Electronic sourcing with multi-attribute auctions

Stefan Strecker
University of Karlsruhe
Department of Economics and Business Engineering
Information Management and Systems
Englerstr. 14, D-76131 Karlsruhe, Germany
Email: strecker@iw.uni-karlsruhe.de

Stefan Seifert
University of Karlsruhe
Department of Economics and Business Engineering
Information Management and Systems
Englerstr. 14, D-76131 Karlsruhe, Germany
Email: seifert@iw.uni-karlsruhe.de

***Abstract*— Multi-attribute reverse auctions have been proposed as market institutions for "electronic request for quotation" buying processes. The choice of a multi-attribute auction institution for corporate sourcing is a challenge for the auctioneer in terms of utility maximization and allocational efficiency. The authors report on a computer-based laboratory experiment in a sole sourcing scenario of a single, indivisible object and investigate whether a multi-attribute reverse English and a multi-attribute reverse Vickrey auction institution lead to identical outcomes with respect to the buyer's utility, suppliers' profits and allocational efficiency. The results show no significant difference in suppliers' profits. However, the English auction institution leads to both higher allocational efficiency and buyer's utility and is thus recommendable to corporate buyers. The documented breakdown of the outcome equivalence of the two auction institutions is attributed to bidders deviating from the dominant bidding strategy. The deviations are analyzed and explained by learning effects.**

I. INTRODUCTION

Corporate sourcing of heterogeneous, differentiated goods and services (henceforth, objects) is typically based on "requests for quotations" (RFQ). In an RFQ process, a corporate buyer announces the technical specification of the object in question, lists a number of negotiable attributes and invites potential suppliers to submit multidimensional bids on the negotiable attributes. Subsequently, the buyer evaluates the submitted bids (offers), ranks them according to her preference relation regarding the negotiable attributes and awards the contract to the supplier who has submitted the highest ranked bid. The heterogeneity and complexity of objects regularly requires corporate buyers to consider further attributes in addition to the price of the deal in the buying decision [1], e. g. object quality, lead time, terms of transportation, or warranty as well as internal criteria such as supplier reputation or incumbent switching costs [2]. The rationale underlying these procurement processes is that the buyer seeks to designate the contract to the supplier who offers the best price/performance ratio and not necessarily to the supplier who offers the lowest price, since often the lowest cost seller does not provide the best combination of price and quality [3]. On the other hand, the buyer assumes that (i) the offered objects vary in quality (object heterogeneity) and (ii) that suppliers possess comparative advantages in production costs along the quality dimensions (supplier heterogeneity) [4]. These buying processes apply to a diverse spectrum of inputs, e. g. the sourcing of contract programming [3], [5], truck fleets or coal [6].

In an RFQ-based buying process, bid evaluation and winner selection are labor-intensive, time-consuming, and costly which is why procurement departments are seeking to (partially) automate the RFQ process [2]. However, negotiations in electronic sourcing are commonly based on reverse auctions in which the price is the unique strategic dimension and all non-price attributes of an object are fixed prior to the negotiation ("price-only auctions") [1]. Although price-only auctions have been reported to lower explicit and implicit transaction costs for the buyer [7], they potentially lead to inefficient outcomes when differences in quality exist and suppliers exhibit comparative advantages in production costs [4]. An inefficient outcome foregoes gains from trade and leaves potential value unrealized [8].

Recent advances in information and communication technology facilitate the implementation of electronic auctions, which closely resemble the RFQ buying process. These multi-attribute auctions provide means to automate bid submission, bid evaluation and winner selection in terms of an "electronic request for quotation" (eRFQ) [2]. In a multi-attribute reverse auction, the buyer (bid-taker, auctioneer) specifies her value trade-offs among multiple negotiable attributes of an object by defining a scoring rule (value or utility function) based on her preference relation. During the auction process, the buyer solicits bids from invited suppliers (bidders) according to the rules of the bidding procedure. The buyer's scoring rule is used to evaluate submitted bids and to designate the contract to the bidder providing the highest utility score to the buyer [9].

However, when designing and implementing multi-attribute auctions for the application to corporate sourcing, buyers have essentially to rely on their intuition, since (i) experience and know-how are typically missing for the lack of exemplars and (ii) because the theoretical as well as empirical findings about multi-attribute auctions are rudimentary [4]. In particular, the choice of a multi-attribute auction institution remains a particular challenge for the auctioneer as she is faced by two sometimes conflicting goals: utility maximization and allocational efficiency [10]. Obviously, the auctioneer seeks to maximize her utility. However, a sole focus on maximizing the buyer's utility may chase suppliers away in the long run, which is counterproductive in a sourcing case where repeated buying is key [11]. Moreover, the selection of an appropriate sourcing software or provider is a difficult task as a multitude of vendors advertises a wide variety of auction-based multi-attribute electronic sourcing solutions [12], e. g. FrictionlessCommerce [2], Perfect Commerce [11], and Moai [13].

This paper reports on the results of a computer-based laboratory experiment designed to compare the performance of two multi-attribute auction institutions. It makes a contribution to the selection of a suitable bidding procedure for the application to corporate sourcing, which in turn assists corporate buyers in choosing an electronic sourcing solution. In the experiment, the authors benchmark a multi-attribute reverse English auction with a multi-attribute reverse Vickrey auction for the sourcing of a single, indivisible object with two non-price, quality attributes. From a theoretical point of view both auction institutions lead to identical and efficient outcomes. We compare the allocative efficiency of auction outcomes and analyze whether the buyer or the suppliers are better off with either institution. Section II briefly summarizes related work on multi-attribute auctions. Section III presents the experiment set-up and introduces the theoretical framework underlying the experiment. The experimental results are presented in Sec. IV, and Sec. V concludes with the implications of the experimental evidence.

II. Related work

Multi-attribute auctions are an extension to standard auction theory [14], among others, e. g. multiunit or combinatorial auctions [15]. Different approaches to auctioning over multiple characteristics of an object have been proposed. Related auction institutions have been termed multidimensional [4], [16], [17], multiple issue [18], and multicriteria [19] auctions. A basic distinction exists between multi-attribute auctions based on a scoring function and those without any explicit scoring rule. The class of multi-attribute auctions considered in this paper is based on an explicit model of the buyer's preferences in form of a scoring rule.

Generalizations of standard auction theory to the multi-attribute case have been discussed by Thiel [20], Che [16], Branco [17] and more recently by David et al. [21] and De Smet [22]. Thiel shows that the design of multidimensional auctions is equivalent to the design of standard single-dimensional auctions, assuming that the buyer has a fixed budget and does not value any price reduction [20]. The latter assumption does in general not hold in the corporate sourcing context considered here [4]. Che discusses the design of optimal multidimensional auctions in government contracting [16]. He investigates sealed-bid auctions in a two-dimensional (price and quality) procurement problem. The suppliers' type is modeled by a single cost parameter which is independently and identically distributed across suppliers. The buyer is assumed to know the probability distribution of the symmetric bidders' cost parameters. Che analyzes a first- and second-score as well as a second-preferred offer auction institution, where the latter differs from the second-score institution in that the winning supplier is obligated to deliver the exact specification of the second-best bid, not just an equivalent utility score. He shows that in case the scoring rule reflects the buyer's true preferences, all three institutions yield the same auctioneer's utility. However, Che finds that it is optimal for the auctioneer in the first- and second-score institutions to manipulate the scoring rule in order to discriminate quality in relation to price. The assumption of independent costs seems unrealistic in the case of corporate procurement where manufacturing processes can be assumed similar among a set of suppliers. Branco generalizes Che's model to correlated costs among suppliers and investigates welfare maximization in sealed-bid institutions [17]. He finds that a two-stage first- and a second-score auction are optimal: In the first stage, a supplier is selected and in the second stage, the buyer bargains about the quality dimension.

David et al. study a multi-round variant of a multi-attribute reverse English auction in which the buyer announces a scoring rule and suppliers bid sequentially in a randomly defined order [21]. In every round, bidders are eligible to submit bids with the same utility score in which case the new high bid is chosen randomly. The buyer's and suppliers' utility functions are based on multi-attribute utility theory (MAUT) [23]. The suppliers' costs are independently and identically distributed and the distribution function is known by the buyer. The authors show that rational bidders first choose the Pareto optimal non-price attributes with respect to the buyer's scoring rule independent of the current best bid and then choose a price with respect to the desired utility score given the levels for the non-price attributes. This holds in a model of supplier types with a single cost parameter and is extended to cases when supplier types possess two or more cost parameters. David et al. derive the optimal bidding strategy for suppliers in both cases as well as the expected buyer's utility and optimal weights for the buyer's scoring rule. De Smet criticizes (i) the assumption of total comparability among bids and (ii) the need to a priori determine weights in MAUT-based institutions [22]. His approach does not require total comparability between multi-criteria alternatives [24]. De Smet models an English auction that accepts incomparabilities among bids by restricting comparisons to "similar" bids and allows for updates of weights during the bidding procedure. Yet, the proposed model compromises on the uniqueness of the final outcome and on other properties of game theoretic auction models.

Although MAUT has been widely used to model decision-maker's preferences [25], [26] and has been employed in multi-attribute auctions [27], the preference model underlying this experiment is formalized by a stylized quasi-linear utility function proposed by Milgrom [11]. Note that the issues of preference elicitation and misrepresentation of preferences are not subject to the present experiment [2], [27]. The multi-attribute Vickrey auction in the present experiment follows Milgrom's approach and is similar to Che's second-score auction. In contrast to the approach by Branco, the present experiment investigates single-stage bidding procedures, in which price and non-price attributes are negotiated simultaneously. Different from the multi-round variant in David et al., the English auction institution considered here is based on real-time bid submission instead of sequential bidding rounds.

III. Experiment

A. Microeconomic system

The experiment implements a multi-attribute bidding scenario in which a single buyer (bid-taker, auctioneer) intends to acquire a single, indivisible object from exactly one of five potential suppliers (bidders), denoted by $i \in I = \{1, \ldots, 5\}$. The bid-taker specifies the required characteristics of the object in question except for three negotiable attributes, namely the price p and two abstract qualitative, non-price attributes x and y.

The buyer announces her intention to acquire the object and asks the suppliers to submit bids on the negotiable attributes of the object. Each of the two non-price attributes has six discrete, abstract quality levels $x \in X = \{1, \ldots, 6\}$ and $y \in Y = \{1, \ldots, 6\}$. A technical specification (x, y) of the object is a combination of quality levels of the two non-price attributes. The price $p \in P = \{0, 1, 2, \ldots, 150\}$ is a nonnegative integer. A bid b comprises a technical specification and a price, i. e. $b = (x, y, p) \in X \times Y \times P$.

The buyer perceives the discrete quality levels of each non-price attribute as measures of increasing quality. Other attributes held equal, she strictly prefers a higher quality over a lower quality in each non-price attribute. Her valuation function $v : X \times Y \to \mathbb{R}$ is monotonically increasing in both x and y with decreasing marginal value. Moreover, the buyer trades off price for quality. She demands a lower price for a lower quality and is willing to pay a higher price for a higher quality. In the experiment, her utility function u is given by

$$u(x, y, p) = v(x, y) - p \ . \tag{1}$$

Each supplier is able to produce any technical specification in the set $X \times Y$. A supplier i's production cost function $c_i : X \times Y \to \mathbb{R}$, $i \in I$ is monotonically increasing in both x and y with increasing marginal costs. His profit is given by the profit function

$$u_i(x, y, p) = \begin{cases} p - c_i(x, y) & \text{, if } i \text{ supplies the object} \\ 0 & \text{, otherwise .} \end{cases} \tag{2}$$

In the experiment, we investigate two auction institutions, a multi-attribute reverse English auction and a multi-attribute reverse second-score (Vickrey) auction [9].

The multi-attribute reverse English procurement auction constitutes an iterative bidding procedure in which each bidder is eligible to submit multiple subsequent bids. Each submitted bid b is evaluated by the buyer w. r. t. her utility function $u(b)$. At any point in time, the bid b^* which achieves the highest buyer's utility is publicly announced as current high bid. If a bid b' is submitted which provides a higher utility to the buyer, i. e. $u(b') > u(b^*)$, b' becomes the new high bid ($b^* := b'$). The auction ends if no new high bid has been received for 120 seconds. The bidder who submits the last high bid produces and delivers the object with the technical specification of his last bid and is paid the price of that bid. Note that this auction institution constitutes a reverse auction, because a buyer solicits bids from multiple suppliers. It is nonetheless an ascending auction, since the bids gradually increase the buyer's utility.

The multi-attribute reverse Vickrey auction constitutes a one-shot bidding procedure. Each bidder is eligible to submit exactly one bid. The bids are not publicly announced, but submitted sealed and evaluated only after the auction has been closed. An auction closes if all bidders have submitted their bid or the announced duration of five minutes runs out. Again, each submitted bid b is evaluated by the buyer w. r. t. her utility function $u(b)$. The bidder who submitted the bid which achieves the highest buyer's utility score is designated the contract of the bid-taker. He produces and delivers the object with the technical specification he offered to the buyer in his bid, but is paid a price increased by a *surcharge*, so that the utility score of the transaction equals the utility score of the second-highest bid. This is an adaptation of the Vickrey principle to multi-attribute bidding procedures [11], [28]. If two high bids exist which achieve the same buyer's utility score, the winning bidder is selected randomly and the price surcharge is zero since the second highest utility score equals the winning bid's utility score. If only one bid is submitted, the bid wins the auction and the price surcharge is the winning bid's utility score since the second highest utility score is zero. If no bid has been submitted until the clock runs down, no winning supplier is selected.

The supplier selected by the auction institution to supply the object is denoted by $\hat{\imath}$ and the transaction price and the delivered technical specification by $\hat{p}$ and $(\hat{x}, \hat{y})$, respectively. Hence, an outcome $\hat{o}$ is denoted by a quadruple $\hat{o} = (\hat{\imath}, \hat{x}, \hat{y}, \hat{p}) \in I \times X \times Y \times P$. The social welfare of an outcome $\hat{o}$ is defined as the sum of buyer's and the selected supplier's surplus [11], i. e. $w(\hat{\imath}, \hat{x}, \hat{y}, \hat{p}) = u(\hat{x}, \hat{y}, \hat{p}) + u_{\hat{\imath}}(\hat{x}, \hat{y}, \hat{p})$. Given Eq. (1) and (2), it follows that the social welfare depends on the technical specification $(\hat{x}, \hat{y})$ and the supplier $\hat{\imath}$, but not on the transaction price $\hat{p}$, i. e. $w(\hat{\imath}, \hat{x}, \hat{y}, \hat{p}) = w(\hat{\imath}, \hat{x}, \hat{y}) = v(\hat{x}, \hat{y}) - c_{\hat{\imath}}(\hat{x}, \hat{y})$. Notice that in order to ensure comparability of results, the auction outcomes are standardized for the analysis. The maximum social welfare of the standardized outcome is set to a constant value and is denoted by $\bar{w}(\bar{\imath}, \bar{x}, \bar{y}) = \max_{(i,x,y)}\{v(x, y) - c_i(x, y)\}$.

An outcome $\hat{o}$ is called allocational *efficient* if and only if the auction outcome $\hat{o} = (\hat{\imath}, \hat{x}, \hat{y}, \hat{p})$ maximizes the social welfare, i. e. $(\hat{\imath}, \hat{x}, \hat{y}) \in \arg\max_{(i,x,y)} \{v(x, y) - c_i(x, y)\}$ among *all* five suppliers. Note that whether an outcome is efficient depends on the technical specification $(\hat{x}, \hat{y})$ *and* the supplier $\hat{\imath}$, but not on the transaction price $\hat{p}$.

An outcome $\hat{o}$ is called *Pareto efficient* if and only if the technical specification $(\hat{x}, \hat{y})$ supplied by the selected supplier maximizes the social welfare given the buyer's valuation function and the selected supplier $\hat{\imath}$'s production costs schedule, i. e. $(\hat{x}, \hat{y}) \in \arg\max_{(x,y)}\{v(x, y) - c_{\hat{\imath}}(x, y)\}$. Note that the buyer's valuation function and suppliers' production costs schedules have been prepared, so that there is exactly one Pareto optimal technical specification $(x', y')_i$ for each supplier $i \in I$ in an auction. Again, whether an outcome is Pareto efficient depends the technical specification $(\hat{x}, \hat{y})$, but not on the transaction price $\hat{p}$. If an auction's outcome is inefficient, either a combination of non-price attributes exist that would make both the buyer and the supplier better off (the outcome is not Pareto efficient) or the buyer could profit from choosing another supplier (the outcome is not allocational efficient) or both.

B. Experimental design

We analyze two treatments, E (multi-attribute reverse English auction) and V (multi-attribute reverse Vickrey auction). In both treatments, the buyer fully reveals her preferences by publicly announcing the utility function $u(x, y, p)$. In the instructions, the bidders receive the following information (monotonicity constraints) about the buyer's preferences:

(1) Given identical qualitative attributes, the buyer prefers the bid with the lower price.
(2) The buyer prefers a higher quality level to a lower quality level within a qualitative attribute all other attributes being equal.
(3) A lower quality level in one qualitative attribute can be compensated by a higher quality level in the other qualitative attribute.
(4) Likewise is it possible to compensate a lower quality level by a lower price and vice versa.

In addition to the verbal information, the bidders receive a printout of the buyer's valuation for each technical specification and a printout of the buyer's utility score for each technical specification in a price range between 41 and 150. Additional decision support is provided by a calculation tool embedded into the bidding screen, which bidders may use to calculate either the utility score u, a quality level for attribute x or y or the price p given the values of the remaining three parameters out of u, x, y, p (see Fig. 1).

Treatment E employs the multi-attribute reverse English auction institution. Figure 1(a) shows the bidding screen in treatment E. The left-hand panel hosts the decision support tool while the right-hand panel shows the bid submission interface. The current high bid as well as remaining time for bid submission is permanently shown to the bidder in the panel above (the clock counts down to zero and is reset to two minutes whenever a new high bid is received).

In treatment V, the multi-attribute reverse Vickrey auction institution is employed. As shown in Fig. 1(b), the bidding screen is identical to treatment E except for the missing panel of the current high bid and of the different logic of the clock. The clock functions as a fixed count-down from five minutes to zero and ends the auction, unless all bidders submitted their bid earlier.

Each treatment is investigated in eight experimental sessions. In every session, five experimental subjects participate in six consecutive procurement auctions (rounds or trading periods) of the *same* treatment. Each of the five subjects takes on the role of a supplier. The buyer was not physically present during a session, but built into the experiment software. In each of the six consecutive auctions within a session, the buyer has a different valuation for technical specifications and each supplier is assigned a different production cost schedule. The suppliers' production cost schedules and the buyer's valuation functions were randomized a priori and varied between auctions, but the sequence of cost schedules was kept identical across sessions in order to ensure comparability of results. In other words, in every session the *same* production cost schedules and buyer's valuations are deployed in the *same* sequence. Note that in each of the six auctions a unique bidding equilibrium exists.

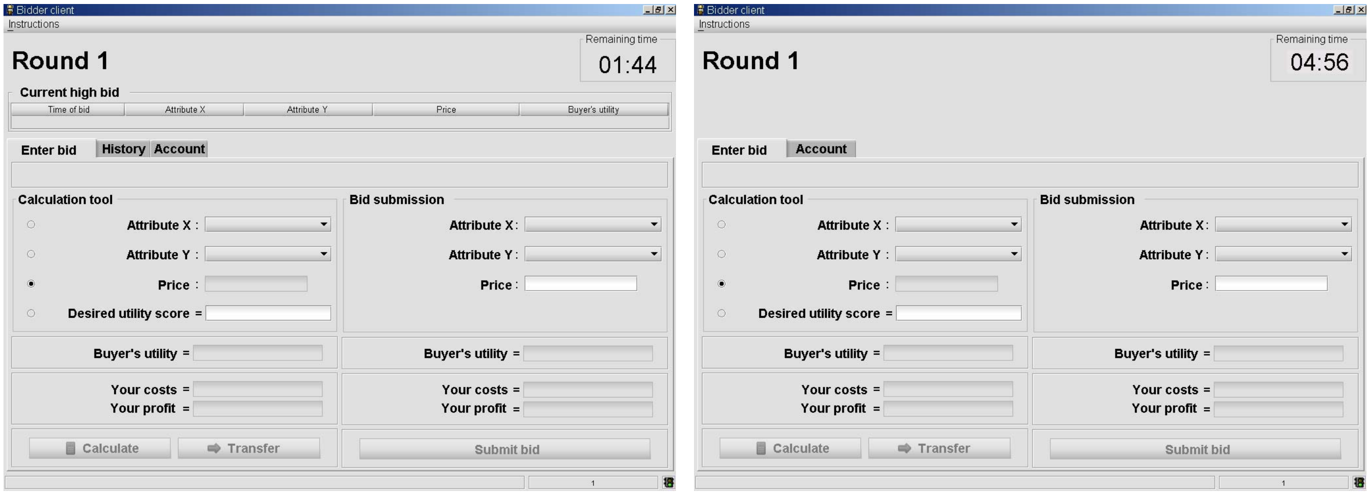
The number of competing suppliers and the number of consecutive auctions are public information. The bidders also know that in each auction only one supplier is designated the contract by the buyer and that only this winning bidder makes a profit or loss. However, the production cost schedule is private information to the respective supplier and a supplier is provided no information about the competing suppliers' production costs. The subjects remain anonymous during an experimental session and communication among subjects is not permitted. The history of winning bids is available to all bidders, but the identity of the winning or any other bidder is not revealed. It is thus not possible for the subjects to identify which competitor submitted a bid or is awarded the contract of the buyer.

At the beginning of a session, each subject is credited a show-up fee of 10.00 experimental currency units (ECU) to his experiment account. In each of the six consecutive auctions, the payoff of the winning bidder is charged to his experiment account: A loss is deduced from his balance, while a profit is credited to his account.[1] The equilibrium payoff of the winning bidder ranges from 3.30 to 4.70 ECU. Throughout an experimental session, subjects have access to their current payoff (account balance). At the end of a session, the account balance is converted to Euro, where one ECU equals one Euro.

C. Experiment software

The experiment software implements the depicted sole sourcing scenario and provides a platform for laboratory experiments. The platform has been conceived according to the usances of experimental research with a focus on economic experiments: In addition to the bidding functionality, online information on subjects' current account balance, and the results of passed auction rounds, the software provides a screen-based questionnaire, help functions, as well as provisions for client and server failures [29].

[1]For legal reasons, the instructions of the experiment ruled that a subject will be paid a zero payoff, if its experimental balance is negative at the end of a session. However, even though some subjects achieved a negative payoff in single auction rounds, their losses never exceeded the initial endowment.



(a) Bidding screen in treatment E

(b) Bidding screen in treatment V

Fig. 1. Graphical user interfaces of bidder clients

The software architecture of the experiment software is a three-tier web application based on the Sun Java 2 Enterprise Edition (J2EE) 1.3 specification [30]. The web application is based on a relational database management system in the data layer and a J2EE 1.3-compliant application server in the application logic layer. The presentation layer is implemented as Java 1.4.1 applications using the Java Foundation Classes, Project Swing graphical user interface class library [31]. A message-oriented middleware provides asynchronous communication between the server and client applications. The experiment software consists of a server application and two client applications: the experimenter client used by the experimenter to set up and operate an experimental session and the bidder client used by the subjects for bidding and information.

The central notion to the server application is a single experimental session: A session is configured, conducted and settled. The experiment preparation starts with the configuration of an experimental session which is described by Extensible Markup Language (XML) documents and validated against XML schemata [32]–[34]. All parameters of an experimental design, e. g. the initial endowment of the subjects or the maximum time per round are configurable. Moreover, the configuration contains the microeconomic system used in each round of a session. For example, the induced preferences of the participating agents are configured using production costs and buyer's valuation schedules.

The execution of an experimental session pertains to application components for monitoring and controlling an auction and provisions for software or hardware failures. During the bidding phase, the server application acts as an electronic negotiation medium [35]. It implements the auction institutions and performs bid routing and evaluation, winner determination and notification. At the same time, the back-end application provides services for market surveillance (providing market information on previous bids and the current high bid together with information on the identity of the bidder) and market control (including provisions for starting, pausing and stopping an auction).

The server permanently sends information to an authorized client application i.e. the experimenter client about the state of an auction, the state of subscribed bidder clients, and submitted bids. If necessary, the experimenter can start, pause, and stop an auction or even restart an auction round at any given state in the past of a session. After the end of an experimental session, the server application calculates the payoffs and earnings of every subject. Furthermore, the experimenter has access to the experimental data persistently collected in a database.

D. *Theoretical framework and research hypothesis*

The experiment is conducted under the assumptions of a private values model, i. e. each bidder knows his costs with certainty but has no information about other bidders' valuations [15, p. 3]. Contrary to literature on the *independent* private values model, e. g. [14], bidders do not know the distribution from which the other bidders' costs (valuations) are drawn.

The institutions investigated in this experiment are adaptations of standard auctions to the multi-attribute case. Treatment E is based on the principle of an English auction and the principle underlying the sealed-bid auction is adapted from the second-price (Vickrey) auction following [11]. It has been shown that under the independent private values model (as opposed to the common value model) both, the English and the Vickrey auction have a dominant bidding strategy regardless of the number of bidders, risk attitudes of bidders, or the distribution of private values, see e. g. [36].

Applied to the microeconomic system described in Sec. III-A, there is a dominant bidding strategy in both institutions, even though, in the present experiment, participants are not informed about the distribution of other bidders' costs (private valuations). The dominant strategy is truthful revelation of valuations:

Proposition 1 *The dominant strategy for a bidder i in the multi-attribute Vickrey auction is to bid the Pareto optimal technical specification $(x', y')_i$ at a price $p = c_i(x', y')$.*

Proposition 2 *The dominant strategy for a bidder i in the multi-attribute English auction is to (repeatedly) bid the Pareto optimal technical specification $(x', y')_i$ at the maximum price that is just low enough to outbid the current high bid. The bidder quits the auction as the required price drops below his production costs.*

To proof propositions 1 and 2, assume that a bidder deviates from that strategy. The resulting profit can then be lower but never be higher. It follows immediately that both auction institutions lead to the same outcome if bidders stick to their dominant strategy.

Experimental investigations of standard English and Vickrey auctions have repeatedly shown failures of equivalent outcomes due to deviations from the dominant strategy [37]. Replicated experimental results exist in which some bidders consistently bid above the dominant strategy price in second-price auctions, which in our reverse auction setting translates to bidding above the dominant strategy utility score or below bidders' costs (i. e. bidding too aggressively). This deviation from rational bidding behavior is attributed to "the illusion that it improves the probability of winning with little costs" [36]. Overbidding persists for a core of subjects even despite learning, i. e. prior experience with second-price or other auction formats [38]. Vice versa, bidders who deviate from the dominant strategy in second-price auctions by too defensive bids can also be observed, but to a much lesser degree [39]. In order to explain the behavioral breakdown of the strategic equivalence of second-price and English auctions, Kagel makes an analogy to preferences reversal phenomena, in which theoretically equivalent methods of preference elicitation lead to different preference orderings [36]. This psychological phenomenon has been observed in individual choice experiments [40] and is explained by perceptual errors (response mode effects), which occur when the weights attached to a dimension (in our case to an attribute) vary with the response mode and lead to a violation of the procedural invariance principle. Harstad attributes the behavioral breakdown to the particular feedback mechanism that is symptomatic for the Vickrey auction: "in a second-price auction, a subject might overbid, win, and still make money" [38, p. 262]. The bidder might (mistakenly) consider such an experience as positive feedback.

Experimental evidence on the English auction regularly shows convergence to the dominant strategy price with little or no overbidding at all, e. g. [41]. One explanation of the bidding behavior in English auctions is "observational learning" through the instant information feedback [36]. Only a few economic experiments have been undertaken with multi-attribute auctions, e. g., by Koppius and Bichler. While the former does not investigate a multi-attribute Vickrey auction [4], Bichler reports a failure of outcome equivalence between multi-attribute English and Vickrey auction institutions [27]. The bidders on average bid 0.40 percent below the dominant strategy score in the Vickrey and 5.36 percent below their highest valuations in the English auction. The author explains the latter result by the heterogeneity of the bidders' valuations and risk attitudes. The observed efficiency, defined by the percentage of auctions in which the high value holder is designated the contract of the buyer, is on average higher in the Vickrey than in the English institution. In the experiment, the two institutions also lead to different utility scores for the buyer with the Vickrey variant yielding 4.32 percent lower scores than the English variant on average. The scenario investigated by Bichler, however, differs from the one studied here. For instance, Bichler bases his experimental payoffs on market prices of financial instruments actually traded at the Vienna Stock exchange. Instead, we chose a controlled setting with allotted private valuations.

Given the earlier experimental results, we expected (i) bidders to deviate from the dominant strategy and (ii) more subjects to overbid than to underbid. Note that overbidding refers to bids that are more attractive to the auctioneer than bids according to the dominant strategy, i. e. in the chosen *procurement* setting bidders understate their true production costs and turn in bids with prices *below* these costs. We therefore conjecture that the multi-attribute generalization of the English and Vickrey auction will not always lead to identical and efficient outcomes.

E. Conducting the experiment

The experiment was conducted at the experimental laboratory of the Chair for Information Management and Systems at the University of Karlsruhe. The experiment language was German and the shown bidding screens have been translated to English for publication. Subjects were drawn randomly from a large pool of student volunteers. The subjects were undergraduate and graduate students from different disciplines with a majority from the Department of Economics.

None of the subjects had ever participated in a sourcing experiment before and none of the subjects participated repeatedly. Upon arrival at the laboratory, subjects were randomly seated at a visually isolated computer terminal. Sixteen sessions were conducted in which 80 different subjects participated. Both treatments were conducted with the same experiment software except for the necessary adjustments in the bidding screens.

The subjects received written instructions which were read aloud by a research assistant prior to the bidding. Before the session started, each subject had to answer an extensive questionnaire about the rules of the experiment. Prior to starting each of the six consecutive auctions, the subjects received a printout of their individual production cost schedule in addition to two printouts of the buyer's valuation and utility score. At the end of an experimental session, the subjects were paid privately in cash according to their final account balance. The average earning of a subject was 13.33 Euros including

TABLE I
COMPARISON OF TREATMENTS: MEAN VALUES FOR STANDARDIZED VARIABLES

	Treatment E			Treatment V		
Session	SP in percent	BU in percent	RE in percent	SP in percent	BU in percent	RE in percent
1	4.7	94.6	99.2	5.8	93.4	99.2
2	3.3	94.3	97.6	5.5	93.7	99.2
3	6.8	93.2	100.0	4.8	93.6	98.4
4	5.2	94.8	100.0	4.1	91.5	95.6
5	5.2	94.8	100.0	8.0	89.2	97.1
6	4.0	95.2	99.2	−0.7	95.2	94.5
7	3.6	96.4	100.0	8.4	90.4	98.7
8	2.1	97.2	99.2	2.8	91.1	93.9
Median θ	4.6	95.0	100.0	5.8	92.1	98.4
Mean $\bar{x}$	4.4	95.0	99.4	4.8	92.2	97.1
Std dev s	2.4	2.4	1.5	4.7	2.8	3.5

the show-up fee and a session lasted on average about 95 minutes including reading the instructions and answering the questionnaire.

IV. EXPERIMENTAL RESULTS

A. Comparison of treatments

In this section, a statistical analysis of the experimental data is presented. The two treatments are compared by distribution-free tests. For each test, a significance level of 5 percent (strong significance) or 10 percent (weak significance) is required. Recall that the maximum achievable social welfare of an auction outcome is standardized. The tests are based on the standardized outcomes of the *last four* auction rounds in each independently conducted session. The first two of the six trading periods are considered as trial rounds. However, the subjects did *not* know about this differentiation and a monetary reward was paid in all six rounds of a session.

The relative efficiency of an outcome is defined as the actual achieved social welfare as a percentage of the potential maximum social welfare, $RE = w(\hat{\imath}, \hat{x}, \hat{y})/\bar{w}(\bar{\imath}, \bar{x}, \bar{y})$. Larger values of RE indicate a higher level of efficiency. The division of the social welfare between the buyer and the winning supplier is measured in terms of deviations of actual buyer's and winning supplier's surplus from the maximum achievable social welfare. The measure BU is defined as the buyer's surplus as a percentage of the maximum social welfare $BU = u(\hat{x}, \hat{y}, \hat{p})/\bar{w}(\bar{\imath}, \bar{x}, \bar{y})$ and the measure SP is defined as the winning supplier's surplus as a percentage of the maximum social welfare in a given auction $SP = u_{\hat{\imath}}(\hat{x}, \hat{y}, \hat{p})/\bar{w}(\bar{\imath}, \bar{x}, \bar{y})$. Larger values of BU and SP indicate larger shares by the buyer and suppliers, respectively.

Table I reports the mean values for the standardized performance measures relative efficiency (RE), buyer's (BU) and suppliers' (SP) surplus for each session. The eight mean values for each performance measure per treatment represent the samples analyzed in the inferential analysis.

The overall mean relative efficiency in treatment E is 99.4 percent with a range from 97.6 percent to 100.0 percent efficiency. Consequently, allocational inefficiencies, measured by unrealized gains from trade, were usually below 1.0 percent in treatment E with an average of 0.6 percent. The overall mean buyer's utility in treatment E is roughly 95.0 percent with a range from 93.2 percent to 97.2 percent, while the average suppliers' profits range from 2.1 percent to 6.8 percent with a mean of 4.4 percent.

The mean relative efficiency is lower in treatment V with an overall average of 97.1 percent, but exhibits a larger dispersion of observed mean values with a standard deviation of 3.5 percent. In contrast to treatment E, there is not a single session in treatment V in which all auctions yield 100.0 percent efficiency. Regarding the buyer's surplus, the Vickrey variant leads on average to a lower utility score than the English auction, while the suppliers' profits are on average slightly higher in the second-score sealed-bid institution. Note the negative mean suppliers' profits in session 6 of treatment V, which is a result of overbidding by suppliers, i.e. the bid price is lower than the production costs for the offered technical specification.

The difference between treatments E and V with respect to relative allocational efficiency is highly significant (Mann-Whitney U-test, or MWU for short, 2-tailed: $N = 16$, $U = 7$, $p = 0.0061$). The mean and median buyer's surplus is higher in the English auction variant than in the Vickrey adaptation. The difference between the two treatments with regard to buyer's surplus is highly significant (MWU, 2-tailed: $N = 16$, $U = 8$, $p = 0.0096$). The results regarding the suppliers' profits are less definite. There are three sessions in which the benchmark treatment E leads to a higher mean sellers' surplus, but the differences in surplus in the other five sessions are substantial. Both, the mean and median suppliers' profits are slightly higher in treatment V than in E, but the difference is not significant (MWU, 2-tailed: $N = 16$, $U = 40$, $p = 0.4252$).

B. Deviations from dominant bidding strategy

The experimental results demonstrate deviations from the dominant bidding strategy in both, the English and the Vickrey auction institution. The previously noted phenomenon of over- and underbidding in second-price auctions is similarly

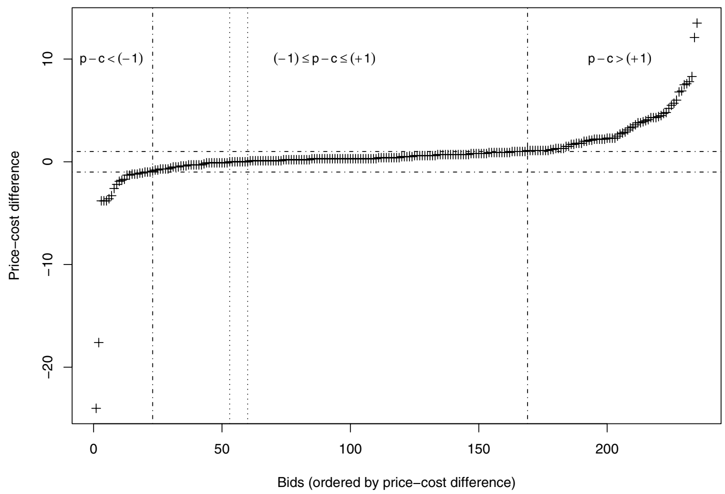


Fig. 2. Over- and underbidding in treatment V

observed in the second-score sealed-bid auction in our experiment. Figure 2 shows the difference between bid price and production costs for each bid submitted in treatment V taking all auction rounds into account. A negative difference indicates overbidding, i. e. a bid price below the production costs at the offered technical specification, and a positive difference means underbidding, i. e. a bid price above the production costs at the offered technical specification. Since the production cost schedules contain real numbers and bidders could only bid integer prices, a price-cost difference in the interval $[-1, +1]$ is assumed to indicate accordance with bidding the true valuation. Any price-cost difference outside of that interval is considered a deviation from the dominant bidding strategy in the second-score sealed-bid auction.

On average, suppliers bid slightly below the dominant strategy score in treatment V. Considering only the last four auction rounds, the analysis reveals that 74.5 percent of the bids are in accordance with our notion of the dominant strategy while 25.5 percent violate that strategy. Overbidding is observed in 8.3 percent of the bids in the last four rounds, while we find underbidding in 17.2 percent.

We were interested whether bidders stick to their deviation from the dominant strategy or if they switch between over- and underbidding and analyzed the data of all rounds. The results show that 45 percent of the bidders deviate from the dominant strategy, but only one bidder deviates in both directions, i.e. he both over- and underbids. Twelve bidders (30 percent) submit one or more bids which overstate their production costs (underbidding) and seven bidders (17.5 percent) submit one or more bids which understate their production costs (overbidding). Eight bidders (20 percent) repeatedly underbid and five bidders overbid more than one time (12.5 percent). Hence, a core of subjects persistently deviates from the dominant bidding strategy. Interestingly, we find more bidders to underbid than overbid.

The relation of under- to overbidding is remarkable in that overbidding is explained by the illusion of increasing the probability of winning at no or little cost [36], but underbidding seems hard to justify. Recall that overbidding rather than underbidding is predominantly observed in second-price auctions [39]. Departing from the dominant strategy by submitting a bid price higher than the production costs at the offered technical specification lowers the likelihood of winning an auction, since the buyer's utility score decreases with increasing prices (see Eq. (1)). Moreover, the fact that bidders expect a non-negative price surcharge with a positive probability renders possible explanations even more difficult. Recall that the price surcharge is zero only if two high bids achieve the same utility score. Taking again only the last four auction rounds into account, in the English auction variant 391 bids were received by the buyer and only one bid with a negative price-cost difference of -0.5 is observed. Our results are thus in line with experimental evidence on standard English auctions, i. e. that little, if any overbidding is observed. Deviation from the dominant bidding strategy is also observed in treatment E in case bidders fail to bid up to their true valuation at the Pareto optimal technical specification ("early withdrawal", see Prop. 2). We observe 15 auction outcomes (31.25 percent) with a buyer's utility score less than other (non-winning) bidders' dominant strategy score. In these cases, one of the non-winning bidders could have outbid the winning bidder without incurring losses; failure to do so marks a deviation from the dominant strategy. In one auction, two bidders fail to submit one or more bids according to their dominant strategy. In all other observed deviations only the pivotal bidder fails to submit one or more dominant strategy bids. Seven of the 15 failures (46.7 percent) occur in the first two auction rounds of a session and only a single failure is observed in the last round.

C. Learning effects

In the experiment, subjects participate in six consecutive auctions of the same treatment. The repeated exposure enables experiential learning, i.e. subjects obtain additional knowledge

TABLE II
LEARNING EFFECTS: SUPPLIERS' PROFITS, BUYER'S UTILITY, AND RELATIVE EFFICIENCY

	Treatment E			Treatment V		
Round	SP in percent	BU in percent	RE in percent	SP in percent	BU in percent	RE in percent
1	4.5	93.7	98.1	5.7	87.2	93.0
2	3.1	95.3	98.4	1.8	91.4	93.2
3	3.9	94.6	98.4	2.4	92.6	95.1
4	4.3	94.9	99.2	6.1	91.4	97.4
5	4.2	95.9	100.0	5.7	92.7	98.4
6	5.1	94.9	100.0	5.2	92.2	97.4

about the consequences of their behavior and the interaction of strategies. Subjects apply that knowledge in consecutive auctions. In the English auction, bidders may additionally learn during the course of bidding by observing current high bids and relating that information to their own, private information without incurring any costs (observational learning) [36]. Note, however, that observational learning is an approach to explain bidding behavior, which cannot be proven with the experimental data. It is thus not subject of this analysis. In contrast to treatment E, the bidding procedure in treatment V is a one-shot process. Observational learning during the bidding process cannot occur. Nonetheless, experiential learning from round to round is possible. Table II shows the mean values of the suppliers' profits, buyer's utility and relative efficienca grouped by subsequent rounds instead of independent sessions (note that all six auction rounds are considered).

The data in Tab. II shows that treatment E leads to a higher efficiency than treatment V in each round. Moreover, Tab. II illustrates that efficiency increases from round to round in both treatments (linear regression, 2-tailed: $p < 0.01$, respectively). This incline is attributed to the increasing experience of bidders and thus to experiential learning. Interestingly, not only the bidders seem to profit from the increasing efficiency, but also the bid-taker. Besides the bidders' profits, the buyer's utility increases slightly. Yet, neither the increase in profits nor in utility is significant on the 10 percent significance level.

As a result, experiential learning by bidders increases the chance of achieving a higher efficiency. Consequently, the buyer seems well-advised to provide participating suppliers with training and consultation about the auction institution before inviting them to bid in a multi-attribute procurement auction.

V. CONCLUSIONS

The presented laboratory study compares the sourcing of differentiated, heterogeneous objects by a multi-attribute reverse English auction and a multi-attribute reverse second-score sealed-bid (Vickrey) auction. The buyer's scoring rule is revealed by means of printouts of the buyer's valuation and utility scores for combinations of the two non-price attributes and the price as well as by a decision support tool embedded in the bidding screens. The bidders receive an instant information feedback about submitted bids in the English auction variant, while the Vickrey auction is a one-shot, sealed-bid procedure.

The study finds that the multi-attribute reverse English auction leads to a higher allocative efficiency and buyer's surplus than the multi-attribute Vickrey auction institution, which documents a breakdown of the outcome equivalence of the two auction designs. The breakdown is attributed to bidders deviating from the dominant strategy. This result is in line with earlier experimental findings. The experimental results also support the finding that the English auction leads to higher auctioneer's utility, but contradict the result that the multi-attribute generalization of the Vickrey auction leads to a higher efficiency [27].

The investigation of learning effects shows that bidders learn from round to round in both the multi-attribute English and Vickrey auction and that the experiential learning is twofold. The bidders learn to bid the Pareto optimal technical specification and learn to bid (up to) the dominant strategy bid price. However, a core of subjects persists which deviates from the dominant bidding strategy in the Vickrey auction with respect to bidding the dominant strategy price.

Based on these findings, we recommend corporate buyers to deploy the English auction format when conducting a multi-attribute auction for electronic sourcing, because it does not hamper the suppliers' profits, yet increases the buyer's utility significantly. Moreover, we recommend corporate buyers to consult with bidders and to train bidding in multi-attribute auctions, since our results show that additional experience of bidders increases the auction efficiency, which in turn is likely to increase the buyer's utility.

ACKNOWLEDGEMENT

Financial support by the Chair for Information Management and Systems is gratefully acknowledged. This research was funded in part by a grant from the Social Sciences and Humanities Research Council Canada (SSHRC). The authors are grateful to Christof Weinhardt, Karl-Martin Ehrhart, Martin Bichler, and Gregory Kersten for their support and helpful suggestions. Special thanks are due to Ilka Weber and Henner Gimpel for proof-reading the manuscript. Two anonymous referees provided helpful comments and suggestions. Remaining shortcomings are ours.

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