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Allocation, externalities, and the fair division approach: An experimental study*

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March 31, 2008

Abstract

We experimentally investigate four allocation mechanisms - all based on the fair division approach, with varying bid elicitation methods and price rules - in terms of their allocation efficiency, distributional effects, and regularities in individual bidding behavior. In a repeated design, an indivisible good is assigned that generates profits for its owner but, at the same time, exerts negative externalities on the non-acquiring bidders. Both the bidders' valuations of the good and their potentially incurred damages are stochastic and denote private information, inciting strategic bidding and complicating an efficient allocation. Indeed, observed bidding is dominated by strategic reporting which, however, only marginally diminishes efficiency. One particular allocation mechanism, relying on sparse information elicitation and the first-price rule, is found to yield economically superior results to both more complex and second-price based allocation mechanisms.

JEL classification C92, D44, D62, L14

Keywords Allocation; auction; fair division; externalities; experiment

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1 Introduction

Allocating scarce resources in efficient ways to achieve desirable goals in the future is a central objective of administrative and managerial activity. Regularly, decision makers have to make irrevocable decisions with important economic consequences while they are only incompletely informed about the private and social costs and gains of the projects under consideration. Depending on the particular context, scenarios of this kind can be classified into individual and strategic decisions problems.

In the following, we will focus our attention on the latter case. More specifically, we are interested in exploring behavioral regularities and typical outcomes in allocation settings in which agents compete for a single, indivisible good via an auction mechanism. In this vein, we study four different auction scenarios. In the pertaining literature on 'implementation,' such bidding contests generally are considered as suitable approaches to elicit private valuations of a good of unknown quality and to determine the winning bidder (see Hendricks and Paarsch, 1995; Klemperer, 2004, for recent surveys).

In contrast to the bulk of the auction literature, our concern is to explore a particular auction framework in which a traded good is assumed to exert negative externalities on its environment. Think of these externalities as third-party spillovers which arise from production and/or consumption activities that inflict damages via air and water pollution or noise emission. In the considered scenario, neighboring communities negotiate about where to site an industrial facility that, on the one side, generates profits for the hosting community but, on the other side, simultaneously causes damages to neighboring communities. This framework differs from traditional modeling approaches of noxious facility siting since the traded object is assumed to be profitable for, rather than damaging to its owner.[1]

Our model features similarities with those of several other studies on noxious facility siting (e.g., Kunreuther et al., 1987; O'Sullivan, 1993) in the sense that eliciting the bidders' valuations of the indivisible resource is a necessary, but insufficient step to bring about the efficient allocation. At the same time, it is indispensable to also reveal the magnitude of the damages that accrue to affected parties as a result of the good's negative externalities. Hence, any mechanism that is supposed to increase allocation efficiency crucially depends on two pieces of information from each bidder; her valuation of the resource in case of acquiring it and the size of the damage that she suffers otherwise.

Searching for suitable mechanism candidates, we note that most standard auc-

[1] Classical "not-in-my-backyard" (or NIMBY) scenarios are, for instance, investigated by Frey et al. (1996) and Marchetti and Serra (2003).

tion formats like open and closed single unit auctions (e.g., English-, Dutch-, and variants of sealed bid auctions) by default only elicit one-dimensional private information from the bidders. In most standard (single-unit) auctions, one seller and several buyers interact whereby the latter are asked to reveal their actual valuation of the auctioned resource, i.e., their reservation price. Once all bids are collected, the auction mechanism unambiguously assigns the good to the bidder with the highest bid who, supposedly, derives the largest utility from the good. Conversely, the seller obtains the revenue equivalent to the winning agent's or - depending on the price rule - a subsequent agent's bid. This class of auction formats garnered substantial interest among economists for the last two decades and, as a result, brought about an abundant theoretical and empirical literature on the issue (cf., Milgrom and Weber, 1982; McAfee and McMillan, 1987; Wolfstetter, 1996; Klemperer, 1999). In many of these studies, the authors share the ambition to identify optimal mechanisms, i.e., means to maximize the expected revenue of the seller and to characterize these mechanisms' central properties (cf., Myerson, 1981; Riley and Samuelson, 1981; Bulow and Roberts, 1989).

Auction formats which more closely pertain to our research interest - in the sense of eliciting entire bid vectors rather than only inquiring scalar bids from the agents - are less frequently encountered in the literature. These approaches which are also referred to as "multidimensional allocation mechanisms" often employ combinatorial or multi-unit auctions in which bidders place bids on whole combinations or packages of goods (cf., Cramton et al., 2006). The above mechanisms have the advantage of lending more flexibility to the allocation process, but simultaneously pose new economic and computational challenges with respect to incentive-compatibility, suitable bid elicitation methods, and the unambiguous determination of the winning bidder.

Let us briefly enumerate several contributions in this field that feature some overlap with our study. McAfee and McMillan (1988) explore an allocation scenario in terms of its incentive-compatibility in which players' types are, analogously to our scenario, modeled as being multidimensional. Yet closer to our research problem, Jehiel et al. (1999) investigate an auction with externalities where bidders exhibit a vector of payoffs for several outcomes. In line with our study, they also discuss the issues of the mechanism's incentive-compatibility, participation constraints, and endogenous and type-dependent outside options. Finally, Währer (2003) focuses on instances of hazardous facility siting within a group of neighboring communities whose damages depend on the identity of the hosting community and are only known to the communities to whom they accrue.

Apart from auction mechanisms, a variety of suggestions was made on how to solve allocation problems which resemble our scenario of interdependent agents and (winner) identity-dependent payoffs. These comprise lotteries (Kunreuther and Portney, 1991), insurances policies (Goetze, 1982), and equitable division schemes (cf., Crawford and Heller, 1979; Tadenuma and Thomson, 1995; Brams et al., 2003). Bearing in mind that our research focus is set on auction based solution concepts, we deliberately omit the initial two approaches and concentrate our attention on the latter one. In the economic literature on social choice, the above scheme is also known as the "fair division mechanism" and its basic properties already have been extensively studied (see, e.g., Güth and van Damme, 1986; Güth et al., 2002). In the fair division game, a single, indivisible good is collectively owned by a group of bidders. The aim of the mechanism is to assign the good to the bidder with the highest valuation who, in a second step, has to compensate the other bidders by transferring equitable shares of her valuation to the former. Due to these monetary side payments that are inherent to this mechanism, every bidder (and not only the auction winner) benefits from the allocation outcome.

More broadly, this paper contributes to the literature on (nearly) efficient allocation mechanisms by characterizing four distinct auction environments and by assessing their relative economic performance. As a secondary goal, we also evaluate the mechanisms' social welfare implications, i.e., their degree of "equity" in distributing the benefits from the allocation (cf., Bouveret and Lang, 2005).[2] In our view, equity concerns with respect to the distribution of proceeds from allocation outcomes are (at least politically) relevant, as they may significantly ease or hamper the introduction of the respective mechanisms in the first place. If a mechanism is perceived as being neither procedurally fair nor largely equitable in dividing the allocation surplus, it will - in all likelihood - lack the necessary political support for either its initiation or retention. To the contrary, those mechanisms that yield outcomes which are both (largely) efficient and equitable should enjoy widespread acceptance. In the same vein, seminal contributions such as the ones by Rabin (1993) and Kaplow and Shavell (2002) further underline the academic interest in the relationship between fairness and social welfare.

The remainder of the paper is structured as follows. The next section introduces the central characteristics of the fair division approach and presents the four allocation mechanisms that will subsequently be examined. In section 3, we present the experimental protocol. In section 4, we discuss observed regularities in individuals'

[2] Generally, the criteria of "equity" and "envy-freeness" are seen as relevant mechanism properties in fair division games. In the following we, however, will restrict our analysis to the former and leave the investigation of the mechanisms' envy-freeness property to a follow-up study.

bidding behavior and compare the aggregate performance of the distinct allocation mechanisms. Lastly, in section 5, we summarize our findings and conclude.

2 Model and treatment design

We consider four allocation mechanisms which partly differ in their bid elicitation protocols and price rules, but uniformly allow for compensating side payments (cf., Güth, 1998; Güth et al., 2002). The manner in which the regulation of negative externalities is implemented in the various mechanisms was substantially influenced by preceding works on noxious facility siting (cf., O'Sullivan, 1993; Jehiel et al., 1996). While the allocation mechanisms universally satisfy individual rationality, i.e., induce bidders to voluntarily participate in the auction in anticipation of a positive expected profit, the mechanisms, however, are not incentive compatible, i.e., do not incite bidders to truthfully reveal their private information.[3]

More specifically, the allocation mechanisms are characterized by the following properties:

- A single, discrete good is assigned within the group of bidders.
- The good generates profits for the winning bidder, but simultaneously harms all non-acquiring bidders.
- Valuations of the good and incurred damages denote private information of the pertaining bidders and are independently drawn from uniform distributions.
- While incurred damages of non-acquiring bidders do not depend on the identity of the winning bidder - i.e., they are a bidder-specific constant - the magnitudes of side payments crucially condition on the winning bidder's identity.

Furthermore, an economically sensible allocation mechanism that incorporates the fair division property should specify

- the bidder who acquires the good (e.g., the right to establish a polluting plant), and
- whether, and if so, how incurred damages are to be regulated (e.g., how compensation payments should be quantified and directed).

[3] Given the mechanisms' compliance with individual rationality, strategic "threats" (cf., Jehiel et al., 1996) to enforce the bidders' participation need not be considered.

Bidding in the four treatments takes place in groups of size n. Each bidder i in the group is characterized by her type (H_i, K_i) which is comprised of her private valuation of the good (H_i) in case of winning the auction and her damage (K_i) which she incurs otherwise. Both parameters are independently drawn for each bidder i from two uniform distributions, i.e., valuations H_i and damages K_i are uncorrelated.

Jehiel et al. (1996) and Jehiel et al. (1999) explore a centralized allocation mechanism (a vertical contracting scenario) through which a seller vends a particular right to one of several potential buyers and derive the seller's profit maximizing mechanism. By contrast, we are interested in decentralized allocation mechanisms in which bidders collectively own an indivisible resource. As an illustration of our scenario, think of political negotiation processes in the spirit of the "Kyoto Environmental Conference." Therein, the participating nations as a group own the right to define rules on how pollution at the international scope shall be treated. To reach a consensual agreement, the participating nations must balance their particular interests, a task which also comprises the regulation of external effects. These externalities are assumed to be pervasive in the sense that they cannot simply be avoided by refusing to participate in the negotiation. Analogously, the bidders' outside option in our model, i.e., their payoff in case of not acquiring the good, is endogenous and directly depends on the winning bidder's valuation. Conversely, damages of non-acquiring bidders are assumed to be independent of the winning bidder's identity.

Let us point out the primary similarities and differences between the four treatments. All mechanisms share that a single, indivisible good is assigned to the bidder i whose net trade ν_i with

$$\nu_i = \eta_i - \sum_{j \neq i} \kappa_j, \tag{1}$$

i.e., the difference between her stated valuation of the good η_i and the sum of the $(n-1)$ co-bidders' damage claims κ_j is maximized $\left(\nu_i = \nu_{(n)}\right)$.

Constituting the first treatment variable, the allocation mechanisms differ in how the (expected) net trade ν_i is elicited from the bidders.[4] Whereas the expected net trade is only indirectly elicited in the more complex two-dimensional treatments (T1/2) (via eliciting valuations and damages), bidders in the one-dimensional treatments (O1/2) are directly asked to state their expected net trade. As a second line of comparison, we separately examine both classes of treatments (T1/2) and (O1/2) to quantify the partial effects of the alternative (first- vs. second-) price rules. The

[4] In (O1/2), each bidder is asked to predict the surplus that would be generated if she were assigned the good. This evaluation is not trivial, considering that bidder i must speculate about the likely realization of two stochastic processes (her two co-bidders' damages κ_{-i}) of which only the type of the underlying distribution is known.

Table 1: Factorial treatment design

	Elicited information	
Price rule	Valuation & damage	Expected net trade
Highest net trade	(T1)	(O1)
Second highest net trade	(T2)	(O2)

composition of the four allocation mechanisms as a 2×2 factorial design is shown in Table 1. The bidders' payoff functions and the formulation of their (expected) net trades in the distinct treatments are presented in Table 2.

We start by introducing the class of two-dimensional trading mechanisms (T1/2), in which individual valuations of the good η_i and incurred damages κ_i are directly elicited. The difference between bidder i's valuation η_i and the sum of her co-bidders' stated damages $\sum\limits_{j \neq i} \kappa_j$ yields bidder i's net trade denoted by ν_i. Hence, individual net trades are determined by all bidders' types rather than by a single bidder's type alone.

In a second step, the bidders' net trades are ranked and the bidder with the largest net trade $\big(\nu_i = \nu_{(n)}\big)$, with $\nu_{(n)}$ being the n-th order statistic of the set of net trades) wins the auction and, hence, obtains the good. The determination of payoffs in the distinct treatments universally follows the same structure. The first of each payoff function's two additive terms denotes the bidder's income if she wins the auction. In this case, bidder i earns her actual valuation H_i but, at the same time, must compensate the other bidders $-i$ for their stated damages $\sum \kappa_{-i}$ and, additionally, must cede $(n-1)$ equitable portions of her net trade ν_i to the latter. Depending on whether the first or second price rule applies, the highest $(\nu_{(n)})$ or second highest net trade $(\nu_{(n-1)})$ is equally divided among the n bidders. By contrast, the payoff functions' latter additive term denotes bidder i's income if she is surpassed in the auction by another bidder. In that case, bidder i suffers the damage K_i and receives an equitable portion of the winner j's net trade ν_j in compensation.[5]

Summarizing, the bidders' ex-post roles are determined by the rank of their stated net trades, whereby the good always is assigned to the bidder with the highest net trade. Depending on the applicable first- (or second-) price rule, the winning bidder then is required to transfer an equitable share of her stated net trade, i.e.,

[5] For simplicity, the magnitude of the bidder i's damage is assumed to be independent of the winning bidder j's identity. In this respect, our modeling of externalities structurally differs from the one in Jehiel et al. (1996).

Table 2: Payoff functions across treatments

Treatment	Payoff function	(Expected) net trade
(T1)	$\pi_i(\eta_i,\kappa_i) = \left[H_i - \sum_{j\neq i}\kappa_j - \frac{(n-1)\cdot\nu_{(n)}}{n}\right]\cdot \text{Prob}\left(\nu_i = \nu_{(n)}\right) +$ $\left[\frac{\nu_{(n)}}{n} - K_i\right]\cdot \text{Prob}\left(\nu_i < \nu_{(n)}\right)$	$\nu_i = \eta_i - \sum_{j\neq i}\kappa_j$
(T2)	$\pi_i(\eta_i,\kappa_i) = \left[H_i - \sum_{j\neq i}\kappa_j - \frac{(n-1)\cdot\nu_{(n-1)}}{n}\right]\cdot \text{Prob}\left(\nu_i = \nu_{(n)}\right) +$ $\left[\frac{\nu_{(n-1)}}{n} - K_i\right]\cdot \text{Prob}\left(\nu_i < \nu_{(n)}\right)$	
(O1)	$\pi_i(\nu_i) = \left[H_i - \frac{(n-1)\cdot\nu_{(n)}}{n}\right]\cdot \text{Prob}\left(\nu_i = \nu_{(n)}\right) +$ $\left[\frac{\nu_{(n)}}{n} - K_i\right]\cdot \text{Prob}\left(\nu_i < \nu_{(n)}\right)$	ν_i
(O2)	$\pi_i(\nu_i) = \left[H_i - \frac{(n-1)\cdot\nu_{(n-1)}}{n}\right]\cdot \text{Prob}\left(\nu_i = \nu_{(n)}\right) +$ $\left[\frac{\nu_{(n-1)}}{n} - K_i\right]\cdot \text{Prob}\left(\nu_i < \nu_{(n)}\right)$	

either $\nu_{(n)}$ or $\nu_{(n-1)}$, to each of her co-bidders. General truth-telling would prompt the bidders to equate their statements of η_i and κ_i with their actual type characteristics (H_i, K_i). However, since the four auction mechanisms are not incentive compatible[6], bidders uniformly are incited to strategically misrepresent their types. In Appendix B, we present a series of numerical benchmarks for the distinct allocation mechanisms and discuss why it therein is not individually rational for the bidders to truthfully report their types. More specifically, we show that by strategically misrepresenting their valuation and damage statements, bidders can influence the allocation outcome, i.e., the winning bidder's identity and the structure of side payments, to their personal economic advantage.[7]

Having introduced the two-dimensional bid elicitation mechanisms (T1/2), let us now address their one-dimensional equivalents (O1/O2). Whereas the former mechanisms were designed to directly elicit the bidders' types (H_i, K_i), an indirect elicitation procedure is chosen in (O1/2). The latter mechanism design is based on the conjecture that rational bidders will invariably misrepresent their actual types in any direct and non strategy-proof mechanism. This strategic reporting of valuations and damages ($H_i \neq \eta_i$ and $K_i \neq \kappa_i$) generally diminishes the value of the elicited information and - particularly in asymmetric settings - reduces the efficiency of allocation decisions which crucially depend on truthful type statements.

Anticipating the manipulability of the (T1/2) mechanisms, we simplify the elicitation procedure in (O1/2) from a bid vector to a scalar bid, as a result bidders only are prompted to state their expected net trade ν_i (see Equation 1). Since this elicitation format aims at revealing ν_i directly (thereby constituting a direct mechanism), it is not longer necessary to define a functional relationship between η_i, κ_i, and ν_i. We speak of a net trade "expectation," because bidder i cannot perfectly quantify her co-bidders' (stochastically determined) damages κ_{-i}. Rather, bidder i may predict ν_i via stochastic inference, i.e., by identifying the mean of the value range of possible realizations of $\kappa\ (\in U\ (\underline{\kappa}, \overline{\kappa}))$ and multiplying that value by $(n-1)$. The relevant design tweak of the mechanisms (O1/2) is that the stated net trades of the various bidders are now independent, as bidders cannot anymore influence their co-bidders' net trades ν_{-i} by strategically misrepresenting their own damage claims κ_i.

[6] A mechanism is considered to be "incentive compatible" or "strategy-proof" if it is the subject's best response to truthfully reveal the private information that the mechanism asks for.

[7] The simulation exercise yields that the bias is especially pronounced in treatments (T1/2) which elicit damage claims in a clearly non-incentiviced manner. By contrast, the bias is weaker in treatments (O1/2) of which the latter treatment shares similarities with the incentive compatible Vickrey auction format (Vickrey, 1961).

Determining the winning bidder and deriving the bidders' profits is straightforward in treatments (O1/2). The winning bidder i always is the one who states the largest expected net trade ($\nu_i = \nu_{(n)} > \nu_{-i}$) within the group of bidders. She earns her valuation H_i and passes on $\frac{(n-1)\nu_{(n)}}{n}$ in (O1), respectively $\frac{(n-1)\nu_{(n-1)}}{n}$ in (O2) to her $(n-1)$ co-bidders. Each losing bidder i incurs the negative externality K_i and receives the amount $\frac{\nu_{(n)}}{n}$ (O1), respectively $\frac{\nu_{(n-1)}}{n}$ (O2) from the winning bidder in compensation. Moreover, since damage claims of unsuccessful bidders are no longer considered, negative externalities actually may not be fully compensated. This situation occurs when the equitable portion of the winning bidder's net trade is insufficient to cover the non-acquiring bidder i's actual damage $\frac{\nu_{(n)}}{n} < K_i$ in (O1) or $\frac{\nu_{(n-1)}}{n} < K_i$ in (O2).

3 Laboratory protocol

The computerized experiment was conducted at the Max Planck Institute in Jena (Germany) in May 2006. The experiment was programmed in z-Tree (Fischbacher, 2007) and lasted between 80 and 90 minutes. Overall, we ran four sessions which altogether comprised 120 participants, all of them being undergraduate students at the University of Jena.[8] Thirty participants each took part in the four treatments in a between-subject design.

The experiment employs a factorial design across bid structures (valuation- and damage- vs. expected net trade elicitation) and price rules (first- vs. second-price). In each treatment, they were confronted with an interactive decision task that was repeated for 50 times (see Appendix A for detailed instructions). After each decision task, participants were reassigned to form new groups in a random stranger design.[9] While the bid elicitation formats differed across treatments, the same parameterization was uniformly applied in all four sessions. Each decision task comprised $n(= 3)$ interacting bidders whose two-dimensional types (constituted by valuation H_i and damage K_i) were independently drawn from the two uniform distributions $H_i \in U\,(125, 200)$ and $K_i \in U\,(1, 50)$.[10] The value ranges of H_i and K_i were chosen such that bidders always would want to participate in the four allocation mechanisms, given that bidding games uniformly are profitable ($\underline{H} - 2\overline{K} > 0$).

Analogously to the restrictions on H_i and K_i, the permissible ranges for partic-

[8] Participants were invited via the online recruitment system ORSEE (Greiner, 2004).

[9] The employed matching design did not consider matching groups and, consequently, yielded only one independent observation per treatment. To deal with the issue of dependent observations, we limit our statistical testing to the appropriate cases and focus on regression analysis instead.

[10] Note that bidder types were limited to discrete vectors, i.e., draws from uniform distributions were rounded to integers.

ipants' valuation and damage claims also were limited. More precisely, valuation- (η_i), damage- (κ_i), and expected net trade statements (ν_i) had to be stated within the limits of $\eta_i \in \{125, \ldots, 200\}$, $\kappa_i \in \{1, \ldots, 50\}$, and $\nu_i \in \{1, \ldots, 198\}$.[11] If, by contrast, statements of η_i, κ_i, and particularly ν_i had been unbounded in (T1/2), the undesirable case may have occurred that winning bidder i's net payoff becomes negative as she is required to compensate her co-bidders' to the amount of their claimed damages $H_i - \sum_{j \neq i} \kappa_j - \frac{(n-1)\nu_{(n)}}{n} < 0$. Anticipating this strategic opportunity, non-acquiring bidders would be incited to exaggerate their damage claims to obtain a larger compensation from the winning bidder. As a result, winning the auction would become a dominated strategy, as the winner of the auction - in all likelihood - incurs an economic loss. Additionally, the game would no longer be individually rational, considering that potential winners would prefer to altogether abstain from the auction.

In the same vein, it is evident that the four net trade-based allocation mechanisms crucially depend on the presence of informative net trade statements to perform efficiently. If these statements were to exhibit very unfavorable information-to-noise ratios - in the sense that they are not helpful anymore in identifying the bidder who maximizes the transaction's allocation efficiency (e.g., due to grossly overstated damage claims) - the distinct allocation algorithms would be reduced to inefficient random processes.

All choice variables (valuations, damages, and net trade claims) and outcome statistics (periodic and final profits) in the experiment were denoted in the fictitious currency ECU. Throughout each treatment, periodic profits were aggregated to finally be converted into euros at the rate of 100 ECU = €0.50. The resulting amount was then disbursed to the participants in cash. Total earnings in the experiment ranged from €6.97 to €14.37 (excluding a show-up bonus of €2.50) with a mean of 10.41 and a standard deviation of 1.42. Lastly, and barring further refinements, the treatment variable by itself (i.e., the four distinct allocation mechanisms) was not found to significantly affect payoffs ($p = 0.356$, Kruskal-Wallis test).[12]

4 Experimental results

We start our analysis by identifying behavioral regularities in competitive bidding. In particular, we examine the participants' truthfulness in revealing their private

[11] All preceding information was made commonly known in the instructions (see Appendix A).

[12] Irrespective of this initial assertion, we will subsequently show that the partial effect of the price rule (but not the one of the bid elicitation format) in fact is significant.

information. In a second step, we evaluate the partial effects of the two treatment variables, i.e., the sophistication of the mechanisms' elicitation format and the underlying price rule, on individuals' bidding behavior. Finally, we assess the mechanisms' economic performance at the aggregate level while focusing on the former's allocation efficiency, distributional effects, and desirability from a welfare-economic viewpoint.

4.1 Bidding behavior

In a first step, we explore regularities in the individuals' bidding behavior in treatments (T1) and (T2) which involve the elicitation of the bid vector (η_i, κ_i). Figure 1 contrasts the bidders' actual and stated valuations of the good (H_i vs. η_i) and their equivalents with respect to damages (K_i vs. κ_i).

If bidders' statements were truthful, we would expect pairs of H_i and η_i, as well as of K_i and κ_i, to be located along the 45 degree line. By contrast, we observe that the regression line explaining stated valuations and damages and the 45 degree line are far from coinciding in all four scatterplots, revealing that systematic truthful bidding does not occur.[13] Strikingly, only 5.1% (13.2%) of all bid statements perfectly (approximately, i.e., ±10%) depict the bidders' actual types. Most subjects seemingly determine their bid vector (η_i, κ_i) via bid functions that feature a positive intercept ($\beta_0 > 0$) and slope parameter ($\beta_1 < 1$). As a result, we discern a positive, but only moderately strong correlation between actual and claimed valuations and damages ($\rho = 0.46$ for valuations and $\rho = 0.15$ for damages, Pearson correlations).

Summarizing, we find that most bidders (81.7%) do not truthfully reveal their type, but strategically adjust their valuation and damage claims. Generally, valuations are reported more truthfully ($\rho = 0.456$ in (T1), $\rho = 0.391$ in (T2)) than damages ($\rho = 0.146$ in (T1), $\rho = 0.120$ in (T2)), with the latter ones being systematically overstated.[14] This finding is unsurprising considering that the winning bidder i must compensate her co-bidders to the amount of their stated damages κ_{-i}. Consequently, it is lucrative for non-acquiring bidders to deliberately exaggerate their damage claims to extort a higher transfer from the winning bidder.

Nonetheless, the strategy of uniformly demanding the largest possible compensation ($\kappa_i = \overline{\kappa}$) may not necessarily be dominant. Rather, it should also be taken into account that by overstating her damages, the bidder raises the probability of winning the auction. This follows because, by raising κ_i, bidder i decreases each co-

[13] Given that bidders' payoffs are directly related to their statements of (η_i, κ_i), it is evident that truthful reporting with respect to κ_i must be a dominated strategy.

[14] In 24.5% (48.9%) of all cases, bidders in T1 (T2) overstate their actual valuations. Damages, by contrast, are overstated by 77.7% (75.1%) of all bidders.

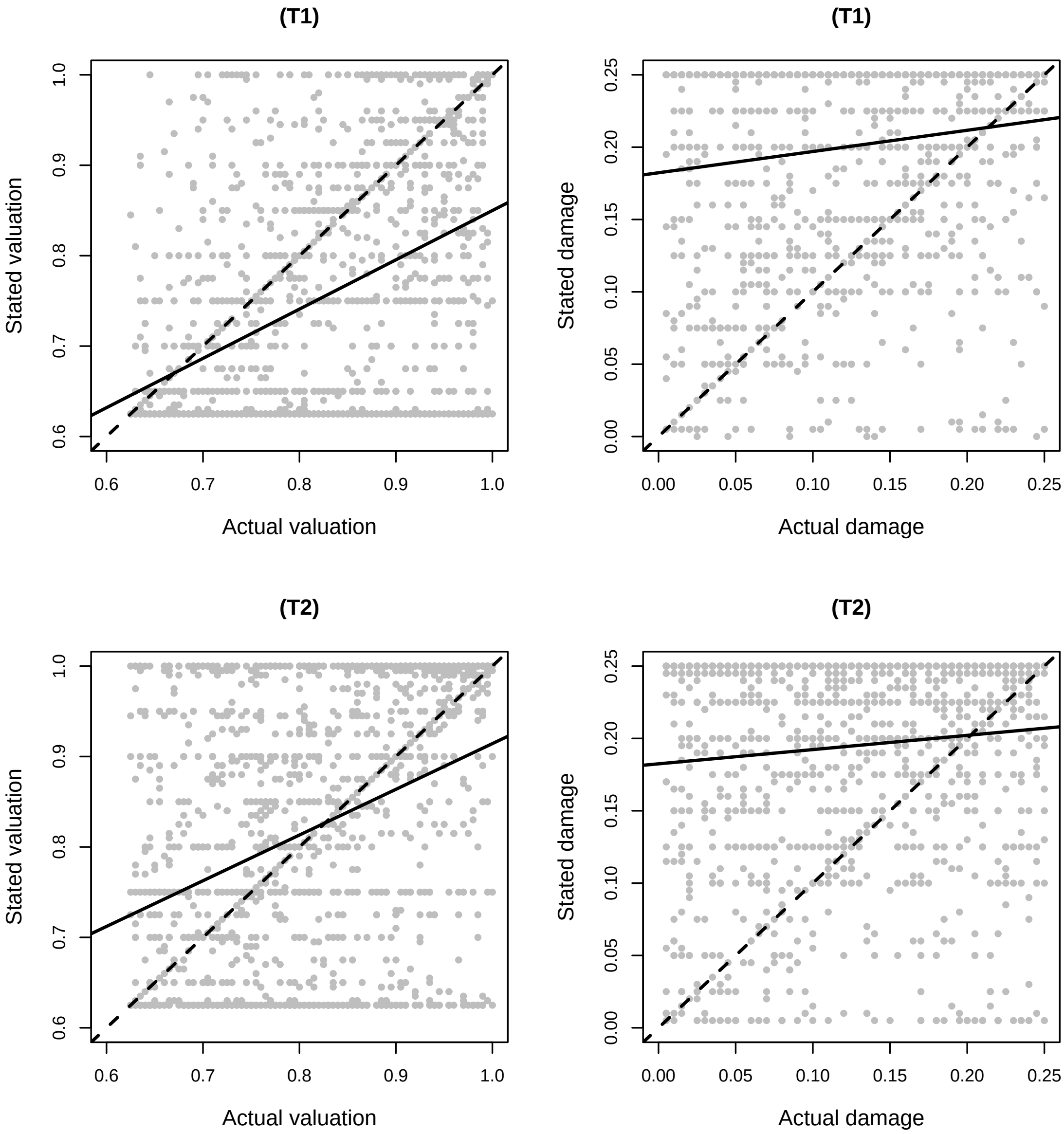

Figure 1: Bidding behavior in treatments (T1/2)

Note: Horizontal axes denote actual valuations and damages while vertical axes denote corresponding valuation and damage claims. The solid (dashed) line marks the regression line (45 degree line). Valuations and damages are transformed via division by 200 ($0.625 \leq H_i, \eta_i \leq 1$ and $0 < K_i, \kappa_i < 0.25$).

bidder j's net trade $\nu_j = \eta_j - \sum_{i \neq j} \kappa_i$ which, in turn, increases the chance that her net trade ν_i exceeds the ones of her co-bidders. If, in this case, the bidder's valuation is far below her co-bidders' ones ($H_i \approx \underline{H} \ll H_{-i}$), the allocation outcome clearly will be inefficient. Yet, stating inappropriately low damage claims ($K_i > \kappa_i \approx \underline{\kappa}$) also is risky. Should bidder i eventually lose the auction, this strategy would invariably limit her receivable transfer from the winning bidder j ($\kappa_i \ll \overline{\kappa}$). As yet another possibility, the interdependence between valuations and damages actually may work in both directions. For instance, a bidder i who were to incur a relatively large damage ($K_i \approx \overline{K}$) may want to increase her stated valuation beyond her actual valuation ($\eta_i > H_i$) to raise her net trade ν_i and, thereby, to improve her chance of winning the auction. If successful, she then effectively circumvents the damage K_i that she otherwise would have suffered.

However, by comparing the above conjectures with the results of the simulation exercise (see Appendix B), we find that stating damages below the largest possible compensation ($\kappa_i < \overline{\kappa}$) is suboptimal and, as a result, cannot constitute equilibrium play. By contrast, we find support in the simulation results for the conjecture that individuals' stated valuations should strongly (positively) correlate with their actual damages ($\beta_2 > 0$ for (T1/2) in Table 5).

To more thoroughly explore the influence of bidders' actual valuations, damages, and their interaction on ensuing valuation and damage claims, we turn to regression analysis. More specifically, we estimate two linear mixed-effects models per treatment which explain the bidders' valuation- (η_i) and damage (κ_i) statements. The set of covariates comprises an intercept, the bidders' actual valuations (H_i) and damages (K_i), and the period of observation (Period) to control for learning. Table 3 presents the regression results of the four models that are related to treatments (T1/2).[15]

Let us first inspect how, on average, valuation statements are derived from the bidders' actual valuations and damages. If valuations were reported truthfully, the coefficient estimates of the bid function $\eta_i(H_i, K_i)$ - which is used to predict valuations - should satisfy $\beta_0 = 0$, $\beta_1 = 1$, and $\beta_2 = 0$. However, this conjecture must be rejected in light of the estimation results ($\beta_1 \leq 0.540$ and $\beta_2 \geq 0.237$). Our initial presumption that at least a sizable minority of bidders would refrain from strategically misrepresenting their valuations and damages to avoid inefficient allocation outcomes thus cannot be uphold.

Most bidders overstate (understate) their actual valuations of H_i for low (high)

[15] Further, it also provides the regression results of two corresponding models in (O1/O2) that will be addressed later in this section.

Table 3: Empirical bid functions

Treatment	Dependent variable	Coefficient estimates Intercept (β_0)	Valuation (H_i) (β_1)	Damage (K_i) (β_2)	Period
(T1)	η_i	0.307***	0.540***	0.237***	−0.001***
	κ_i	0.197***	−0.037*	0.145***	0.001***
(T2)	η_i	0.394***	0.512***	0.277***	−0.001***
	κ_i	0.169***	−0.013	0.117***	0.001***
(O1)	ν_i	−0.110***	0.935***	0.653***	0.002***
(O2)	ν_i	0.278***	0.606***	0.276***	0.002***

Note: η_i, κ_i, and ν_i denote the bidder's stated valuation, damage, and expected net trade. Stars indicate significance levels, i.e., significant at the 10% (*), 5% (**), or 1% (***) level.

realizations of H_i. On average, they only partially account for their true valuations and damages - as expressed by $\beta_1 < 1$ in $\eta_i(H_i, K_i)$ and $\beta_2 < 1$ in $\kappa_i(H_i, K_i)$ - while adding a sizable fixed markup $\beta_0 > 0$ in compensation. As expected, underbidding actual valuations under the first-price rule is significantly more pronounced than under the second-price rule (mean bid shading of 13.17 and -1.06 in (T1) and (T2); $p < 0.001$, one-sided MWU-test). Note that bidding above one's actual valuation H_i in (T1/2) need not necessarily imply irrational behavior, because the winning bidder i merely has to pass on a fraction of her profit π_i, namely $\sum_{j \neq i} \kappa_j + \frac{2\nu_i}{3}$, to her co-bidders, which may still ensure her a positive profit.

We expectedly find that bidder i's valuation H_i is the factor with the highest explanatory power with respect to her stated valuation η_i ($\rho = 0.405$, Pearson correlation). Moreover, the claimed valuation also is significantly affected by her damage parameter κ_i. This indicates that bidders, on average, take the interdependence between actual valuations H_i and damages K_i into account when determining their claims η_i and κ_i. In doing so, they raise their net trade v_i which, in turn, decreases the risk of suffering the anticipated negative externality K_i. By contrast, when defining their damage claims κ_i, most bidders entirely disregard their valuations H_i and merely set κ_i to a sizable, but otherwise largely arbitrary amount ($\rho = 0.121$ between K_i and κ_i).

Overall, we discern that the empirically derived bid functions and their corresponding simulation-based equivalents show meaningful similarities (compare Tables 3 and 5). While the intercepts in the empirical bid functions are systematically larger than their benchmark counterparts, we observe some conformity with respect to the scaling factor for valuations (β_1). The scaling factor for damages (β_2), to the contrary, is substantially smaller in treatments (T1/2) than in the benchmark case. While the benchmark for damage claims equates to $\kappa_i = \overline{\kappa} = 0.25$, the empirical estimate for $\kappa_i (= 0.20)$ is significantly below this level ($p < 0.001$, one-sided, one-sample Wilcoxon signed rank test).

In the second stage of this section, we characterize the allocation mechanisms (O1) and (O2). To this end, we first descriptively summarize individuals' bidding behavior. In a second step, we then compare identified behavioral regularities with those from the (T1/2) treatments. Figure 2 shows the partial correlation between bidders' expected net trades ν_i and their actual valuations H_i and damages K_i.

Inspecting the correlation between actual valuations H_i and corresponding stated net trades ν_i, we observe that the regression line nearly coincides with (largely corresponds to) the dashed 45 degree line in (O1) (in (O2)). This implies that bidders, on average, derive their net trade claim ν_i almost exactly from their valuation H_i ($\rho = 0.502$ in (O1) and $\rho = 0.346$ in (O2)). Aligning net trade claims with actual valuations ($\nu_i \approx H_i$) is slightly more pronounced in (O1) whereas some overbidding of actual valuations is observed for smaller realizations of H_i in (O2). Conversely, the impact of actual damages K_i on ν_i is negligible, meaning that actual damages - irrespective of their magnitude - do not significantly affect stated net trades. The weak correlation between K_i and ν_i ($\rho = 0.221$ in (O1) and $\rho = 0.107$ in (O2), Pearson correlation) also is illustrated by the almost flat regression line in both respective scatterplots.

The above bidding pattern, i.e., the manner in which net trade claims ν_i are defined, is corroborated by two linear regressions that are based on bidders' actual valuations and damages (see Table 3). We find that bidders primarily condition their net trade claims on their actual valuations ($\beta_1 = 0.935$ in (O1) and $\beta_1 = 0.606$ in (O2)) whereas actual damages only are partially considered ($\beta_2 = 0.653$ in (O1) and $\beta_2 = 0.276$ in (O2)). Analogously to the benchmark comparison for (T1/2), similarities between the empirical bid functions in (O1/2) and their simulation equivalents are discerned. In both cases, net trade claims ν_i strongly react to changes in actual valuations H_i ($\beta_1 \geq 0.720$ ($\beta_1 \geq 0.606$) in the benchmark (empirical) bid functions). Differently, the empirical bid functions are less responsive to changes in actual damages K_i than the ones of the simulation benchmark ($\beta_2 \geq 0.276$ vs. $\beta_2 \geq 0.750$).

In interpreting the two models, we take the view that bidders correctly discern the central role of their actual valuations in quantifying their net trade statements. In all, we conclude that while bidding behavior in (O1/2) does not yet closely approximate equilibrium play, it nevertheless can be described as largely regular and

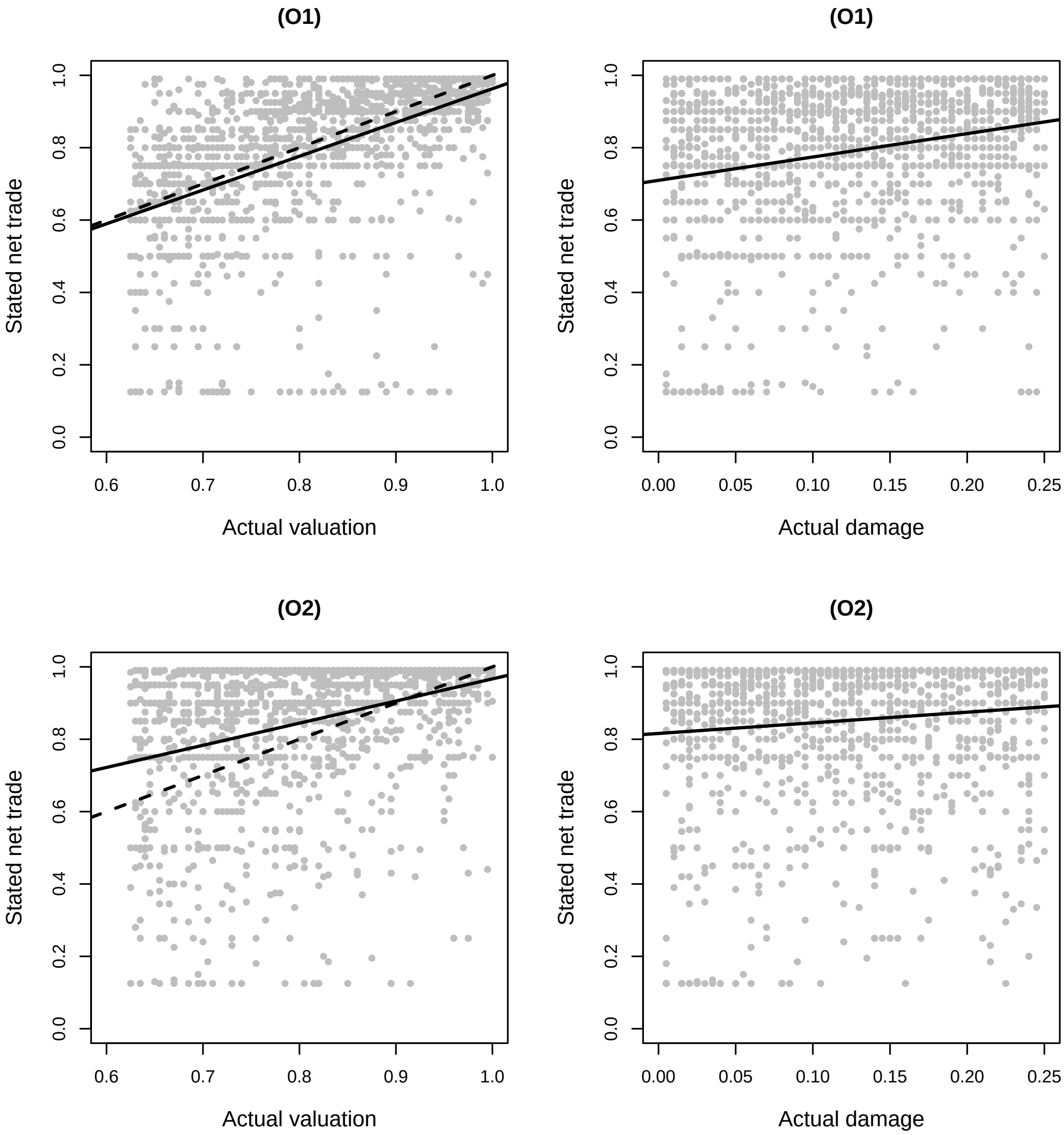

Figure 2: Bidding behavior in treatments (O1/2)

Note: Horizontal axes denote actual valuations and damages while vertical axes denote bidders' stated net trades. The solid (dashed) line marks the regression line (45 degree line).

economically sensible.

To conclude this section, let us briefly examine the data with respect to possible temporal dynamics in bidding behavior. In the preceding analysis, learning dynamics were primarily noticeable via the coefficient “Period” which was included in the series of regressions that are summarized in Table 3. In all six regressions, the presence of learning dynamics is affirmed, as the coefficient universally is significant. Hence, individual learning clearly is directional, resulting in valuation claims being lowered whereas damage- and expected net trade claims are being raised as time progresses.

Further evaluating the impact of experience on regular bid choices, we also fitted another series of regressions. Replicating the above regressions and allowing for a quadratic “Period” term yields that the latter term also is significant. This implies that the effect of time (hence learning) on valuation-, damage-, and net trade claims is characterized by a concave function, in the sense that initial familiarizing with the allocation mechanisms leads to more pronounced revisions in subjects’ bidding strategies than subsequent continued play.

4.2 Mechanism performance

In this section, we evaluate the economic suitability of the four allocation mechanisms with respect to their performance in regulating externalities, attaining high levels of allocation efficiency, and implementing socially desirable income distributions. While the former two evaluation criteria are apparent, the third one may require some further motivation. Performance appraisals of allocation mechanisms in general and auctions in particular typically assume the seller’s perspective and address the mechanisms’ revenue equivalence or -disparity. Mechanisms based on the fair division property, by contrast, feature a common ownership structure which precludes argumentations centered on the seller’s revenue. In this setting, the welfare-economic property of income variance minimization comes to mind as an alternative benchmark.

Regulation of externalities

As one central evaluation criterion, we rate the distinct mechanisms by their ability to regulate negative externalities. Theoretically, both the one- (O1/2) and the two-dimensional mechanisms (T1/2) perfectly protect bidders against net losses that result from the allocation outcome. In (T1/2), truthful bidding ($\kappa_i = K_i$) guarantees the neutralization of incurred damages, while the same result is achieved in (O1/2) by stating an expected net trade satisfying $\nu_i \geq 3K_i$. If the bidder acquires the good in the latter case, she earns $\frac{2\nu_i}{3} \geq 0$ in (O1/2) whereas, otherwise, she earns $\frac{\nu_{(n)}}{3} - K_i \geq 0$ in (O1) and $\frac{\nu_{(n-1)}}{3} - K_i \geq 0$ in (O2). Irrespective of the particular allocation outcome, bidders thus are able to secure themselves a non-negative income.

We discern that bidders, on average, make sensible choices in all four auction formats and commonly manage to avoid economic losses. Putting economic gains and losses into perspective, we find that the sum of realized losses in (T1) merely amounts to 0.7% of the corresponding sum of realized gains. In the remaining treatments, this rate is even less pronounced (≤0.6%). Nonetheless, we discern a small minority of bidders who commit apparent bidding errors and, consequently, sporadically suffer losses in single periods. In a series of histograms, Figure 3 shows the relative frequency of realized losses in the various treatments. Such incidences are most frequent in (T2), but are economically most severe in (T1). Inefficiencies in (T1/2) are primarily related to overstating one's valuation ($\eta_i > H_i$) rather than to understating one's damage ($\kappa_i < K_i$).[16] Differently, inefficiencies in (O1/2) are primarily attributable to stating unduly low expected net trades ($\nu_i < 3K_i$) or grossly overstating one's valuation ($\nu_i > \frac{3H_i}{2}$).[17] Summarizing, all four allocation mechanisms perform adequately in regulating negative externalities and in preventing individuals from realizing economic losses.

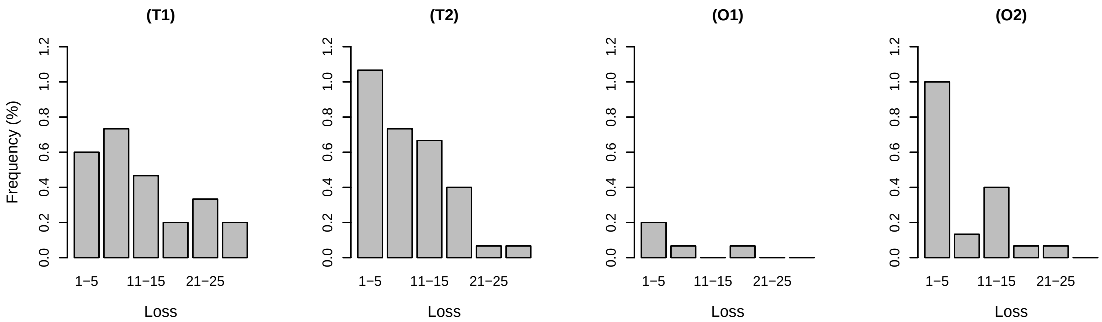

Figure 3: Frequency of realized losses

Allocation efficiency

An allocation mechanism's efficiency is arguably the most important economic decision criterion for or against its implementation. We consider two efficiency

[16] 57% (75%) of all bidders in T1 (T2) at least once succumb to the former error whereas only 30% (42%) at least once commit the latter one.

[17] 7% (40%) of all bidders in O1 (O2) at least once commit the former error and 10% (23%) commit the latter one.

statistics which are commonly employed in the literature (see Davis and Holt, 1992). Once, one may be interested in the mechanism's relative efficiency E which is based on the realized surplus of the allocation S and the maximal possible surplus $\overline{S}$ and is computed as $E = \frac{S}{\overline{S}}$. Alternatively, we may consider the mechanism's rate of optimal allocation outcomes O which relies on the number of realized optimal allocations m in relation to the number of allocation tasks n and is described by $O = \frac{m}{n}$. Timeline charts for the two efficiency statistics E and O are shown in Figure 4. To put the empirical efficiency rates in perspective, consider that random bidding, on average, yields a relative efficiency of $E = 0.835$ and an allocation efficiency of $O = 0.333$.[18]

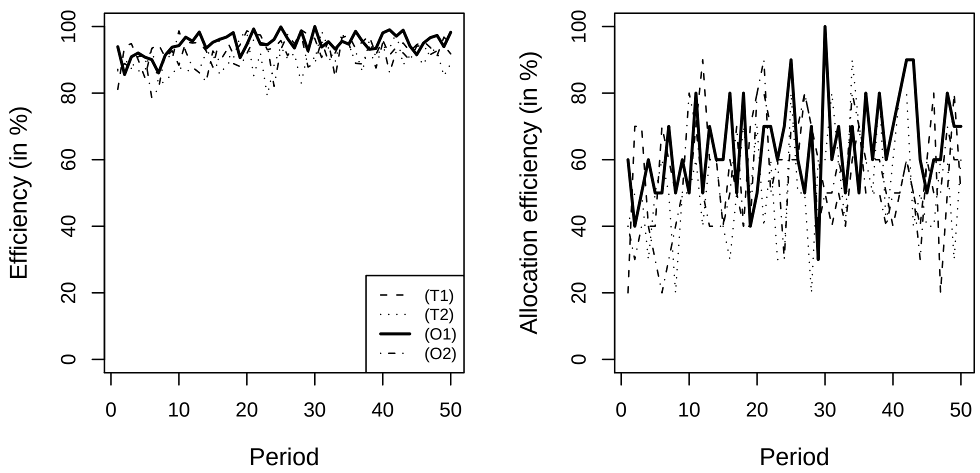

Figure 4: Efficiency and learning

Inspecting the relative efficiency of allocation outcomes yields that the empirical value range of E actually is rather small ($E \in [0.79, 1]$). Considering its small variation - which is a regular finding in appraisals of allocation mechanisms' relative efficiency (e.g., Isacsson and Nilsson, 2003) - the E-statistic is not very indicative and, arguably, not the best criterion to rank allocation mechanisms by their performance. The rate of optimal allocation outcomes O, by contrast, features more dispersed efficiency realizations in the range of $[0.40, 0.71]$ and, hence, may be seen as the more suitable ranking criterion. In fact, efficiency improvements over time become more apparent when the O-statistic is used and amount to 0.60% per period in (O2), where the improvement is the strongest, and 0.04% in (T1), where it is the

[18] Assuming that there are three bidders who uniformly state random bids, it is trivial to see that each of these agents, on average, wins the auction once in three periods. By contrast, the relative efficiency benchmark is less apparent and was derived by simulating 10000 allocation tasks in which bidders made random statements concerning η_i and κ_i in (T1/2) or ν_i in (O1/2).

Table 4: Linear regression explaining (relative) efficiency

Coefficient	*Estimate*	*Std.Error*	*p-value*
Intercept	92.586	0.717	< 0.001
Bid vector	-1.229	0.768	0.110
2nd price	-3.889	0.768	< 0.001
Bid vector × 2nd price	0.625	1.063	0.557
Period	0.090	0.018	< 0.001
	# obs.: 2000		adj.R^2: 0.032

weakest.

Besides, the data analysis brings up two further insights. One is that the relative efficiency rate E and the rate of optimal allocation outcomes O are strongly correlated. Hence, the more efficient an allocation mechanism becomes in terms of E, the more frequently it coincides with the optimal allocation based on the bidders' (un)truthful reports on their types. And second, we discern that applying the first- (second-) price rule leads to, on average, higher (lower) levels of allocation efficiency. This finding is not novel, bearing in mind that the same conclusion already was drawn in related experimental studies on auction- and fair division allocation mechanisms (see, e.g., Güth et al., 2002).

One possible explanation for this regularity is that bidders simply are more familiar with the first-price rule which they may know from practical economic interactions. Additionally, they may appreciate the mechanism's plainness, in the sense that bids and payments are equivalent. The second-price rule, by contrast, arguably is more sophisticated and may confuse inexperienced bidders, as a result of which they may bid less systematically and, ultimately, less efficiently.[19] Lastly, according to theoretical considerations, both auction formats should bring about the efficient allocation whereas the expected price for the seller may vary, in particular if buyers are risk averse (e.g., Matthews, 1987).

To evaluate the systematic influence of the alternative elicitation methods and price rules more thoroughly, we fit a linear model explaining the relative efficiency E in the four allocation treatments. The corresponding regression results are shown in Table 4.

The explained variable is expressed as a rate and is bounded between $[0, 100]$. As covariates, we include the bid elicitation format "Bid vector" (vs. "scalar bid"), the

[19] Further discouraging factors of second-price auctions that are regularly mentioned in the auction literature are the fear of (bid-taker) cheating and disincentives for bidders to follow truth-revealing strategies (cf., Rothkopf et al., 1990)

price rule "2nd price" (vs. first-price), and their interaction term "Bid vector × 2nd price." Lastly, to control for learning dynamics, we also include the time dummy "Period." The estimated model corroborates our preceding conjectures. Strikingly, the relative efficiency E of allocation outcomes universally is high across treatments. Moreover, we find that the relative efficiency of allocation outcomes significantly conditions on the implemented price rule in the sense that implementing the first-price rule uniformly leads to more efficient results. Conversely, the partial effect of the employed bid elicitation format on the mechanism's relative efficiency is negligible, as is the interaction effect between the bid elicitation format and the price rule. Finally, we discern that bidders achieve to systematically - even if only marginally - improve their bidding strategies over time, as a result of which E steadily increases.

Income distribution

In evaluating the allocation mechanisms' distributional effects, we first compare the profits of winning- and non-acquiring bidders and, in a second step, contrast the distinct mechanisms at the aggregate level. Figure 5 shows a series of boxplots that summarize the winning bidder's (W) and the indemnified bidders' (I) periodic profits in the four treatments. We immediately discern a characteristic pattern in the distribution of profits between the two ex-post bidder roles. In treatments (T1/2), indemnified bidders, on average, earn significantly more than their winning counterparts in (T1), respectively realize comparable profits in (T2).[20] Conversely, the payoff ranking for the two roles is reversed in (O1/2). In these treatments, winning bidders earn significantly more than their non-acquiring co-bidders.[21]

The primary reason for this regularity is that in (T1/2), the winning bidder i is obliged (by the mechanism design) to compensate the two non-acquiring bidders to the amount of their stated damages κ_{-i}. Additionally, bidder i also has the liability to pass on equitable shares of $\nu_{(n)}$, respectively $\nu_{(n-1)}$ to her co-bidders. Bidders in (O1/2), to the contrary, exclusively compete in terms of their stated net trades ν_i. Any damages κ_{-i} which are incurred by the non-acquiring bidders may only be neutralized through the equitable transfer $\frac{\nu_{(n)}}{3}$ in (O1) or $\frac{\nu_{(n-1)}}{3}$ in (O2) from the winning bidder. In these two treatments, a direct compensation for stated damages does not exist.

Most bidders quickly become aware of the non-negligible income gap between the two ex-post bidder roles and - with experience - persistently work toward obtaining

[20] $\pi_W < \pi_I$ in 33 out of 50 periods in (T1) ($p < 0.05$, one-sided MWU-tests), respectively $\pi_W = \pi_I$ in 44 out of 50 periods in (T2) ($p < 0.05$, two-sided MWU-tests).

[21] $\pi_W > \pi_I$ in 41 (34) out of 50 periods in O1 (O2) ($p < 0.05$, one-sided MWU-tests).

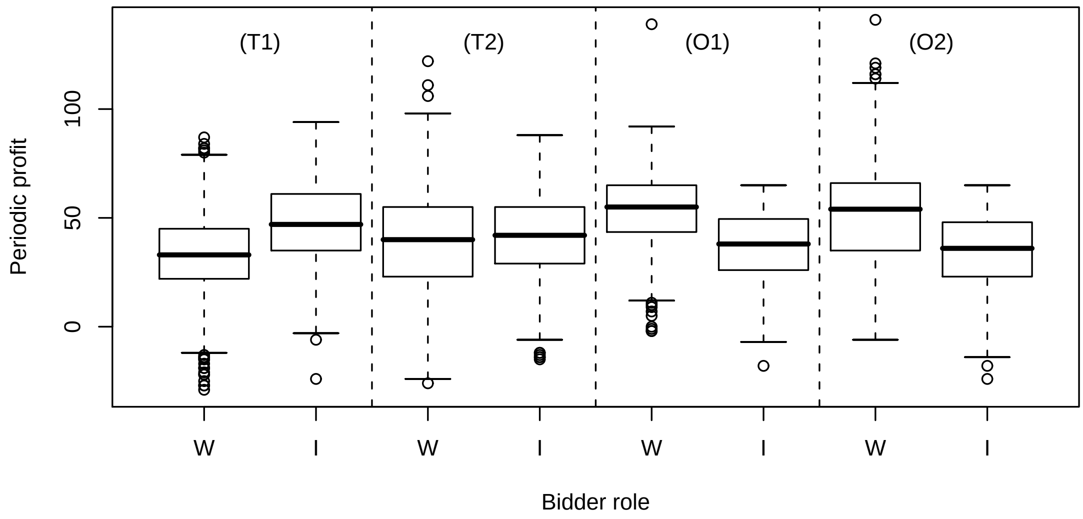

Figure 5: Periodic profits

Note: W (I) denotes the group of winning (indemnified) bidders.

the more rewarding bidder role in their treatment.[22] To this end, they systematically decrease their stated valuation in (T1/2), respectively post higher stated net trades in (O1/2). As yet another income-raising strategy, many bidders in (T1/2) also overstate their damages κ_i to take advantage of this risk-free income premium $\kappa_i - K_i$ in case that they eventually should become a non-acquiring bidder.[23]

Turning to aggregate statistics, Figure 6 shows the cumulative distribution function (CDF) of the relative efficiency rate (left panel) and the income concentration rate (right panel) of the four allocation mechanisms. With respect to the latter rate, the degree of income concentration within a group is expressed by the corresponding Gini coefficient. Although the respective CDF-curves generally run in close proximity, we observe that the CDF for (O1), the bold curve, is almost universally below (above) the three other CDF-curves in the relative efficiency (income concentration) plot. The former point signifies that (O1) brings about more highly efficient allocation outcomes than any other of the remaining allocation mechanisms. The latter

[22] Bidders in the less-earning ex-post bidder role, i.e., winning bidders in (T1/2) and non-acquiring bidders in (O1/2), generally are successful in improving their income at the expense of their respective counterpart. As a result, winning bidders in (T1) and non-acquiring bidders in (O1/2) are able to significantly reduce their gap in period income over time ($p \leq 0.044$, periods 1-25 vs. periods 26-50, one-sided MWU-tests).

[23] We already pointed out these learning dynamics while discussing the results of a series of regression models explaining individuals' empirical bid functions (see Table 3).

point reveals that in (O1) - out of the four treatments - the generated income from the allocation is most evenly distributed among the bidders.

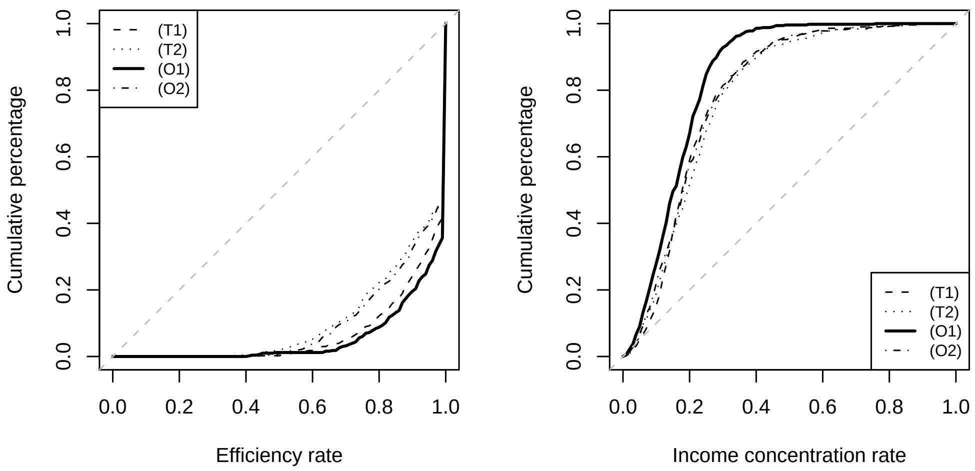

Figure 6: Efficiency and income concentration

Altogether, treatment (O1) combines three attractive properties: First, the allocation mechanism almost perfectly resolves negative externalities and, hence, secures a non-negative income for all participating bidders. Second, it provides for the, on average, highest level of allocation efficiency. And third, it achieves the most equitable income distribution of the four inspected allocation mechanisms.

5 Discussion

We experimentally implemented four distinct allocation mechanisms - which all exhibit the fair division property - with two main research goals in mind. The primary objective of the study was to characterize individuals' bidding behavior, to identify regularities, and to evaluate the conformity between participants' empirical bidding behavior and a normative benchmark. The secondary objective then was to characterize and compare the various mechanisms' (welfare-) economic performances.

The experiment relied on a 2×2 factorial design in which the applicable price rule (first- vs. second-price, denoted by $(\ldots 1)$ and $(\ldots 2)$) and the underlying bid elicitation format (valuation and damage statements vs. expected net trade claims, denoted by $(T \ldots)$ and $(O \ldots)$) were systematically varied. Bearing in mind that the bidders' valuations and damages constituted private information, the investigated mechanisms represent games of incomplete information. This fact immediately raises questions concerning the mechanisms' practical incentive compatibility which can be assessed by inspecting the prominence of both truthful reporting and strategic bid manipulations. With respect to the secondary objective, we quantified the distinct mechanisms' relative and allocation efficiency and investigated their distributional effects.

Most bidders exhibit largely systematic and economically sensible bidding patterns. As a general rule, stated bids (i.e., valuations, damages, or expected net trades) monotonically increase in the value of their underlying values (i.e., the bidders' types). We further observe that the empirical bid functions in the various treatments and their simulation counterparts feature meaningful similarities. Most bidders immediately discern the lacking incentive compatibility of all four allocation mechanisms and, as a result, strategically misrepresent their private information with the aim of appropriating extra rents. While private valuations of the auctioned good are partly under- (T1) and partly overstated (T2), potential damages - due to the good's external effect - are almost uniformly overstated. Truthful reporting despite the mechanisms' adverse incentive structure only is observed in a small minority of bidders (14% in (T1/2)) and, moreover, is found to further decline with experience.

This regularity is indicative in pointing out that - when having to choose between truthfully reporting one's private information or bidding strategically in auction settings - a sizable fraction of individuals will opt for the latter. In view of our results, individuals, on average, do not entertain strong intrinsic preferences for truth-telling in auction scenarios that feature asymmetric information and lack the economic incentives to make truthful reporting the dominant strategy. More broadly, this behavioral attitude takes on economic relevance when we consider that deviations from truthful reporting increase the likelihood of inefficient allocation outcomes.

Nonetheless, we also observe that bidders converge in their individual behavior over time such that - despite strategic bid manipulations - the bidder with the actually superior net trade is correctly identified with increasing probability. As a consequence, both allocation efficiency and individual profits systematically rise over time to eventually attain appreciable levels. Despite the mechanisms' lack of incentive compatibility, the efficiency of observed allocation outcomes thus only is marginally inferior to the full efficiency outcome that would result from truthful reporting. In all, it seems that the absence of strategy proofness in the four allocation mechanisms only is of secondary economic relevance.

Corroborating preceding experimental findings (e.g., Güth et al., 2002), we further provide supporting evidence that allocation mechanisms implementing the first-price rule may systematically outperform their second-price counterparts. By contrast, we do not discern structural differences between one- and two-dimensional allocation mechanisms in terms of their respective efficiency, once the applicable price rule is controlled for. Lastly, we identify one allocation mechanism which relies on eliciting expected net trades and employs the first-price rule (i.e., mechanism (O1)) to systematically outperform all other considered mechanisms in terms of externality regulation, allocation efficiency, and an equitable income distribution. Hence, this mechanism may be considered as a helpful tool to solve particular classes of allocation problems that involve private information, asymmetric bidders, and negative externalities.

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A Experimental instructions

The following instructions originally were written in German.

Welcome and thank you for participating in this experiment. For arriving in time, you receive a fixed amount of €2.50. Please read the following instructions - which are identical for all participants - carefully and, from now on, do not talk to fellow participants anymore. In the experiment you can earn money whose amount will depend on your own choices, as well as on the choices of other participants. As a general rule, all of your decisions remain anonymous and cannot be related to your name. If you have questions, please raise your hand. An experimenter will then come to your place and answer your questions individually.

The general setting

In this experiment, you and other participants repeatedly bid for a single license to implement a project which generates profits but, at the same time, hurts its environment (e.g., an industrial plant). Throughout the experiment, you take part in fifty bidding games in each of which you interact with two other bidders who were randomly assigned to your group (of size three).

In each bidding game, every bidder is informed about two individual characteristics that were randomly assigned to her, namely her "valuation" of the project and her incured "damage" from the project. The former value denotes the bidder's economic gain if she were awarded the license. Think of this gain as earnings that directly result from the profitable operation of an industrial plant. Valuations are randomly and independently drawn for each bidder from the interval $[125, 200]$. In this interval, all values have the same probability of being chosen.

The latter of the two values refers to the economic damage that the bidder incurs if the license were issued to another bidder. In this case, the damage is caused via negative side effects that originate from the winning bidder's operating facility. Analogously to valuations, damage values are randomly and independently drawn from the interval $[1, 50]$ with, again, all values therein being equally likely.

Bidders differ in the extent to which they derive benefits from implementing their own project, as well as in the extent to which they are harmed by another bidder's production activity. Consequently, bidders' individual valuations and damages are very likely to - at times even substantially - differ.

Summarizing, each bidder hence is characterized by her "valuation" of the project, i.e., the profit that she derives from implementing the project provided that she is awarded the license, and her "damage" from the project, i.e., the loss she suffers if another bidder is awarded the license instead.

As a general rule, the license is awarded to the bidder

- for whom the difference between her stated valuation of the project and the sum of the stated damages of her co-bidders is maximal (in (T1) and (T2)), respectively
- who states the largest difference between her own valuation of the project and her expectation about her co-bidders' sum of damages (in (O1) and (O2)).

Prior to placing their bids, each bidder is informed about her individual valuation and damage parameters. Note that each bidder only is informed about her own characteristics, i.e, does not receive any information about her co-bidders' characteristics. At the end of each bidding game, bidders learn whether they were successful in acquiring the license and are informed about their period incomes. In the following, all participants are randomly reassigned to form new groups, as a consequence they - in all likelihood - interact with a different set of bidders in the subsequent bidding game.

In a nutshell, the four bidding mechanism can be summarized as follows:

- In (T1/2): Each bidder must state her individual valuation and damage whereby these statements may - but need not - conform to the bidder's true valuation and damage. Stated valuations (damages) must assume values in the interval $[125, 200]$ ($[1, 50]$).
- In (O1/2): Each bidder must state her expected net trade which corresponds to the difference between the bidder's valuation and the sum of her co-bidders' expected damages (as predicted by the bidder herself). The stated value must lie within the interval $[1, 198]$.
- Universally: One of the three bidders in a group - namely the one who wins the bidding process - eventually is awarded the single license. More specifically, the license is acquired by the bidder for whom the difference between her stated valuation and the sum of the co-bidders' stated damages is the maximal (T1/T2), respectively who states the largest expected net trade (O1/2).
- To avoid excessive waiting periods, bidders are encouraged to enter their valuations and damages (T1/2), respectively their expected net trades (O1/2) within a timespan of sixty seconds.

How your periodic income is determined

Both as the winner of the auction or as an non-acquiring bidder, your period income consists of several additive payments. As the winning bidder, you earn your valuation of the project from which a specific portion is transfered to your co-bidders. As a non-acquiring bidder, you incur an economic loss equal to your damage value, but simultaneously receive a positive payment from the winning bidder as a compensation. The latter payment which is transfered from the winning to each of the two non-acquiring bidders is determined as follows:

transfer = $\frac{1}{3}$ * (winning bidder's stated valuation -
sum of co-bidders' stated damages) (T1/2)

transfer = $\frac{1}{3}$ * (winning bidder's stated expected net trade) (O1/2)

Your periodic income in either of the two possible ex-post roles then equates to:

Income winner (T1/2):
own actual valuation - sum of co-bidders' stated damages - 2 * transfer

Income winner (O1/2):
own actual valuation - 2 * transfer

Income non-acquirer (T1/2):
own stated damage - own actual damage + transfer

Income non-acquirer (O1/2):
transfer - own actual damage

Your final payment

At the end of the experiment, your periodic earnings over the fifty bidding games are summed up and converted into euros at the rate of 100 ECU = €0.50, to which the above mentioned fixed amount of €2.50 is added. The resulting amount then is disbursed to you in cash.

Miscellaneous

Before starting with the experiment, we kindly ask you to fill in a control questionnaire on your computer screen. The questions therein are asked to ensure that you have fully understood how the allocation mechanism operates and how your and others' payoffs are determined.

If you brought a mobile phone with you, please switch it off now. Also, please remain calmly seated at your place throughout the entire experiment. If you have any questions, please raise your hand and an experimenter will come to your place and answer them.

B Simulation exercise

In the following, we rely on numerical methods to generate suitable benchmarks for the four allocation mechanisms. While we acknowledge that an analytic solution clearly is preferable to a numerically derived one, we cannot yet present the former at this point.

In particular, the following aspects are problematic. Bidders interact in a stochastic model in which private valuations (H_i) and damages (K_i) are independently drawn from uniform distributions. In each treatment, the bidders' payoff function thus comprises two stochastic elements and additionally relies on order statistics of the set of (expected) net trades ($\nu_{(n)}$ in (T1) and (O1), $\nu_{(n-1)}$ in (T2) and (O2)). As a result, the specification of the functional forms of the single bid function in (O1/2) and the two separate bid functions in (T1/2) is not immediately evident. For simplicity, we henceforth arbitrarily assume all bid functions to be linear. As a second issue, it is not evident either whether the two bid functions that yield the predictions for η_i and κ_i in (T1/T2) should incorporate both the bidders' valuations H_i and damages K_i or whether they should only consider one of the two parameters (see also Table 3).[24]

Considering the above difficulties in deriving the analytic solutions of the four allocation mechanisms, it seems legitimate to also consider alternative approaches. Numerical optimization may be one of them. This computational technique can be applied to study problems where real-valued target functions are to be maximized or minimized. In the following, we are particularly interested in a derivative-free optimization algorithm referred to as "hill climbing" (see Norvig and Russell, 2002). This approach belongs to the family of local search algorithms, is relatively simply applied, and frequently yields solutions that are close approximations of those of more advanced search algorithms.

In our setting, the target function denotes the economic gain from a marginal, unilateral deviation from a particularly defined (set of) bid function(s). This approach equates to solving a fixed point problem and relies on the Nash equilibrium property. Evidently, the four simulation exercises (one per treatment) are implemented under the same conditions and constraints as the four auction treatments.[25] In the initial step of the simulation, an arbitrary vector of bid function coefficients is defined. From this starting point, the algorithm then repeatedly evaluates the bid-

[24] The question is whether a bidder's damage parameter K_i (valuation H_i) also shapes her stated valuation η_i (stated damage κ_i).

[25] Hence, each auction format always involves three bidders whose types are randomly drawn from corresponding uniform distributions.

der's gains from deviating into the immediate surroundings of that vector. In this process, the algorithm for instance investigates whether it pays to state a marginally higher (lower) valuation than what is suggested by the current bid function specification.[26] In a second step, the vector of coefficients is marginally adjusted in the direction of the steepest ascend in profits. As a result, the bidder's expected profit henceforth surpasses the ones of her co-bidders. And third, in response to this unilateral deviation, the latter bidders adopt the perpetrator's bid vector and thereby neutralize her extra rent.[27] This process is iterated during a large number of repetitions until the simulation satisfies a predefined stopping criterion.

Although the algorithm leads to a substantial improvement over the (random) initial bid vector - in the sense that it approximates a fixed point and minimizes the expected profit from unilateral deviations - it, however, fails to converge to a clear-cut terminal state. Rather, the estimated bid vector persistently fluctuates in the vicinity of the presumed terminal state while the intensity of bid vector adjustments fails to monotonically decrease toward zero. In part, this behavior may be due to the imperfect mapping of the uniform distributions which underlie the bidders' valuations and damages (i.e., computer-generated random values actually are not random). Alternatively, the algorithm's failure to converge may be caused by local maxima, ridges, and plateaus in the fitness landscape, or may be due to the hill climbing mechanism itself which is not guaranteed to uniformly converge. To at least obtain a rough estimate of the "optimal" bid vector, we use the coefficient means of the estimated bid vector as "approximate" benchmarks (see Figure 7 and Table 5).[28] In section 4, we compare these simulated benchmarks with the elicited bids from the experiment and their derived bid functions.

The simulation results can be summarized as follows. Coefficient estimates vary substantially in the precision of their interval predictions. While several coefficients (e.g., β_0 and β_3 in (T1/2)) can be ascertained with relative accuracy - in the sense that they feature only small variances and interquartile ranges - others (e.g., β_2 in all treatments) can only be roughly approximated. Most coefficients assume interior

[26] The gain or loss of the ceteris paribus adjustment of a single coefficient of the bid vector is averaged over a sample of 1000 random combinations of valuation and damage parameters for the bidder under consideration and her co-bidders. The simulation script (written in R) can be obtained from the author upon request.

[27] Given the stated adjustment dynamics, the search algorithm is limited to approximating a symmetric equilibrium only.

[28] In a second step, the game theoretical benchmarks should be analytically derived. This would allow to unambiguously determine the correct functional form of the bid function(s) and to exactly quantify - rather than to numerically approximate - the former's respective coefficients. Additionally, this approach would enable a more thorough equilibrium analysis with respect to potential systematic over- or underbidding.

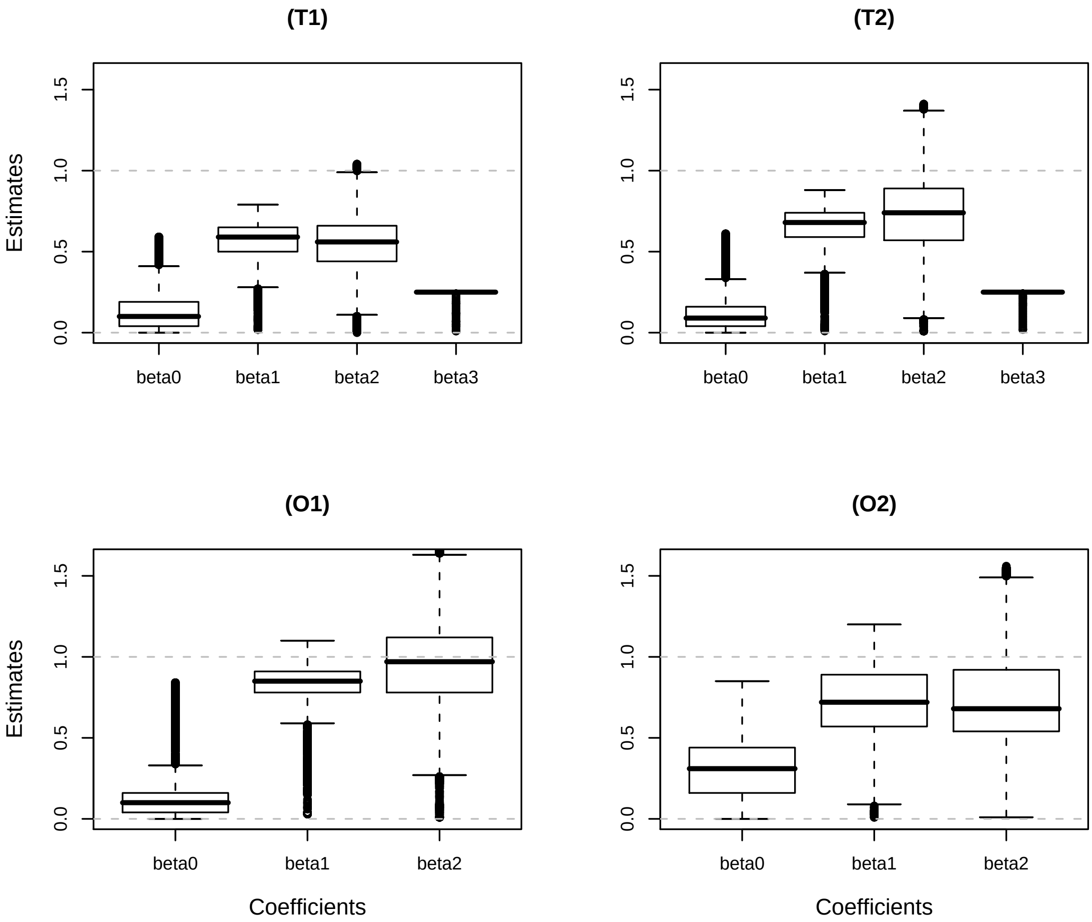

Figure 7: Simulation results

Note: Coefficient estimates are derived from the simulation exercise.

Table 5: Normative benchmarks

Treatment	Dependent variable	Coefficient estimates Intercept β_0 or β_3	Valuation (H_i) β_1	Damage (K_i) β_2
(T1)	η_i	0.13	0.57	0.55
	κ_i	0.25		
(T2)	η_i	0.11	0.66	0.72
	κ_i	0.25		
(O1)	ν_i	0.11	0.84	0.95
(O2)	ν_i	0.31	0.72	0.75

Note: Coefficient estimates are derived from the simulation exercise.

values in their domain, with the exception of $\beta_0(\approx 0)$ in (T1/2) and (O1) and $\beta_3(\approx \overline{\kappa} = 0.25)$ in (T1/2) which may be interpreted as border solutions. Systematic bid shading in the sense of underbidding one's actual valuation η_i is observed in all treatments (with $\beta_1 < 1$ being the scaling factor of H_i) whereby underbidding tends to be slightly more pronounced in (T1) than in (T2). With respect to damage claims, the simulation yields that overstating actual damages ($\beta_3 \approx \overline{\kappa}$) in (T1/2) seemingly is the dominant strategy.