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Abstract

Reverse auctions are used in various fields by public or corporate buyers to purchase goods and services from multiple sellers at the best price. Unlike in selling auctions, in reverse auctions a budget constraint rather than a target quantity is often announced by the auctioneer. However, in auction theory no optimal bidding strategy has yet been found in the case when a budget constraint is announced. Here we compare the two auction formats in an online experiment with 329 participants. We use the strategy method to obtain participants' bidding strategies from which we run exhaustive simulations of auction outcomes. This innovative methodology allows to overcome the issue of randomness of the auction outcome related to bidders' values. When each bidder has a single unit to sell, from the buyer's perspective, we find that, on average, the budget-constrained auction format outperforms the target-constrained auction format.

Keywords— Reverse auctions, Online experiments, Strategy Method, Budget constraint, Target constraint.

JEL Classification— C92 . D44

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1 Introduction

In market design, auctions are often promoted as an alternative to fixed payments to reduce the asymmetry of information between an auctioneer and the bidders. These mechanisms provide an incentive for bidders to bid closer to their reservation value, as they have to trade off between their margin and increasing their probability of winning the auction.

Contrary to standard selling auctions, in reverse or procurement auctions, the auctioneer is the buyer, and the bidders are the sellers. In a multi-unit reverse auction, the buyer can announce the target to the bidders, i.e., the quantity or number of units to be purchased. In such target-constrained auctions (hereafter Target), the buyer accepts the lowest bids until the target is reached. However, in reverse auctions it is quite common that the buyer announces a budget constraint, i.e., his maximum budget for the maximum quantity or number of units. This usually occurs in conservation auctions for example (see. Schilizzi and Latacz-Lohmann, 2013). In such budget-constrained auctions (hereafter Budget), the lowest bids are accepted until the budget is exhausted.

In this study, we compare the performance of these two reverse auction formats (Target and Budget) to determine which constraint would enable the auctioneer, on average, to purchase the maximum quantity for the minimum cost. Surprisingly, the question of how the announced constraint affects the efficiency of a reverse auction outcome remains understudied.

Indeed, auction theory has widely been built on the study of selling auctions. Consequently, in the literature, it is always the quantity or number of units that is announced on share auctions or multi-unit auctions (Milgrom, 2004; Klemperer, 2004; Krishna, 2009). Budget-constrained auctions have received very little attention in the auction literature, yet announcing a budget is relatively common in reverse auctions. In this paper, we attempt to shed some light on this question. We consider the simple case in which each bidder has only one unit to sell and thus competes on price only. All units are identical for the buyer, but the sellers each have independent and private costs to produce their unit. We consider a discriminatory multi-unit reverse auction, i.e., a sealed bid auction where winning bidders are paid their own bid. In a multi-unit target (selling) auction, an optimal bidding strategy exists that is based on maximizing the bidders' expected surplus (Harris and Raviv, 1981; Cox et al., 1984). Hailu et al. (2005) and Liu (2021) extend this result to the reverse auction case in which a target constraint is announced. However, to our knowledge, no optimal bidding strategy has yet been identified for an auction in which a budget has been announced. Therefore, we cannot determine theoretically which format is the most efficient in a reverse auction.

In addition, to make a relevant comparison, we need to define equivalent constraints. In the Target and Budget cases, respectively, the lower the number of units requested by the buyer or the lower the budget announced by the buyer, the greater the degree of competition. However, we can hardly predict a priori the level of each constraint that equalizes the level of competition between Target and Budget. To overcome this issue, we propose an original method using simulations based on experimental bidding strategies. Concretely, to ensure some kind of equivalence, we set the target constraint exogenously and then define the budget constraint endogenously according to the results obtained in the Target treatment (Schilizzi and Latacz-Lohmann, 2007). One of our contributions is the way we calculate the average outcome of the auctions in each treatment. We use the strategy method to obtain the bidding strategy for each subject. The strategy method is a well establish method in experimental economics (see Selten, 1967; Mitzkewitz and Nagel, 1993; Brandts and Charness, 2011) which has been used in few auction experiments (Rapoport and Fuller, 1995; Selten and Buchta, 1999; Güth et al., 2002, 2003; Kirchkamp et al., 2009; Katuščák et al., 2015; Mill and Morgan, 2022), but never in the case of reverse auctions. In experimental auctions, the strategy method consists in asking subjects for their entire bidding strategy (for all cost levels) in a single round. Then, we simulate from the subjects' bidding strategies what we call the "average budget", which is used to set the constraint in the Budget treatment. We also simulate the average number of units purchased in the Budget treatment. Finally, if the average number of units purchased in Budget is significantly higher than the number of units announced in Target, Budget has higher budgetary efficiency than Target and vice versa.

To the best of our knowledge, only Schilizzi and Latacz-Lohmann (2007) and Boxall et al. (2017) have compared Target and Budget. They use laboratory experiments in the context of conservation auctions in which student subjects play the role of farmers (bidders) whose opportunity costs are set randomly. Subjects take part in repeated auctions with three and 15 periods, respectively. Random costs are reshuffled each period in Schilizzi and Latacz-Lohmann (2007) and every five periods in Boxall et al. (2017). Both experiments are multi-unit auctions, but bidders have one unit to sell in Schilizzi and

Latacz-Lohmann (2007) and possibly several in Boxall et al. (2017). Both experiments find that the Target format outperforms the Budget format in the first round but that after several repetitions the auction performance evens out.

Our experiment differs from previous ones in three main ways. First, we propose a totally decontextualized experiment for better control and to allow the results to be extended to any reverse auction. Second, we use the strategy method to obtain subjects' complete bidding strategies from which we simulate exhaustively the possible auction outcomes. Third, we use the above-mentioned exhaustive simulations to compute equivalent target and budget constraints so as to compare both formats in a more rigorous way.

In Section 2, we present some theoretical background underlying our experiment, as well as the equilibrium bidding strategy in the Target format. Then, in Section 3, we introduce our experimental design, based on the strategy method, and its online implementation. Section 3 also details the way we simulate auction outcomes to set equivalent constraints and measure efficiency in Target and Budget. A description of subjects and control variables is conducted in Section 4, while the results are presented in Section 5. Finally, Section 6 gives some discussions and Section 7 concludes.

2 Theory of reverse auctions

In this section, we present a theoretical framework which is derived from auction theory (2.1), the two types of announced constraints (2.2) and the symmetric equilibrium bidding strategy in the Target case (2.3).

2.1 Auction game

We consider a multi-unit procurement or reverse auction with an auctioneer who is the buyer and with N risk-neutral symmetric bidders who are each sellers of a single unit. Thus, each bidder i proposes a single bid b_i which is the selling price for his unit. All the units are homogeneous and perfectly divisible for the auctioneer. Each bidder i produces his unit at a private cost c_i. It is common knowledge that costs are identically and independently drawn from the same distribution with a density function $f(.)$ and a cumulative function $F(.)$ on the interval $[\underline{c}, \overline{c}]$. Let $b_i(c)$ be the bidder i's bidding function (or bidding strategy), which is assumed to be increasing and differentiable. When a N-uple of costs, $(c_1, ..., c_N)$, are assigned to bidders, bids b_i are ranked by the auctioneer in ascending order of price with rank (r), $r = 1, ..., N$.

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

The lowest bids are selected until the announced constraint is reached (see Section 2.2). The auctioneer can split the last selected unit to meet his constraint or in case of ties.

We consider a discriminatory (or first price) reverse auction, thus the price paid to each winning bidder is defined by the bidder's own submitted bid.

2.2 Announced constraint

We distinguish two auction formats: the target-constrained auction (Target) and the budget-constrained auction (Budget). These formats do not impact the payment rule but define differently the limit of the selection rule in a reverse multi-unit auction.

In Target, before the bidders submit their bid, the auctioneer announces the quantity he will buy. Let M^T (with $0 < M^T < N$) be the targeted number of units. Then, to minimize his expenses, the auctioneer selects the lowest bids until the desired quantity is reached. Thus, he buys the M^T least expensive units. Formally, M^T may be any real positive number, not only an integer.

In Budget, the auctioneer announces B, the maximum amount of money he will spend to buy the highest possible quantity. Thus, units are purchased in ascending order of price until the available budget is reached or all the N available units for sale are purchased. In the budget format, it is likely that the announced budget will not fit exactly with the purchase of an integer number of units. This is not a problem, since we consider units to be perfectly divisible. In addition, note that the budget constraint may not be reached, and a balance may remain when the sum of all the bids is lower than the budget announced, i.e., $B > \sum_{i=1}^{N} b_i$.

Announcing one or the other constraint leads to two different auction formats for the bidders which are also based on two different objectives for the auctioneer. In Target his aim is to minimize his expenditure while buying exactly the right number of units (the target). In Budget, his goal is to buy as many units as possible without exceeding his budget.

The choice of the constraint type may be driven by a real constraint or a preferred objective. Of course, in the end, the trade-off between price and quantity can only be solved by setting the buyer's demand function. Nevertheless, to keep the comparison exercise as general as possible, we do not impose a given demand function. Rather, we assume that the buyer does not have any strict constraints: his available budget is unlimited and his marginal utility for each unit until the N^{th} is strictly positive. Thus, we assume that the buyer's objective is to purchase the maximum quantity for the minimum budget.

2.3 Equilibrium bidding function

In Target, when M^T is a positive integer, bidders seek to maximize their expected gain, expressed as:

$$E(b_i, c_i) = (b_i - c_i).Prob(b_i < b_{(M^T+1)}), \tag{1}$$

with $b_{(M^T+1)}$ the first rejected bid (Müller and Weikard, 2002).

Considering the symmetric equilibrium of the auction game introduced in Section 2.1, Hailu et al. (2005) and Liu (2021) demonstrate that the unique optimal bidding function $b^*(c)$ in Target is:

$$b^*(c) = \frac{\int_c^{\overline{c}} uF(u)^{M^T-1}(1-F(u))^{N-M^T-1}f(u)du}{\int_c^{\overline{c}} F(u)^{M^T-1}(1-F(u))^{N-M^T-1}f(u)du}. \tag{2}$$

In Budget, the quantity purchased is unknown to bidders, because it depends on other bids. Therefore, there is no simple equilibrium bidding function (Müller and Weikard, 2002), as strategic interactions can hardly be modelled[1].

Without any theoretical result, we compare the two auction formats in a decontextualized online lab experiment where subjects play the auction game described in Section 2.1.

3 Online experiment and auction outcome simulations

In the current section we describe the strategy method and the reasons we have adopted it in our online lab experiment (3.1). Next, we present our experimental design (3.2) and explain how we compute experimental outcomes based on participants' complete bidding strategies (3.3). Finally, we show how the online experiment has been implemented (3.4).

[1]Note that Latacz-Lohmann and Van der Hamsvoort (1997) study budget-constrained auctions in a decision theory framework which does not take into account bidders' interactions.

3.1 Strategy method

In induced value auction experiments, costs are usually assumed to be uniformly distributed across a given interval $[\underline{c}, \overline{c}]$. In practice, only a discrete sample of costs is necessarily considered. Let J be the number of possible values within this interval. In most experiments, one cost per bidder is drawn in order to perform the auction, and several periods are conducted with different sets of costs to generate more data. In these repeated auctions, results may depend on cost draws even if the same set of costs is kept across treatments. A learning process can also occur over periods that may bias the results, even if no feedback is given to the bidders after each period (e.g., Güth et al., 2003; Lusk and Shogren, 2007). Finally, there may be a wealth effect when several auctions are played and paid for successively.

To overcome these issues, we use the strategy method (or cold strategy) to get the entire bidding strategy of every subject in a single round. In practice, subjects have to fill in a decision table containing the J possible cost values with J corresponding bids. Using the strategy method enables us to easily run an online experiment, since the subjects do not need to be connected at the same time. In each treatment, groups of N bidders are randomly formed ex post, and the N-uple of cost k used to define subjects' earnings among the $K = J^N$ possible cost arrangements is also randomly drawn ex post.

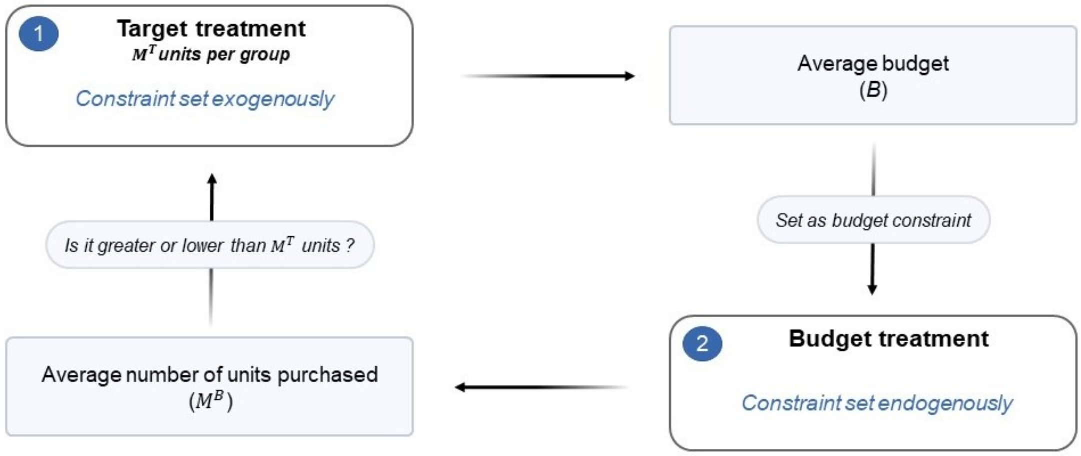
3.2 Experimental design

We choose a between-subjects design where subjects are randomly assigned to a single treatment to prevent any order effect. Indeed, in a pilot lab experiment with a within-subject design, a significant order effect has been found.

Comparing the two auction treatments requires setting equivalent constraints. As stated in the introduction and illustrated in Figure 1, we first run the Target treatment with an exogenous constraint set to M^T units. In the following section, we will detail how we compute the average budget (B) from the bidding functions obtained in Target to buy M^T units. This average budget B is then used as the endogenous constraint in the Budget treatment. Next, we compute the average number of units purchased M^B from the bidding functions obtained in Budget. Finally, if M^B is higher than M^T then Budget outperforms Target and vice-versa.

In the following section (3.3), we explain how we compute exact group-level values of

Figure 1: Overview of the experimental design



outcomes (budget spent or quantity purchased) that sum up all possible cost arrangements k. We aim to obtain one representative group-level value of outcomes over the K possible cost arrangements to eliminate the uncertainty associated with random cost draws. Each treatment is conducted on several groups of N bidders, so to get independent data, groups need to be independent. Therefore, to compute the average auction outcome at the treatment level, each subject is randomly assigned to a single group of N bidders. There are G^T and G^B independent groups, respectively, in Target and Budget.

3.3 Simulation of auction outcomes

The advantage of having the bidding strategies of all subjects is to be able to simulate the auction outcome for any group g of N subjects and for any cost arrangement k. These simulations generate a very rich data set which allows us to eliminate the randomness related to the drawing of costs. Indeed, simulations can be run on all the $K = J^N$ possible cost arrangements.

We define an auction as a group g of N bidders associated to a given N-uple of costs k (corresponding to the k^{th} N-uple of costs). As explained in 2.1, in each group g, bids b_{igk} are ranked by the buyer in ascending order of price: $b_{(1)gk} \leq b_{(2)gk} \leq ... \leq b_{(N)gk}$.

Calculation of the average budget B spent in Target to set equivalent constraints: Here we detail how we compute from subjects' bidding strategies the average budget spent in the Target treatment, which is used as the endogenous constraint in the Budget treatment.

In Target, only the M^T cheapest units are selected. Therefore, the budget spent in that auction is $B_{gk} = \sum_{r=1}^{M^T} b_{(r)gk}$. The exact mean of the budget spent B_g is computed within each group g ($g = 1, ..., G^T$) on all the possible cost arrangements k ($k = 1, ..., K$) such as:

$$B_g = \frac{\sum_{k=1}^{K} B_{gk}}{K} \tag{3}$$

Thus, the average budget B is the combined mean of the G^T exact mean budgets B_g

$$B = \frac{\sum_{g=1}^{G^T} B_g}{G^T}. \tag{4}$$

Calculation of the average number of units auctioned in Budget to compare auction performance: Cost-effectiveness is measured by comparing the average number of units auctioned in Budget (M^B) with the number of units announced in Target (M^T) for an equivalent average budget B (see Figure 1). As for the average budget, the number of units auctioned M_{gk}^B is first defined at the auction level.

Define t as a positive integer such as $0 < t < N$, then

$$M_{gk}^B = \begin{cases} t + \frac{B - \sum_{r=1}^{t} b_{(r)}}{b_{(t+1)}} & \text{if } \sum_{r=1}^{t} b_{(r)} \leq B < \sum_{r=1}^{t+1} b_{(r)} \\ N & \text{if } B \geq \sum_{r=1}^{N} b_{(r)} \end{cases} \tag{5}$$

Note: there may be a non-null residual budget E_{gk} if the budget B is great enough to purchase all the units.

$$E_{gk} = \begin{cases} 0 & \text{if } B \leq \sum_{r=1}^{N} b_{(r)} \\ B - \sum_{r=1}^{N} b_{(r)} & \text{if } B > \sum_{r=1}^{N} b_{(r)} \end{cases} \tag{6}$$

Second, exact mean values are computed at the group level g across all cost arrangements k.

$$M_g^B = \frac{\sum_{k=1}^{K} M_{gk}^B}{K} \tag{7}$$

These are finally summed up in a single treatment-level value M^B. Thus, the average number of units purchased in Budget is given by:

$$M^B = \frac{\sum_{g=1}^{G^B} M_g^B}{G^B} \tag{8}$$

M^B is compared to M^T, the exogenous number of units purchased in Target. The average residual budget in Budget is also computed as:

$$E = \frac{\sum_{g=1}^{G^B} \frac{\sum_{k=1}^{K} E_{gk}}{K}}{G^B} \tag{9}$$

but, after the game has been played, it is assumed to be lost for both the auctioneer and the bidders.

Calculation of the average allocative efficiency in both formats: In addition to the number of units purchased from equivalent budget and target constraints, we check the allocative efficiency of each auction. Allocative efficiency is at the maximum level when all purchased units are from the bidders with the lowest costs. Let $c_{(i)}$ be the cost corresponding to the i^{th}unit in ascending order of cost.

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

In each auction, bids are ranked in order of increasing price and not according to production cost. Therefore, the winning bids do not necessarily correspond to the lowest costs. To measure the allocative efficiency of a given auction, we use as indicator a dummy variable which is equal to one if the purchased units are those with the lowest costs, and equal to zero otherwise.

In Target, the allocative efficiency of auction k of group g is:

$$AE_{gk}^{T} = \begin{cases} 1 & \text{if} \quad \sum_{i=1}^{M^T} c_i = \sum_{i=1}^{M^T} c_{(i)} \\ 0 & else \end{cases} \tag{10}$$

In Budget, the allocative efficiency of auction k of group g is:

$$AE_{gk}^{B} = \begin{cases} 1 & \text{if} \quad \sum_{i=1}^{\lfloor M_{gk}^B \rfloor} c_i + \{M_{gk}^B\} \, c_{\lceil M_{gk}^B \rceil} = \sum_{i=1}^{\lfloor M_{gk}^B \rfloor} c_{(i)} + \{M_{gk}^B\} \, c_{(\lceil M_{gk}^B \rceil)} \\ 0 & else \end{cases} \tag{11}$$

with $\{M_{gk}^B\} = M_{gk}^B - \lfloor M_{gk}^B \rfloor$ the fractional part of M_{gk}^B, $\lfloor M_{gk}^B \rfloor$ its integer part, and $\lceil M_{gk}^B \rceil = \lfloor M_{gk}^B \rfloor + 1$.

The average allocative efficiency in Target is thus expressed as:

$$AE^T = \frac{\sum_{g=1}^{G^T} \frac{\sum_{k=1}^{K} AE_{gk}^T}{K}}{G^T} \tag{12}$$

and in Budget as:

$$AE^B = \frac{\sum_{g=1}^{G^B} \frac{\sum_{k=1}^{K} AE_{gk}^B}{K}}{G^B} \tag{13}$$

The closer these indicators are to one, the greater the allocative efficiency.

3.4 Online implementation of the experiment

The experiment was programmed with o-Tree software (Chen et al., 2016) and implemented online with an instructional video.

In the instructional video, subjects are told they are participating in an experiment in which they are anonymous sellers and that they can earn money depending on their decisions and those of other participants. Indeed, they are randomly assigned to groups of four participants without being able to identify the three other members of their group. The relatively small number of bidders ($N = 4$) was chosen to increase the number of independent observations, i.e., the number of groups. Subjects are given the possibility to sell a unit of a good to a single buyer (the experimenter). To participate in the experimental game, subjects must complete a decision table (Fig. 2) containing 21 possible production costs for their unit. The distribution of private costs c_i is uniform between €0 and €100 and includes $J = 21$ possible cost values corresponding to multiples of €5. We define the exogenous Target $M^T = N/2 = 2$[2]. For each cost, subjects must choose a selling price above or equal to the corresponding cost and rounded up to the nearest euro.

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 2: Decision table

[2] We consider $N/2$ as an average level of competition between bidders.

We explain to the subjects that at the end of the experiment, in order to determine earnings, a production cost will be drawn randomly for each participant. Then, for each subject, the bid associated to his/her randomly drawn cost will be collected from his/her decision table. Finally, in each group of four participants, the cheapest units will be bought until the announced constraint is exhausted (according to the auction treatment).

Subjects' gains are defined as follows. If they do not succeed in selling their unit, they gain nothing. If they do succeed in selling their unit, they receive a payment equal to the difference between their selling price and their production cost. Full instructions for the Target treatment[3] are available in the Appendix A.1.

In such an online environment, subjects cannot ask questions; therefore, they must have a perfect understanding of the instructions. To this end, after the video they are required to answer a comprehension questionnaire consisting of True/False questions (see Appendix A.2). After responding to each question, the correct answer appears on the participant's screen. At any time during the experiment, subjects can access a text version of the instructions.

After completing the decision table, subjects answer a short questionnaire (see Appendix A.3). First, we elicit risk aversion with a self-assessment question, as in Dohmen et al. (2011). As this behavioral characteristic may have an impact on the way subjects bid, it is necessary to ensure that our two treatment groups are balanced with regard to this variable. Second, we assess the difficulty respondents had in proposing selling prices. We speculate that it is more difficult for subjects to bid in Budget than in Target. Finally, we ask a few socio-demographic questions.

4 Data

Our experiment was conducted online in June 2021 and involved 329 subjects from the general French population who were registered on the FouleFactory platform[4]. Participants received a standard fee for a 15-minute survey (€2) and a potential extra gain from auction earnings (€2.56 per subject, on average). Participants knew that they would be assigned ex post to a randomly constituted group of four bidders.

50.8% of the subjects were women and the average age was 41 (Std.Dev. = 13). Some

[3]Instructions for the Budget treatment are available on request.

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

socio-demographic categorical variables are shown in Table 1, in which we see that 48.9% of our subjects had at least a bachelor's degree and (at least) 43.2% earned €1900 or more per month. On the three comprehension questions, 47.4% of the respondents made no mistakes, 42.9% made only one mistake, 9.7% made two mistakes and none made three.

We had 131 participants in Target and 198 in Budget, which allowed us to constitute $G^T = 32$ and $G^B = 49$ groups of four bidders. Three subjects in Target and two subjects in Budget were removed randomly so that the number of subjects was a multiple of four. Although subjects were randomly assigned to the two treatments, we observed (see Appendix B.1) that our treatment samples were not balanced on the *Income* and *Profession* variables. However, robustness checks presented in the Appendix B.2 show that this does not impact the validity of our results.

Table 1: Sample description (n=329)

Variables	**Categories**	**Count**	**% subjects**
Studies Level	No high school diploma	24	7.3
	High school diploma	62	18.9
	Associate's degree	82	24.9
	Bachelor's degree	53	16.1
	Graduate studies	108	32.8
Income	Less than €1100	83	25.2
	Between €1100 and €1899	85	25.8
	Between €1900 and €2299	47	14.3
	Between €2300 and €3099	56	17.0
	Between €3100 and €3999	26	7.9
	Between €4000 and €6499	11	3.4
	More than €6500	2	0.6
	Do not wish to answer	19	5.8
Profession	Farmers	2	0.6
	Craftsmen, retailers, entrepreneurs	21	6.4
	Executives and higher intellectual professions	70	21.3
	Employees	129	39.2
	Students	31	9.4
	Retired	25	7.6
	Unemployed	51	15.5

5 Results

Our main results on the performance comparison between Target and Budget treatments is presented in 5.1. We then analyze the variability of outcomes in each auction format across cost draws (5.2), which is possible because our simulations are exhaustive on the cost arrangements within the groups. Finally, we explain our results by emphasizing both the role of subjects' bidding behavior and the role of the auction formats themselves (5.3).

5.1 Main results

The Target treatment results in an average budget B of €72.32 (see Table 2)[5], which is the amount the auctioneer needs, on average, to purchase $M^T = 2$ units, given the bidding strategies of 128 subjects assigned to $G^T = 32$ groups. This amount was rounded down to €72 to be used as the budget constraint in the Budget treatment[6].

Table 2: Average budget and average nb. of units purchased

Treatment	Nb. subjects*	Nb. groups	Nb. units purchased	Empirical budget (€)
Target	128	32	2 (.)	72.32 (6.56)
Budget	196	49	2.135 (0.099)	72 (.)

Standard deviations in parenthesis.
*Three subjects in Target and two in Budget were removed randomly to get multiples of four in both treatments. Results are robust across various group configurations.

As reported in Table 2, the Budget treatment results in an average purchase of $M^B = 2.135$ units. Note that the Budget treatment also benefits from a positive average balance of $E = €0.09$. We consider this excess budget to be lost. Overall, the Budget format allows subjects to purchase significantly more units (7% more) on average than the Target format with the same average budget (Wilcoxon signed-rank test, $p<0.001$)[7] Here, rounding the budget constraint to the nearest lower integer and having a non-null residual budget are

[5]To ensure no bias is introduced due to group composition, exhaustive simulations on both cost arrangements and group constitutions were also performed. This even more general mean is: €72.19.

[6]We acknowledge that in rounding down the average budget constraint to €72, we potentially underestimate the average number of units purchased in the Budget treatment. However, we were more concerned that giving an overly precise budget (e.g., to the cent) might have seemed strange to the subjects.

[7]We use a non-parametric test, since the number of units purchased is not normally distributed (*Shapiro-Wilk normality test*).

conservative assumptions that support our conclusion that the Budget format outperforms the Target format.

With regard to allocative efficiency, we find a very small difference between the two treatments (0.013 see. Table 3). Not only is this difference not significant (*Wilcoxon rank-sum test with continuity correction*, p-value=0.59), it is so small that it could be ignored. These results show that the allocation efficiency is relatively high in both auction formats, since the purchased units are from the bidders with the lowest costs in about 85% of the auctions.

Table 3: Average allocative efficiency

Treatment	**Nb. subjects***	**Nb. groups**	**Allocative efficiency**
Target	128	32	0.851 (0.115)
Budget	196	49	0.838 (0.161)

Standard deviations in parenthesis.
*Three subjects in Target and two in Budget were removed randomly to get multiples of four in both treatments.

Finally, contrary to our speculation, it was not more difficult for our respondents to bid in Budget than in Target. According to the self-assessment variable *Ease to bid*, with values comprised between zero (absolutely no difficulty to bid) and 10 (very difficult to bid), the average values per treatment (6.81 for Target and 6.54 for Budget) are not significantly different (*Pearson's chi-square test*, p-Value = 0.25)).

5.2 Variability of auction outcomes across cost draws

Results presented in the previous section, and their variance, are computed from the exact mean of each group over the K possible cost arrangements. These exact group means are computed with simulations based on the subjects' complete bidding strategies (see Section 3.3) in order to eliminate any bias related to the randomness of cost draws. Figures 3 and 4 illustrate the variability of outcomes within each group by providing (independent) exact group means (B_g and M_g^B, respectively), with intervals corresponding to their standard deviations. The average group-level standard deviation is €38.95 in Target (which represents 53.86% of the average budget computed at the treatment level) and 0.632 units in Budget (29.59% of the average number of units purchased). Therefore, from the auctioneer's point of view, we observe, on average, a lower uncertainty due to the randomness of costs in Budget than in Target. This result could be another advantage of announcing to bidders a budget rather than a target.

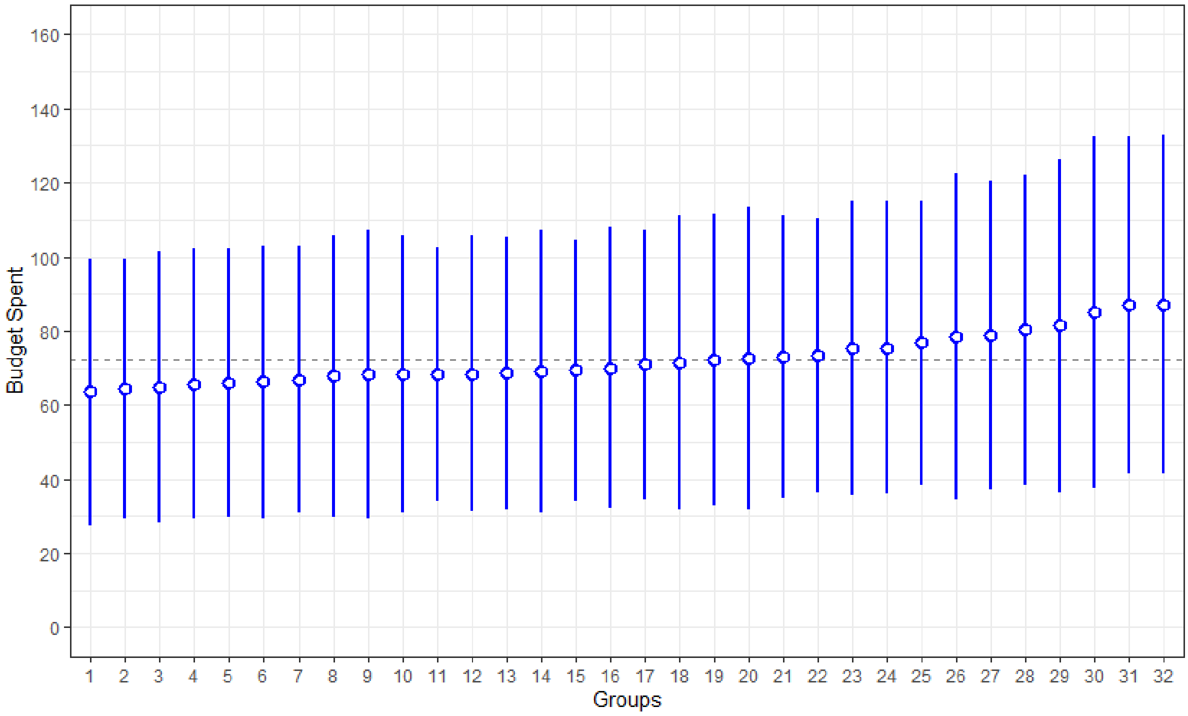


Figure 3: Exact means and standard deviations of the budget spent per group in Target (B_g)

We see from Figure 3 that the group exact means of budget spent in Target vary according to group by a relatively small amount: around €72 (the average budget denoted by the horizontal dashed line). Indeed, the standard deviation of group exact means is only €6.56 (see Table 2). We also observe a low variability in the exact mean of the groups in Budget (Fig. 4). Here the standard deviation is only 0.099 units. Furthermore, the exact mean of units purchased by group is less than two units (the exogenous target constraint denoted by the horizontal dashed line) in only four groups out of 49, which is consistent with the results presented in Table 2. In this paper, however, independent observations are computed on the basis of exhaustive simulations. This ensures that the comparison of the performance of the two treatments is not related to random cost draws.

5.3 Why does Budget outperform Target ?

Budget can outperform Target because the auction constraint format is different but also because bidders bid differently in each treatment. Indeed, an explanation for the higher

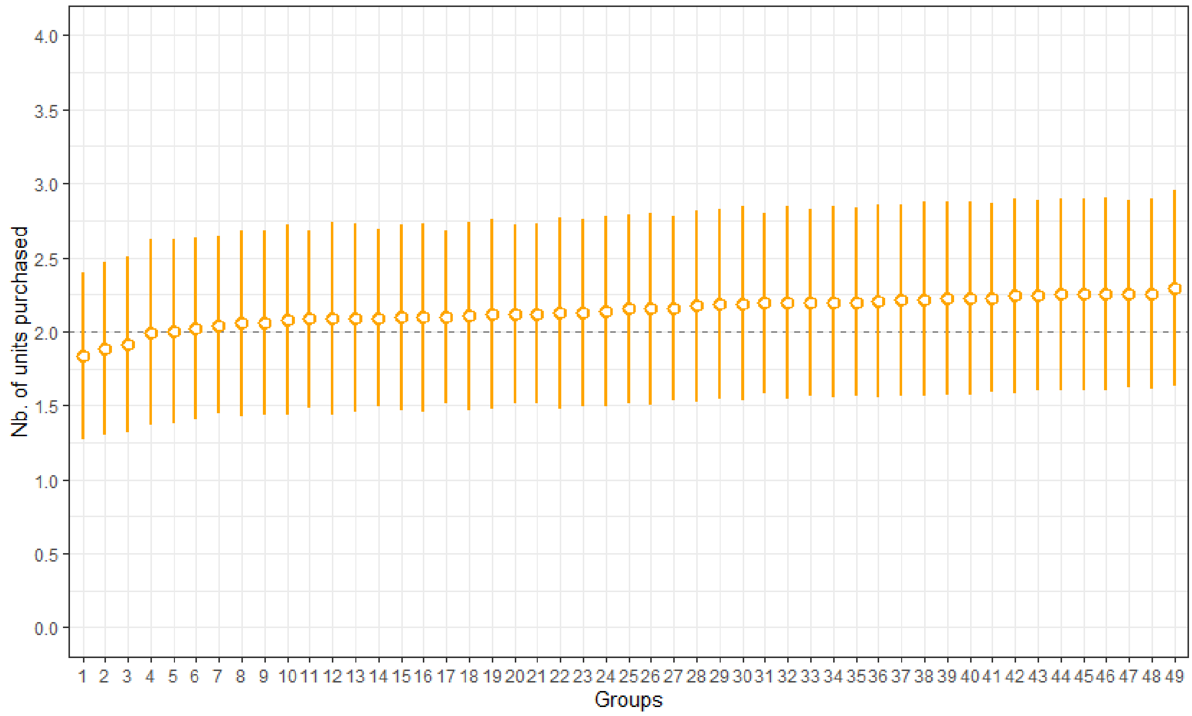


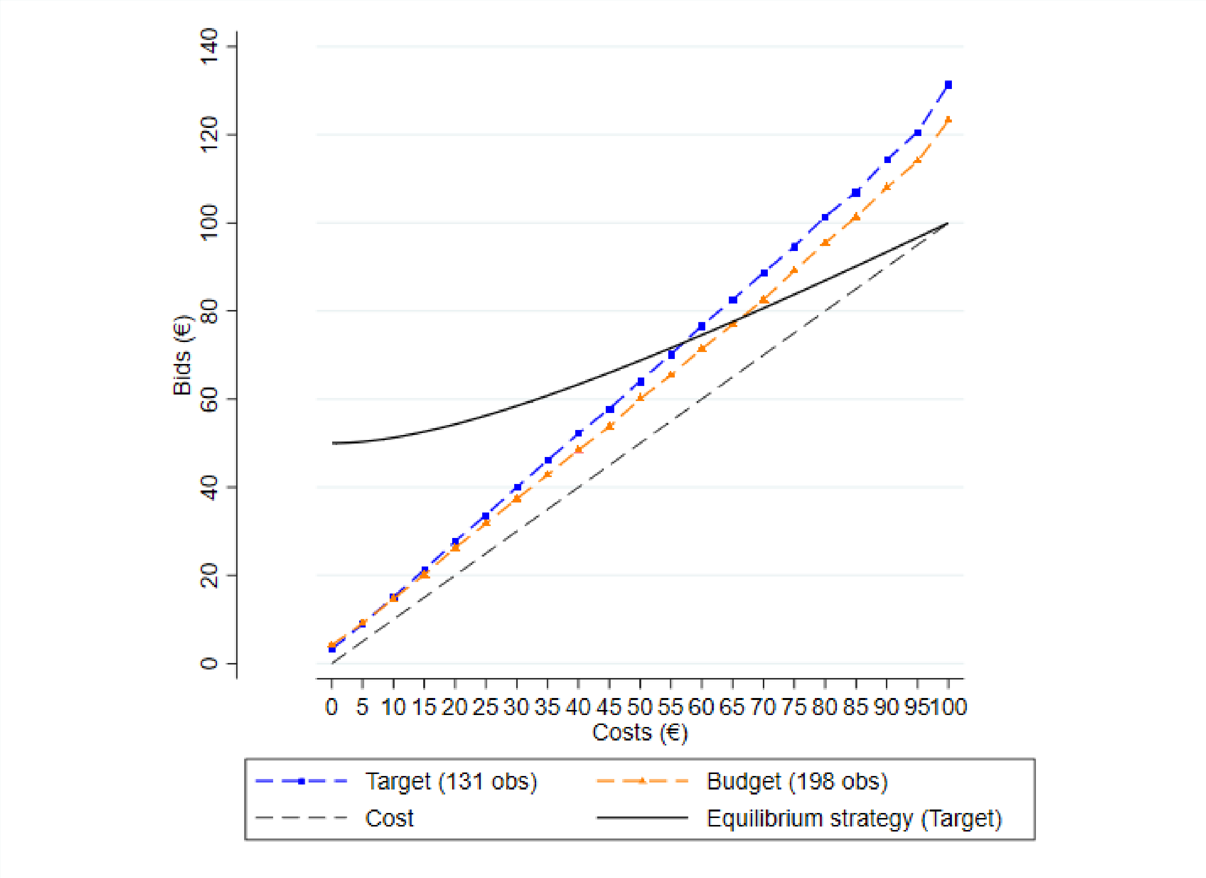
Figure 4: Exact means and standard deviations of the number of units purchased per group in Budget (M_g^B)

budgetary efficiency in Budget is that the offers made by the subjects tend to be lower in Budget than in Target. Figure 5 shows the average bids of the auction strategies, by cost level[8].

At this stage, bidding strategies appear similar in the two treatments (with slightly lower price offers in Budget, which could explain its superiority). Note that experimental bids are very different from the optimal bidding strategy in Target, which is consistent with results found by Liu (2021). To break down the total treatment effect, we consider the average outcome of a fictive treatment, which consists in simulating a Budget constrained auction using subjects' bids from the Target treatment. As illustrated in Figure 6, the comparison of this fictive treatment with the Target treatment allows us to isolate the effect of the constraint format (format effect = 2.086-2 = 0.086 units) since we keep the same bidding strategies (Target bids). We find this effect to be significant only at the 10 percent level (*Wilcoxon signed-rank test*, $p = 0.054$). The comparison of the fictive treatment with the Budget treatment allows us to isolate the effect of the subjects' bidding strategies (bid effect = 2.135-2.086=0.049 units) since we keep the same auction

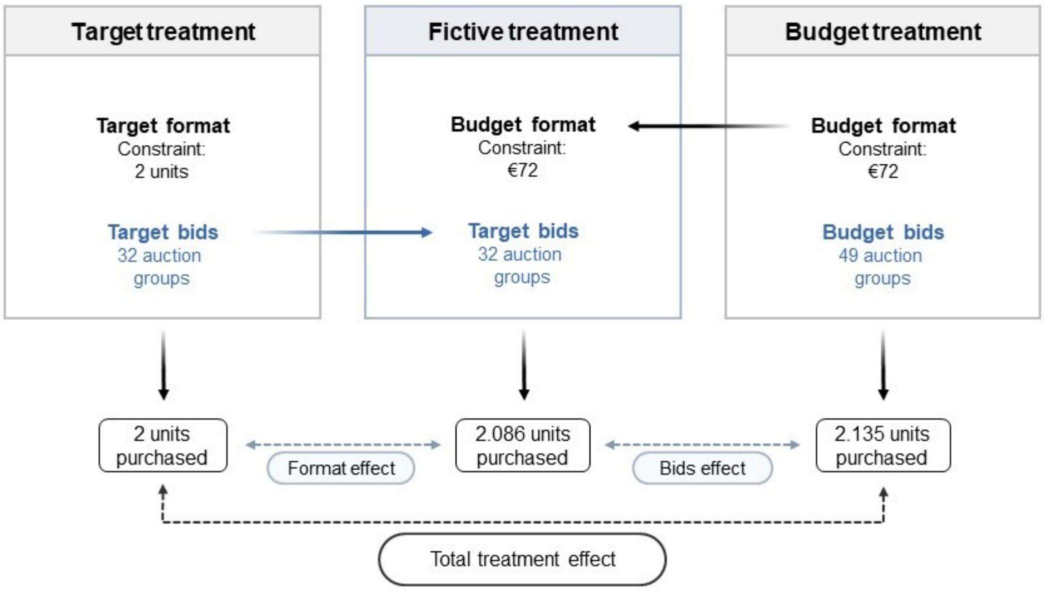
[8] Among the 329 bid functions obtained in the experiment, 22 are not monotonic: 14 in Budget and 8 in Target.

Figure 5: Average bids in Target and Budget



constraint format (Budget contraint of €72). This effect is significant at the 5 percent level (*Wilcoxon rank-sum test*, $p = 0.034$). All these comparisons of units purchased are made with a constant average budget (€72). The total treatment effect is the sum of the two effects ($0.086 + 0.049 = 0.135$ units).

Figure 6: Breakdown of the treatment effect



6 Discussion

We found that the Budget format provides higher budgetary efficiency than Target. This contrasts with results found by Schilizzi and Latacz-Lohmann (2007) and Boxall et al. (2017) in the context of conservation auctions. These experimental studies suggest that Target presents greater cost-effectiveness than Budget in the first auction period but that the performance of Target erodes faster with repetitions. Both papers attribute this relative decrease in Target performance to faster learning by participants of the cut-off price in Target, which we cannot test with our current experimental protocol.

Our online experimental results rely on the use of an innovative methodological framework based on the strategy method which is a "cold" procedure where subjects must bid for several possible costs at the same time (see. Brandts and Charness, 2011). This is a key difference from Schilizzi and Latacz-Lohmann (2007) and Boxall et al. (2017), who used "hot" or direct-response procedures where one individual cost is drawn per period and subjects must bid directly according to the cost drawn. The strategy method has already been used in some previous studies in the context of selling auctions, but only to analyze individual bidding strategies (Rapoport and Fuller, 1995; Selten and Buchta, 1999; Güth et al., 2002, 2003; Kirchkamp et al., 2009; Katuščák et al., 2015; Mill and Morgan, 2022) and not to exhaustively simulate the exact mean of auction outcomes. An extensive literature compares direct-response and strategy methods in various behavioral games (e.g. Fischbacher et al., 2012; Columbus and Böhm, 2021). In some cases, a difference was found between the two methods (e.g. Casari and Cason, 2009), which may be explained by a hypothetical bias related to the strategy method. However, most of the time no or mixed evidence has been found (Brandts and Charness, 2011; Fischbacher et al., 2012; Columbus and Böhm, 2021), in particular in auction experiments (Rapoport and Fuller, 1995; Armantier and Treich, 2009). Moreover, these differences may be explained by learning or wealth effects, which are not present with the strategy method.

We have combined the strategy method with ex post numerical simulations to generate a large number of auctions. With the parameter values in our experiment, it is even possible to simulate exhaustively all possible auction outcomes. A benefit of the strategy method is that our experiment could be conducted online with a large number of subjects without requiring them to be connected at the same time. In addition, we used as independent observations the exact mean of each group computed over all possible induced cost arrangements. This ensures that the comparison of the two treatments is not biased by the randomness of cost draws. Indeed, outcomes may vary considerably according to the cost arrangement considered in each group (see Section 5.2).

7 Conclusion

To summarize, the aim of this paper was to compare the relative performance of target-constrained and budget-constrained reverse auctions (in this paper Target and Budget, respectively). To do so, equivalent constraints were set up by determining the budget constraint endogenously from the average budget spent in the Target treatment. We used the strategy method to obtain subjects' complete bidding strategies, which allowed us to make ex post simulations and avoid any potential bias generated by randomly induced costs. We found that the Budget format provides, on average, a greater amount of units for an equivalent budget than the Target format. But, although the difference is significant, it is relatively small in this experiment. Furthermore, we found that both formats performed similarly in terms of allocative efficiency.

This paper fills a gap in the literature, as this is the first decontextualized study to deal with relative performance of Target and Budget reverse auctions. It also introduces a new way to produce and analyze auction experimental data thanks to the combination of the strategy method and a simulation exercise. We believe that this methodology is an important contribution of the paper and may be useful for future experiments on auctions. We acknowledge that in our study many aspects have not been explored, such as the impact of the auction group size N on auction performance, or alternatively, whether one format would better foster sellers' participation than the other (here N is fixed and exogenous). Indeed, participation and risk of collusion are important issues in auctions. The way the reverse auction is framed and designed may have an important impact on both of these issues, which would nevertheless depend on the context in practice. The uniform distribution of costs we used for practical considerations could also lead to an overestimation of the variability of outcomes compared with a normal distribution. Finally, the performance of both formats with repetitions remains beyond the scope of this study. These issues are to be explored in further work, as is the combination of the two constraints in a single auction treatment.

A Content of the experiment

A.1 Instructional video for Target 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.

1

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.

2

This survey is entirely **anonymous**.

The researchers will not be able to link your identity to your decisions.

In this experiment, **groups of 4** participants will be randomly formed.

Other participants will not be able to identify you and you will not be able to identify them.

You are a <u>seller</u> and we (the researchers) are the <u>buyer</u>.

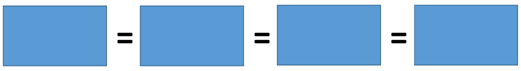
3

We are forced to use a neutral and abstract context in order not to influence your answers.

Each participant is invited to sell **1 unit** of a good.

1 unit = 

The 4 units offered in each group (1 unit for each seller) are perfectly identical.



4

Your task is to propose selling **prices** (in euros) for your unit based on its **production cost**.

To this end, you must complete this table which contains all the possible production ***costs*** for your unit.

These ***costs*** range from 0€ to 100€ in 5€ increments.

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 €	€

5

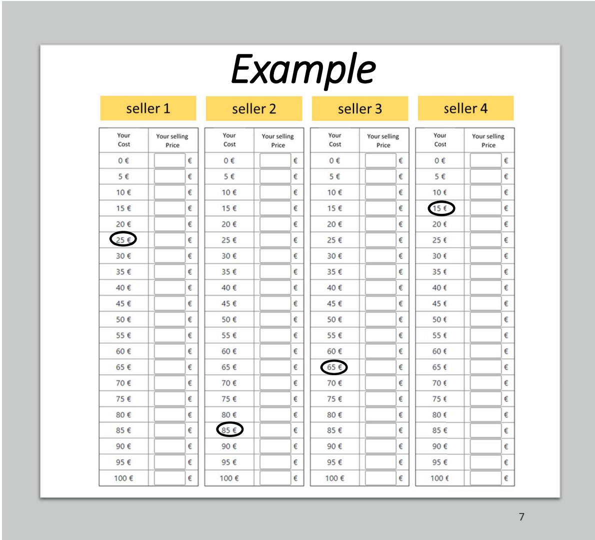
Once all sellers have completed their table,

seller 1		seller 2		seller 3		seller 4	
Your Cost	Your selling Price	Your Cost	Your selling Price	Your Cost	Your selling Price	Your Cost	Your selling Price
0 €	€	0 €	€	0 €	€	0 €	€
5 €	€	5 €	€	5 €	€	5 €	€
10 €	€	10 €	€	10 €	€	10 €	€
15 €	€	15 €	€	15 €	€	15 €	€
20 €	€	20 €	€	20 €	€	20 €	€
25 €	€	25 €	€	25 €	€	25 €	€
30 €	€	30 €	€	30 €	€	30 €	€
35 €	€	35 €	€	35 €	€	35 €	€
40 €	€	40 €	€	40 €	€	40 €	€
45 €	€	45 €	€	45 €	€	45 €	€
50 €	€	50 €	€	50 €	€	50 €	€
55 €	€	55 €	€	55 €	€	55 €	€
60 €	€	60 €	€	60 €	€	60 €	€
65 €	€	65 €	€	65 €	€	65 €	€
70 €	€	70 €	€	70 €	€	70 €	€
75 €	€	75 €	€	75 €	€	75 €	€
80 €	€	80 €	€	80 €	€	80 €	€
85 €	€	85 €	€	85 €	€	85 €	€
90 €	€	90 €	€	90 €	€	90 €	€
95 €	€	95 €	€	95 €	€	95 €	€
100 €	€	100 €	€	100 €	€	100 €	€

6

Once all sellers have completed their table,

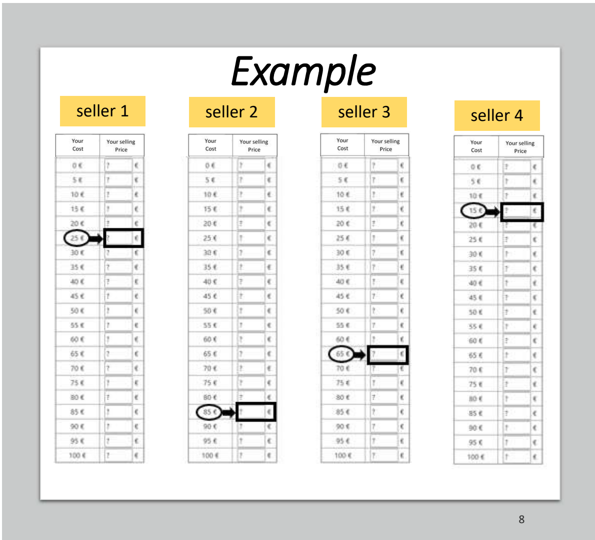
a production ***cost*** will be drawn randomly for each seller.



Once all sellers have completed their table,

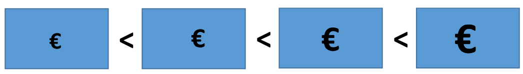
a production ***cost*** will be drawn randomly for each seller.

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

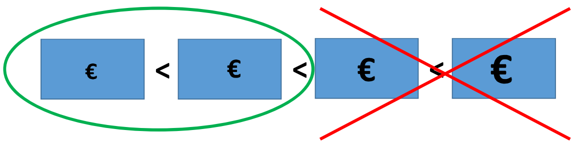


<u>Game rules</u>

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



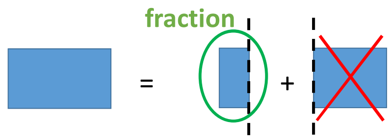
In each group, the buyer will buy the **2 least expensive units**.



9

In case of a tie

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

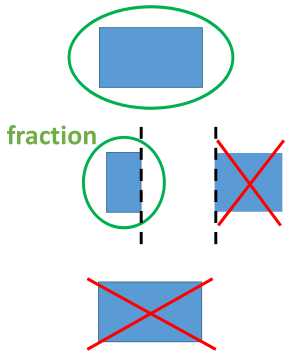


In this case, he will buy the same fraction of a unit from each of the ties.

10

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.

11

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.

12

<u>For each possible production ***cost,***</u> 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 €	€

13

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 <u>better understand the experiment.</u>

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

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

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

See the instructions

14

A.2 Comprehension questions

True/False about the experiment

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

> The answer is **"False"** because the production costs are randomly drawn independently for each vendor. It is therefore highly unlikely that the 4 costs drawn within a 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 win.

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

> The answer is **"True"** because if at least 2 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€. You will therefore have to make a compromise according to your preferences between asking a high price to potentially earn more or offering a lower price to increase your chances of winning (selling your unit).

A.3 Final questions

1. Was it easy for you to choose a price for each cost? From 0: not at all (I chose randomly) to 10: yes completely (I am sure of my choices)

2. Are you generally a risk-taker or do you try to avoid taking risks as much as possible? From 0: avoid taking risks as much as possible, to 10: very comfortable with the idea of taking risks

3. Age:

4. Gender:
Male
Female

5. What is your highest education level? (adapted from French education grade levels)
No high school diploma
High school diploma
Associate's degree
Bachelor's degree
Graduate studies

6. Individual monthly income before income tax:
Less than €1100
Between €1100 and €1899
Between €1900 and €2299
Between €2300 and €3099
Between €3100 and €3999
Between €4000 and €6499
More than €6500
Do not wish to answer

7. What is your socio-professional category?
Farmers

Craftsmen, retailers, entrepreneurs

Executives and higher intellectual professions

Employees

Students

Retired

Unemployed

B Robustness checks using a matching procedure

B.1 Balance across samples

First, we test whether the two samples are well balanced on the control variables of our online experiment. We introduce here the variable *Risk aversion*, which is a self-evaluated variable with values between zero (no risk aversion) and 10 (high risk aversion). We observe in Table 4 that samples are well balanced on *Risk aversion* (*Wilcoxon rank-sum test*), *Age* (*Welch's t-test*) and the *Female* variable (*Pearson's chi-squared test*). This is true also for the variable *Studies level* (*Pearson's chi-squared test*, p-Value = 0.39) and the *Highly educated* variable (*Pearson's chi-squared test*), which is a dummy, constructed from the variable *Studies level*, indicating whether the subject had at least achieved a bachelor's degree.

However, we found that samples were not balanced on the variables *Profession* (*Pearson's chi-squared test*, p-Value < 0.01) and the *Income continuous* variable (*Wilcoxon rank-sum test*, p-Value = 0.02), which was derived from the midpoints of *Income* classes and the lower bound for the highest class. Table 4 also gives more information on the *Profession*, *Studies level* and *Income* variables.

B.2 Matching procedure

The objective here was to obtain two well-balanced samples on all the control variables. The following probit model was used to compute propensity scores (PSs)

$$\begin{aligned} Treat_i = \alpha_0 + \alpha_1\, Riskaversion_i + \alpha_2\, Incomecontinuous_i + \alpha_3\, Age_i \\ + \alpha_4\, Female_i + \alpha_5\, Highlyeducated_i + \alpha_6\, Profession_i + \epsilon_i, \end{aligned} \tag{14}$$

$Treat_i$ being a dummy variable taking the value one if the subject i was in the Budget treatment. In this model, the *Highly educated* dummy is used in the matching procedure instead of *Studies level* to avoid generating too much variance whereas *Studies level* is well balanced in original samples (see Appendix B.1). In order to compute the propensity scores using this model, subjects who did not provide their income had to be removed. This left 122 subjects in the Target group and 188 in Budget. The two subjects with the lowest PSs from Target, i.e., the lowest predicted probability of being from the Budget treatment, were also removed, as the number of subjects must be a multiple of four. Then subjects were matched using the Optimal Pair Matching method from the *MatchIt*

Table 4: Description of original samples

Variables	**Dummies**	**Mean in Target**	**Mean in Budget**	***p*-Value**
Risk aversion		5.10	4.84	0.26
Income continuous		1709.93	2007.32	0.02
Age		42.04	40.13	0.22
Female		0.53	0.49	0.43
Highly educated		0.51	0.47	0.51
Studies level	No high school diploma	0.03	0.10	0.02
	High school diploma	0.20	0.18	0.71
	Associate's degree	0.26	0.24	0.73
	Bachelor's degree	0.17	0.16	0.78
	Graduate studies	0.34	0.32	0.63
Income	Less than €1100	0.33	0.20	0.01
	Between €1100 and €1899	0.24	0.27	0.46
	Between €1900 and €2299	0.13	0.15	0.58
	Between €2300 and €3099	0.12	0.20	0.06
	Between €3100 and €3999	0.09	0.07	0.49
	Between €4000 and €6499	0.02	0.05	0.14
	More than €6500	0.01	0.01	0.77
	Do not wish to answer	0.07	0.05	0.49
Profession	Farmers	0.00	0.01	0.67
	Craftsmen, retailers, entrepreneurs	0.08	0.06	0.45
	Executives and higher intellectual professions	0.18	0.24	0.18
	Employees	0.28	0.46	0.00
	Students	0.15	0.06	0.00
	Retired	0.11	0.06	0.09
	Unemployed	0.21	0.12	0.04

R package (Stuart et al., 2011) with a 1:1 ratio. This consists in minimizing the sum of the absolute pair distances in the matched sample. After this procedure, the two samples were balanced on all control variables (see Table 5) including *Profession* (*Pearson's chi-square test*, p-Value = 0.77).

Table 5: Two sub-samples of 120 subjects

Variables	**Dummies**	**Mean in Target**	**Mean in Budget**	**p-Value**
Risk aversion		5.07	5.09	0.84
Income continuous		1729.26	1693.39	0.84
Age		43.23	42.65	0.74
Female		0.51	0.48	0.70
Highly educated		0.51	0.51	1.00
Profession	Farmers	0.00	0.01	1.00
	Craftsmen, retailers, entrepreneurs	0.08	0.06	1.00
	Executives and higher intellectual professions	0.18	0.24	0.52
	Employees	0.28	0.46	0.34
	Students	0.15	0.06	0.37
	Retired	0.11	0.06	0.39
	Unemployed	0.21	0.12	0.63

Using the procedure described in Section 3.3 with matched samples, we found outcome values presented in Table 6. No significant differences were found with respect to the original samples for the average budget (*Wilcoxon rank-sum test*, p = 0.97) and the average number of units purchased (*Wilcoxon rank-sum test*, p = 0.26), which supports the validity of our results.

Table 6: Average budget and average nb. of units purchased (matched samples)

Treatment	**Nb. subjects**	**Nb. groups**	**Nb. units purchased**	**Empirical budget**
Target	120	30	2	72.26
			(.)	(9.32)
Budget	120	30	2.152	72
			(0.083)	(.)

Standard deviations in parenthesis.

References

Armantier, O. and Treich, N. (2009). Subjective probabilities in games: An application to the overbidding puzzle. International Economic Review, 50(4):1079–1102.

Boxall, P. C., Perger, O., Packman, K., and Weber, M. (2017). An experimental examination of target based conservation auctions. Land Use Policy, 63:592–600.

Brandts, J. and Charness, G. (2011). The strategy versus the direct-response method: A first survey of experimental comparisons. Experimental Economics, 14(3):375–398.

Casari, M. and Cason, T. N. (2009). The strategy method lowers measured trustworthy behavior. Economics Letters, 103(3):157–159.

Chen, D. L., Schonger, M., and Wickens, C. (2016). oTree—An open-source platform for laboratory, online, and field experiments. Journal of Behavioral and Experimental Finance, 9:88–97.

Columbus, S. and Böhm, R. (2021). Norm shifts under the strategy method. Judgment and Decision Making, 16(5):1267–1289.

Cox, J. C., Smith, V. L., and Walker, J. M. (1984). Theory and Behavior of Multiple Unit Discriminative Auctions. The Journal of Finance, 39(4):983–1010.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., and Wagner, G. G. (2011). Individual risk attitudes: Measurement, determinants, and behavioral consequences. Journal of the European Economic Association, 9(3):522–550.

Fischbacher, U., Gächter, S., and Quercia, S. (2012). The behavioral validity of the strategy method in public good experiments. Journal of Economic Psychology, 33(4):897–913.

Güth, W., Ivanova-Stenzel, R., Königstein, M., and Strobel, M. (2002). Bid functions in auctions and fair divisions games: Experimental evidence. German Economic Review, 3(4):461–484.

Güth, W., Ivanova-Stenzel, R., Königstein, M., and Strobel, M. (2003). Learning to bid - An experimental study of bid function adjustments in auctions and fair division games. Economic Journal, 113(487):477–494.

Hailu, A., Schilizzi, S., and Thoyer, S. (2005). Assessing the performance of auctions for the allocation of conservation contracts: Theoretical and computational approaches. In Selected paper prepared for presentation at the American Agricultural Economics Association Annual Meeting, number 378-2016-21416 in Selected Paper 138792, page 20, 2005.

Harris, M. and Raviv, A. (1981). Allocation Mechanisms and the Design of Auctions. Econometrica, 49(6):1477–1499.

Katuščák, P., Michelucci, F., and Zajíček, M. (2015). Does feedback really matter in one-shot first-price auctions? Journal of Economic Behavior and Organization, 119:139–152.

Kirchkamp, O., Poen, E., and Reiß, J. P. (2009). Outside options: Another reason to choose the first-price auction. European Economic Review, 53(2):153–169.

Klemperer, P. (2004). Auctions: theory and practice. Princeton University Press.

Krishna, V. (2009). Auction theory. Academic press.

Latacz-Lohmann, U. and Van der Hamsvoort, C. (1997). Auctioning Conservation Contracts: A Theoretical Analysis and an Application. American Journal of Agricultural Economics, 79(2):407–418.

Liu, P. (2021). Balancing Cost Effectiveness and Incentive Properties in Conservation Auctions : Experimental Evidence from Three Multi-award Reverse Auction Mechanisms. Environmental and Resource Economics, 78(3):417–451.

Lusk, J. L. and Shogren, J. F. (2007). Experimental Auctions. Cambridge University Press.

Milgrom, P. R. (2004). Putting auction theory to work. Cambridge University Press.

Mill, W. and Morgan, J. (2022). Competition between friends and foes. European Economic Review, 147:104171.

Mitzkewitz, M. and Nagel, R. (1993). Experimental results on ultimatum games with incomplete information. International Journal of Game Theory, 22(2):171–198.

Müller, K. and Weikard, P. (2002). Auction Mechanisms for Soil and Habitat Protection Programmes. In Hagedorn, K., editor, Environmental Co-Operation and Institutional

Change: Theories and Policies for European Agriculture, chapter 11, pages 202–213. Edward Elgar Publishing Ltd.

Rapoport, A. and Fuller, M. A. (1995). Bidding Strategies in a Bilateral Monopoly with Two-Sided Incomplete Information. Journal of Mathematical Psychology, 39(2):179–196.

Schilizzi, S. and Latacz-Lohmann, U. (2007). Assessing the Performance of Conservation Auctions : An Experimental Study. Land Economics, 83(4):497–515.

Schilizzi, S. and Latacz-Lohmann, U. (2013). Conservation tenders: linking theory and experiments for policy assessment. Australian Journal of Agricultural and Resource Economics, 57(1):15–37.

Selten, R. (1967). Die Strategiemethode zur Erforschung des eingeschränkt rationalen Verhaltens im Rahmen eines Oligopolexperiments. In Beiträge zur experimentellen Wirtschaftsforschung, pages 136–168. Mohr, Tübingen, h. sauermann edition.

Selten, R. and Buchta, J. (1999). Bidding behavior in first-price auctions with directly observed bid functions. In David V. Budescu, Ido Erev, and Rami Zwick, editors, Games and Human Behavior: Essays in the Honors of Amnon Rapoport, pages 79–102. Psychology Press, Mahwah.

Stuart, E. A., King, G., Imai, K., and Ho, D. E. (2011). MatchIt: Nonparametric preprocessing for parametric causal inference. Journal of Statistical Software, 42(8):1–28.

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