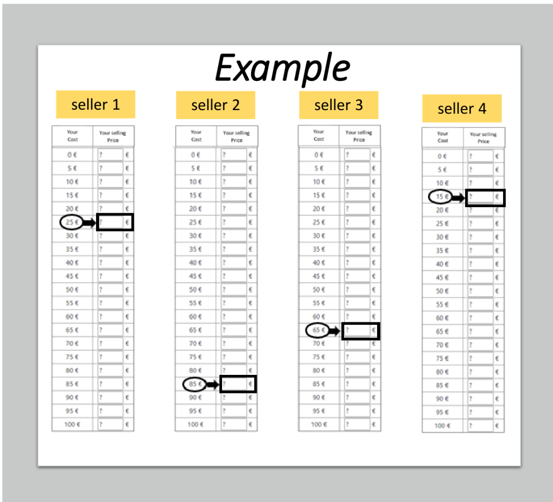
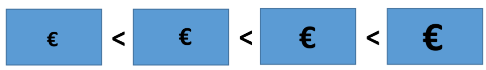


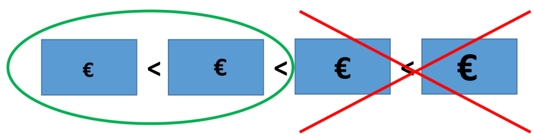
Game rules

The buyer will rank the 4 units offered in your group in ascending order of ***price*** (from lowest to highest).



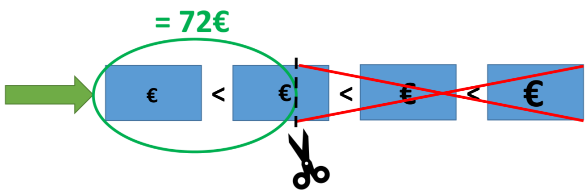
In each group, the buyer will purchase at most **2 units** with a maximum budget of **72€**.

<u>If the 72€ budget is sufficient</u> to purchase the 2 cheapest units, the buyer will purchase exactly **2 unit**.



The budget may not be spent entirely.

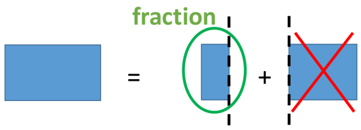
<u>If the 72€ budget is not sufficient</u> to purchase 2 units, the buyer will purchase units from the cheapest **until the 72€ budget is exhausted**.



*To spend **exactly 72€**, he can purchase only a fraction of the last unit selected.*

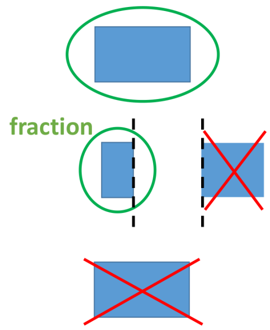
<u>In case of a tie</u>

between several sales ***prices*** in the same group, these units will be divided by the buyer.



In this case, he will buy the same fraction of a unit from each of the ties.

Calculating your earnings



- If your entire unit is purchased:

  gain = price - cost

- If a fraction of your unit is purchased:

  gain = ***fraction*** **×** ***(price - cost)***

- If your unit is not purchased:

  gain **= 0€**

You don't need to pay the cost of producing your unit if you can't sell it.

Remarks

- The ***cost*** that will be drawn at the end of the experiment to calculate your earnings does not depend on the ***cost*** of the other sellers.

- Each production ***cost*** in the table has the same chance of being drawn.

For each possible production ***cost,*** you should ask yourself :

*« For this production **cost**, what is my selling **price**? »*

At this point, you do not know the production costs or the prices that the other 3 sellers will offer.

Each ***price*** should be rounded to the nearest euro and be greater than or equal to the ***cost*** of production.

Your Cost	Your selling Price	
0 €		€
5 €		€
10 €		€
15 €		€
20 €		€
25 €	?	€
30 €		€
35 €		€
40 €		€
45 €		€
50 €		€
55 €		€
60 €		€
65 €		€
70 €		€
75 €		€
80 €		€
85 €		€
90 €		€
95 €		€
100 €		€

Only those who succeed in selling their unit (or fraction of a unit) will receive their ***earnings***.

Before filling in the table,

please answer 3 questions in order to better understand the experiment.

Your answers to these questions will have no impact on your earnings!

After completing the table, you will be asked to answer a short final questionnaire.

During the experiment you can review the instructions at any time by clicking on this button:

See the instructions

A.2 Comprehension questions in DC1 (Translated from French to English)

True/False about the experiment

1. The production cost drawn at random will necessarily be the same for all of the 4 sellers in your group.

   The answer is « **False** » because the production costs are randomly drawn independently for each seller. It is therefore highly unlikely that the 4 costs drawn within your group are identical.

2. When you must set a bid for each row in the table, you know the cost of producing your unit. However, you do not know the cost that will be used to calculate your profit.

   The answer is « **True** » because when you set a selling price this price is necessarily associated with a production cost. However, only one cost (one row in the table) will be **drawn** to calculate your earnings.

3. You are in competition with the other sellers in your group.

   The answer is « **True** » because if the other sellers in your group offer a lower price than yours, you will not be able to sell your unit and your gain will be 0€. Therefore, you have to make a trade-off according to your preferences between asking a higher price to potentially earn more or offering a lower price to increase your chances of winning (selling your unit).

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