ESSAYS ON PROCUREMENT DESIGN

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To Carina.

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CHAPTER 1

INTRODUCTION

Auction theory represents an important branch of economic research and over the last decades structured procurement processes became more and more important in procurement practice. Beall et al. (2003) report that advances in information technology make it possible for buyers and suppliers to directly communicate independent of their location. Electronic procurement platforms allow buyers to easily set up structured procurement mechanisms and to attract offers from potential suppliers from all around the world. Jap (2002) reports that the introduction of electronic reverse auctions resulted in substantial cost savings.

At least part of this observation might be explained by Bulow and Klemperer (1996). They show that attracting additional suppliers in a reverse auction is more profitable for the buyer than any increase in bargaining power. According to Subramanian (2010) reverse auctions have – compared to negotiations – also the advantage that they are more transparent. This transparency becomes especially important when the buyer cannot conduct the procurement on his own and delegates its execution to an agent, because it reduces opportunities for favoritism and corruption.

Procurement mechanisms, which are used in practice, are often similar to those auction mechanisms that are analyzed in the academic literature. However, they often differ in details. These small differences can have strong influence on outcomes as I will show in the following chapters. For example, Jap (2002) reports that in practice most procurement auctions are non-binding. Such a buyer-determined reverse auction looks exactly like a standard procurement auction with the only exception that the buyer reserves the right to select the supplier after observing the offers. One reason to do so is that the agent who is in charge of organizing the procurement is not in the position to make the final decision. Furthermore, it can be demanding to set up a binding scoring rule that makes suppliers' non-price attributes comparable, especially if there are many heterogeneous suppliers.

In chapter 2 with the title *Collusion in dynamic buyer-determined reverse auctions*[1], which is joint work with Elena Katok and Achim Wambach, we will show that dynamic buyer-determined reverse auctions are likely to result in non-competitive outcomes, if suppliers have uncertainty about the buyer's final selection decision. The reason is that the uncertainty about the buyer's award decision allows suppliers to share their profits in expectation by submitting similar offers. This possibility exists independent of the size of the uncertainty. Furthermore, the uncertainty makes it more costly for a supplier to compete by trying to outbid competitors, because it is not sufficient to marginally underbid them to be sure to win. In contrast to that, standard reverse auctions yield low prices. We complement our theoretical findings with evidence from laboratory experiments.

Chapter 3 entitled *Trust in procurement interactions*[2], which is joint work with Elena Katok and Achim Wambach, compares buyer-determined reverse auctions to binding price-based procurement auctions in a setting in which quality cannot be contracted upon. In a laboratory experiment we observe that buyer-determined reverse auctions result in higher prices but also lead to provision of higher quality and more trust between buyer and supplier. We rationalize our experimental findings with a theory based

[1]This chapter is published as Fugger et al. (2016). I presented the project at the Meeting of the European Economic Association 2013 in Gothenburg and the conference of the European Association for Research in Industrial Economics 2013 in Evora. Financial support from the German Research Foundation (DFG) through the research unit Design & Behavior and from the U.S. National Science Foundation is gratefully acknowledged. We also want to thank the Center for Social and Economic Behavior (C-SEB) at the University of Cologne.

[2]I presented the project at the European Conference of the Economic Science Association 2012 in Cologne, at a workshop of the research unit Design & Behavior, at the 26th European Conference on Operational Research 2013 in Rome, at the young scholars workshop at the 9th Annual Behavioral Operations Conference 2014 in Cologne, at the 8th RGS Doctoral Conference in Economics 2015 in Essen, at the Conference on Economic Design 2015 in Istanbul, and at the Annual Conference of the Verein für Socialpolitik 2015 in M"unster. Financial support from the German Research Foundation (DFG) through the research unit Design & Behavior is gratefully acknowledged. We also want to thank the Center for Social and Economic Behavior (C-SEB) at the University of Cologne.

on other-regarding preferences. The theory predicts that the same subjects who coordinate on high prices and high quality provision in the buyer-determined reverse auction will compete to low prices and provide lowest quality in the standard reverse auction.

In chapter 4 entitled *Preferences and decision support in competitive bidding*[3], which is joint work with Philippe Gillen, Alexander Rasch, and Christopher Zeppenfeld, we examine bidding behavior in static first-price sealed-bid auctions and dynamic Dutch auctions. These two auction formats are strategically equivalent, but empirical studies report a breakdown of the equivalence. In a laboratory experiment we investigate whether the breakdown is due to bidders' non-standard preferences or due to different complexity of the two auction formats. To do so, we elicit participants' preferences and manipulate the degree of complexity by offering various levels of decision support in the auction. Our results show that the equivalence only breaks down in absence of decision support. This indicates that the non-equivalence is caused by differing complexity rather than non-standard preferences.

Chapter 5 with the title *Exploiting uncertainty about the number of competitors in procurement auctions*[4], which is joint work with Elena Katok and Achim Wambach, we examine whether the buyer can extract additional surplus from suppliers by conditioning the auction format choice on her private information about the actual number of suppliers. This study is motivated by the observation that in procurement practice a first-price auction is used if the number of suppliers is small and a second-price auction if the number is large. This cannot easily be explained since suppliers should anticipate

[3]Financial support from the German Research Foundation (DFG) through the research unit Design & Behavior is gratefully acknowledged. We also want to thank the Center for Social and Economic Behavior (C-SEB) at the University of Cologne. An earlier version of this work is published in Zeppenfeld (2015).

[4]I presented the project at the brown bag seminar at the University of Cologne, at the Spring Meeting of Young Economists 2015 in Ghent, at a workshop of the research unit Design & Behavior, and at the yound scholars workshop at the 10th Annual Behavioral Operations Conference 2015 in Ithaca. Financial support from the German Research Foundation (DFG) through the research unit Design & Behavior is gratefully acknowledged. We also want to thank the Center for Social and Economic Behavior (C-SEB) at the University of Cologne.

little competition whenever they participate in a first-price auction, which in turn makes the first-price auction unattractive for the buyer. In a laboratory experiment we find that most suppliers are not able to interpret the buyer's format choice correctly and hence overestimate the level of competition in first-price auctions. The resulting biased beliefs of suppliers make it profitable for the buyer to conduct first-price auctions if the number of suppliers is small and second-price auctions if it is large. However, we also observe in our experiment that the buyer is even better off if she can commit to run a first-price reverse auction independent of the number of suppliers, this is due to suppliers underbidding.

Finally, in chapter 6 with the title *Bonuses and handicaps in procurement auctions*[5], which is joint work with Christian Paul and Achim Wambach, we investigate how the framing of quality scores as bonuses or handicaps affects suppliers' bidding behavior. Quality scores play an important role in almost every procurement auction and assign a monetary value to the non-price attributes of a supplier's offer. In contrast to the assumptions of most of the academic literature, suppliers only learn their own quality score in practice and interpret it to update their beliefs about their own relative position. In a laboratory experiment we observe that suppliers who receive a handicap overestimate the strength of their competitor and hence bid more aggressive. As a consequence, the buyer can increase her profits by framing quality scores as handicaps instead of bonuses.

[5]I presented the project at the *World Meeting of the Economic Science Association* 2013 in Zurich. Financial support from the *German Research Foundation (DFG)* through the research unit *Design & Behavior* is gratefully acknowledged. We also want to thank the *Center for Social and Economic Behavior (C-SEB)* at the University of Cologne.

CHAPTER 2

COLLUSION IN DYNAMIC BUYER-DETERMINED REVERSE AUCTIONS

Abstract

While binding reverse auctions have attracted a good deal of interest in the academic literature, in practice dynamic non-binding reverse auctions are the norm in procurement. In those, suppliers submit price quotes and can respond to quotes of their competitors during a live auction event. However, the lowest quote does not necessarily determine the winner. The buyer decides after the contest, taking further supplier information into account, on who will be awarded the contract. We show, both theoretically and empirically, that this bidding format enables suppliers to collude, thus leading to non-competitive prices.

2.1 INTRODUCTION

In non-binding reverse auctions, bidders compete against each other like in a standard reverse auction, but the winner is not necessarily the supplier with the lowest bid. Rather, buyers decide, based on the final quotes and further information about the suppliers, who will be awarded the contract. These buyer-determined reverse auctions (BDRA) are virtually the norm in competitive procurement today. Ariba, a major commercial provider of online reverse auctions and other sourcing solutions, uses non-binding reverse auctions almost exclusively. In a recent survey, Elmaghraby (2007, p. 411) notes that "The exact manner in which the buyer makes her final selection still remains unclear. With either an online auction or a RFP, the buyer may still leave some terms of trade unspecified."[1]

In the context of multi-attribute auction events, the advantage of a non-binding format from the buyer's perspective seems evident. The winner should not be the supplier with the lowest quote, but further attributes, such as quality, reliability, capacity, reputation, incumbent status, and other suppliers' capabilities, should be taken into account. However, we show in this paper that there is a serious disadvantage to such dynamic non-binding reverse auctions: If bidders are uncertain about the exact way different criteria affect the final decision by the buyer, then in equilibrium, a non-binding reverse auction enables them to implicitly coordinate on high prices.

The collusive arrangement in the non-binding reverse auction works as follows: The suppliers begin the contest with a relatively high quote. These offers are such that if the process were to stop at this point, all have a positive probability of winning, given the uncertain criteria of the buyer's award decision. In equilibrium, no supplier makes an improvement on his offer, so the bidding stops at a high price. If one supplier were to lower the offer, it would trigger a response by the other suppliers, who would also lower their quotes. Thus, the deviating supplier has to reduce his price even further, which makes it unattractive to lower the price in the first place. Note that the stabilizing element in this collusion is that suppliers do not know how the buyer will ultimately determine the winner. Thus, with their initial offers, all suppliers have a positive chance of winning.

Binding reverse auctions, where the final decision rule is known in advance, do not allow for this form of collusion. In a (reverse) English auction, for example, at any moment during the auction firms do not have any uncertainty about whether they would receive the contract or not if the auction were to stop at this point. Thus, suppliers who know that they will not be awarded the contract at the current price, have to improve their offer, which

[1] SAP (2006, p. 9) notes in a document on best practice in reverse auctions: "Often, you may find that the lowest bidder is not meeting quality and service grades and thus may select the second-lowest bidder."

in turn puts pressure on their competitors. Therefore collusion cannot be sustainable in binding reverse auctions.

Buyer-determined reverse auction mechanisms have not been widely studied and are not well-understood, especially theoretically. Jap (2002) was the first to point out that most reverse auctions that are conducted in industry do not determine winners - i.e. they are non-binding. Jap (2003) and Jap (2007) show that dynamic non-binding reverse auctions often have a more detrimental effect on buyer-supplier relationships than do sealed-bid reverse auctions. In another study, Engelbrecht-Wiggans et al. (2007) examine sealed-bid first price reverse auctions. They compare price-based and buyer-determined mechanisms, both theoretically and using laboratory experiments, and find that buyer-determined mechanisms generate higher buyer surplus only as long as there are enough suppliers competing for the contract. Haruvy and Katok (2013) investigate the effect of information transparency on sealed-bid and dynamic non-binding auctions and find that sealed-bid formats are generally better for buyers, especially when suppliers are aware of their competitors' non-price attributes. In both of these studies, suppliers know the value the buyer attaches to their own non-price attributes.[2,3]

In contrast, in the present paper we investigate the effect of having this information on the performance of dynamic non-binding reverse auctions. We show that it is precisely the combination of the dynamic nature of the bidding process, which allows bidders to react to their competitors' bids, and the lack of knowledge about the valuation of the non-price attributes by the buyer, which ensures that each bidder has some probability of winning even at a high price, that enables bidders to collude.

The way collusion works in our model has some similarity to the collusive behavior in the context of strategic demand reduction (Brusco and Lopomo,

[2] Thomas and Wilson (2005) compare experimentally multilateral negotiations and auctions. They explicitly assume that during the negotiations offers are observable, so that this case resembles our buyer determined bidding mechanism. However, everyone knew preferences of the parties in advance. So the effect we analyze here could not occur.

[3] Stoll and Zöttl (2014) use field data to make a counterfactual analysis that estimates the consequences of a reduction of non-price information available to bidders.

2002; Ausubel et al., 2014) and to the industrial organization literature on price clauses (see e.g. Salop, 1986; Schnitzer, 1994, and references therein). Strategic demand reduction describes the phenomenon that, in a multi-unit reverse auction, bidders might prefer to win a smaller number of units at a higher price than a larger number of units at a lower price. Our paper analyses a single unit situation in which bidders are content with a small probability of winning at a higher price.

Price clauses such as "meet-the-competition" clause or a price-matching clause might be used to sustain collusion in a market similarly to the present analysis, where suppliers refrain from lowering their quotes, as this will trigger a lower price by their competitors. The literature on price clauses differs from this paper in two respects, however. First, in the pricing literature it is either assumed that trade takes place in several periods (e.g. Schnitzer, 1994) or that contingent contracts can be written in which the price depends on the prices of the competitors (e.g Doyle, 1988; Logan and Lutter, 1989). In the present case, trade only takes place once and contingent bidding is not possible. Second, the main argument why collusion is feasible, namely the remaining uncertainty about the final decision the buyer will take, has to our knowledge not been investigated so far.

Several authors have analyzed collusion in the context of auctions (see e.g. Robinson, 1985; Graham and Marshall, 1987 , for an overview see Klemperer, 1999; Kwasnica and Sherstyuk, 2013). Sherstyuk (1999) and Sherstyuk (2002) show in an experimental study that the bid improvement rule has an influence on the bidders' ability to collude in repeated auctions. Usually this literature assumes that before the auction takes place, a designated winner is selected. In addition, there must be some means to divide the gains of collusion between the participating bidders. This is different from the form of collusion described here. First, all participating firms have a chance of winning the contract, thus there is no predetermined winner and no pre-play communication required. Second, during the contest, all firms have a positive expected profit, even if after the decision by the buyer only one firm receives the contract. This makes it unnecessary to divide the gains of collusion after the contest.

The paper is structured as follows: In the next section we develop the model and analyze the collusive behavior in a dynamic buyer-determined reverse auction. In Section 2.3 we describe our experimental setting and present the results. In section 2.4 we conclude the paper with a discussion of ways for overcoming the problem of collusion.

2.2 ANALYTICAL RESULTS

2.2.1 MODEL SETUP

The auction format we consider is one in which suppliers bid on price, but different suppliers may provide different value to the buyer. This value can be viewed as exogenous attributes of suppliers themselves, rather than a part of their bids, and we will refer to it as *quality*. Our modeling approach is similar to that of Engelbrecht-Wiggans et al. (2007) and Haruvy and Katok (2013). There are n potential suppliers, competing to provide a single unit to a buyer. Suppliers are heterogeneous in costs and quality. In particular, supplier i has cost c_i, which is only known to the supplier i. Each c_i is taken from a common distribution $F(c)$ on $[\underline{c}, \overline{c}]$. The quality component does not enter the profit function of the supplier, so the profit of supplier i if he wins the contract at price p is given by

$$\pi_i(p, c_i) = p - c_i.$$

There are different ways to model quality differences among suppliers. For example, it may be reasonable to assume that there is some commonly known (vertical) quality component for each supplier. For example in the procurement of a customer designed application specific circuit, all suppliers satisfy the necessary technical requirements, but some suppliers might have a superior technology which is commonly known and which provides additional value to the buyer. But there may also be a quality component that is only known to the buyer - a horizontal quality component. This horizontal quality is the focus of our model, so we will assume in the remainder of the analysis that there are no vertical quality differences among suppliers.[4]

Let α_i be buyer's incremental cost of dealing with supplier i relative to dealing with her most preferred supplier, and let all the α_is be the private information of the buyer. Then the vector α containing all α_is represents the buyer's preferences and is distributed independent of the costs of the suppliers according to a commonly known distribution with finite support $[0, \overline{\alpha}]^n$. The utility of the buyer, if she awards the contract at price p to supplier i, is

$$u(p, \alpha_i) = v - p - \alpha_i$$

where v is the value to the buyer from the object, and the parameter α_i measures the extent to which the private preferences of the buyer about dealing with supplier i enter her surplus. Parameter $\overline{\alpha}$ can be quite small: Consider for example the sourcing of a display for a new mobile phone. The overall value of the contract might be several hundreds of millions in US dollars, which is captured by the term v. There may be some individual observable differences between the suppliers – e.g. one firm is known to be the technology leader – that are in the range of ten million US dollar (that we omit from the model). Unobservable preferences by the buyer, i.e. a preference for a particular provider, whose engineers speak English fluently, might differ in the size of several hundred thousand US dollars. These are captured by the term $\overline{\alpha}$.

But $\overline{\alpha}$ might also be large relative to the overall project value: Consider a company recruiting a marketing agency. An optimal marketing campaign would provide value v for the company. The decision, which agency to hire, will be strongly influenced by the specific preference parameter - the extent to which the board of the firm prefers one marketing agency over the others, which includes preferences about their people, their ideas, and their creativity. This is expressed by $\overline{\alpha}$ which might be similar in size to v.

We are assuming that the bidders do not know the buyer's preferences α. If the buyer already knows her preferences α before the auction, then

[4] Extending the model to include commonly known vertical quality is relatively straightforward and does not change our results qualitatively.

she can simply announce them and conduct a binding auction in which the lowest α_i-adjusted bid wins.[5]

The main focus of our paper is what we believe to be a more realistic setting, in which the buyer does not know α before the auction. This may be because bidders have not been fully vetted prior to the auction, or because determining the α_is is a group decision that cannot be done in the abstract. In this case, announcing α before the auction and adjusting bids by α_i is not feasible, and the buyer has to choose between two formats. The buyer can conduct a binding price-based reverse auction (PB), which we analyze in section 2.2.2. In this auction the bidder who submits the lowest bid is guaranteed to win, but the buyer may incur additional cost due to misfit, from dealing with this bidder. The buyer can also conduct a non-binding, or dynamic, buyer-determined reverse auction (BDRA), which we analyze in section 2.2.3. In this auction, bidders submit bids and the buyer selects the bidder when all final bids are on the table. The buyer will then choose the bidder with the lowest quality-adjusted bid, which we also call total cost. Thus, the lowest bid in the BDRA is not guaranteed to win.

2.2.2 BINDING PRICE-BASED REVERSE AUCTION

The rules of the binding price-based reverse auction are standard. Each bidder i submits a price bid b_i. The highest allowable bid is the reservation price R. During the auction, bidders observe full price feedback – they see all b_is that have been submitted. They can place new bids that must be lower than the lowest current standing bid by some pre-determined minimum bid decrement in order to become the leading bid. The bidder with

[5] If the buyer communicates the horizontal qualities α_i to all bidders and monetizes the horizontal quality differences, she can conduct a binding auction in which the bidder with the lowest quality-adjusted bid wins and is paid the amount of the second lowest quality-adjusted cost, $(c_i + \alpha_i)^{(n-1)}$. A commonly used way to monetize α_i is to set up a bonus/handicap system, which quantifies differences between suppliers with respect to the different dimensions, e.g. quality, payment terms, technical criteria, and so on. It is important to note that whether revealing private preferences α (if that is possible at all) is beneficial to the buyer is an interesting question that is beyond the scope of our paper. We refer the reader to Che (1993) who finds that the optimal revenue maximizing mechanism discriminates against non-price attributes in order to make price competition tougher.

the lowest bid is the leading bidder in the auction and would win the auction if it were to stop at this point. The auction ends when there are no new bids placed for a certain amount of time. The price the buyer pays is equal to the lowest price bid b_i.

Under this rule, it is a dominant strategy for each supplier to keep lowering his bid as long as he is not currently winning the auction, until $b_i = c_i$.[6] Thus the auction ends when the bidder with the second lowest cost exits the auction. The bidder with the lowest cost wins the auction. If bidder i with horizontal quality α_i wins, and bidder j, with the second lowest bid exited at c_j, then the price the buyer pays is equal to c_j. The utility of the buyer is then:

$$u = v - c_j - \alpha_i,$$

where c_j is the second lowest bid, which we denote by $(c_i)^{(n-1)}$. As the distribution of α_i is independent of costs and quality realization (by assumption), the expected buyer surplus is

$$v - E\left[(c_i)^{(n-1)}\right] - E\left[\alpha_i\right].$$

The buyer pays, in expectation, the second lowest cost, and the expected value of the horizontal quality parameter.

2.2.3 DYNAMIC BUYER-DETERMINED REVERSE AUCTION

General framework

Now consider a non-binding reverse auction, which, as we noted in the introduction is commonly used in procurement practice. The auction works exactly the same way as the binding price-based reverse auction in terms of the bids that bidders observe during the auction, and the ending rule. The main difference is that after the auction ends, the buyer is not obligated to award the contract to the bidder with the lowest bid b_i, but may instead

[6] The binding price-based reverse auction has also several other equilibria, however, these are ruled out if one eliminates weakly dominated strategies or requires subgame perfection.

award the contract to a different bidder, taking her preferences α_i into account.

The fundamental difference between the non-binding auction and its binding counterpart is that bidders might not know if at current bids they would win or lose in the non-binding auction. A bidder j only knows for certain that he is losing when his bid b_j is more than $\overline{\alpha}$ above the current lowest bid. On the other hand a bidder i only knows for certain that he is winning when his bid b_i is more than $\overline{\alpha}$ below the next lowest bid. While it is optimal for a bidder who knows that he is winning not to lower his bid further, it is optimal to lower his bid for a bidder who knows that he is losing as long as the bid is still larger than his costs.

Let us call the lowest standing bid $B = \min\{b_1, b_2, \cdots, b_n\}$ and the lowest bid of the competitors B_{-i}. A bidder i whose bid is within $\overline{\alpha}$ of B_{-i}, $B_{-i} - \overline{\alpha} \leq b_i \leq B_{-i} + \overline{\alpha}$, does not know his winning status, and thus there is no obvious best action for him. In general, his strategy will depend on his beliefs about the other suppliers' future actions. A bidder who believes that lowering the bid would lead to an outright bidding war is less likely to lower his bid than a bidder who merely expects competitors to lower their bids by a small amount.

In the collusive equilibrium we analyze, all suppliers initially bid very high in a way such that the probability of winning for every supplier is the same. When one supplier lowers his bid to increase his probability of winning, those suppliers whose probability of winning is decreased will follow suit and lower their bids as well. This makes the initial deviation unattractive and thus collusion can be sustained.

In the most general formulation, the bidding behavior off the equilibrium path, i.e. if bidders deviate from colluding on high prices, is complex. In order to facilitate the analysis, we set the information structure such that if someone lowers his bid in order to increase his probability of winning, the probability of winning for at least one other supplier falls to zero.[7] Thus,

[7] This can be achieved by assuming that the horizontal quality of each buyer is taken from a discrete set, i.e. $\alpha_i \in \{0, \overline{\alpha}\}$, which is the approach we take in the remainder of this paper.

it is dominant for this supplier to lower his bid as well as long as he bids above costs.

Specific bidding model

We now consider a special case in which we can characterize the conditions for a collusive equilibrium to exist. The buyer has one preferred supplier, but the suppliers do not know the identity of this supplier. Let $\overline{\alpha} > 0$ be the additional cost the buyer incurs when she has to deal with a non-preferred supplier. Let $\alpha_i = 0$ if i is the buyer's preferred supplier, and $\alpha_i = \overline{\alpha}$ otherwise. As before, the α_is are not known by the suppliers. Since suppliers are ex ante symmetric, each supplier i believes that the probability that $\alpha_i = 0$ is $1/n$.[8] We assume that bids must be in multiples of the minimum bid decrement ϵ, where ϵ is sufficiently small. Discreteness of prices is used to ensure that there are no ties. This is achieved by assuming that $\overline{\alpha}$ is not a multiple of ϵ.

Before specifying the equilibrium formally, one definition is necessary. Let b_{-i} be a vector of bids of all suppliers apart from supplier i. If supplier i were to bid b_i and the bidding would stop at this point, then the probability for supplier i of obtaining the contract is given by

$$P_i(b_i^t, b_{-i}^t) = \Pr(\alpha_i + b_i < \alpha_j + b_j \ \forall j \neq i).$$

Note that form the point of view of supplier i, both α_i and all α_j are random variables. We now describe the following collusive bidding strategy β^c:

- $b_i^1 = R$: All bidders start bidding at the reservation price R.
- For bidder i, if $P_i(b_i^t, b_{-i}^t) \geq 1/n$ then $b_i^{t+1} = b_i^t$.
- If $P_i(b_i^t, b_{-i}^t) < 1/n$ then $b_i^{t+1} = \max\{c_i, b^*(b_{-i}^t)\}$, where $b^*(b_{-i}^t)$ is the maximum bid b which satisfies $P_i(b, b_{-i}^t) \geq 1/n$.[9]

[8] The situation is thus like in the spokes model of horizontal product differentiation Chen and Riordan (2007). All suppliers are located at the end of different spokes of a wheel. The buyer is located at the end of one spoke. Thus the "distance" to one supplier is zero, while the distance to all other suppliers is the same given by twice the length of a spoke, here modeled by $\overline{\alpha}$.

[9] $b^*(b_{-i}^t)$ exists, as the optimization is done over a finite set of possible bids.

If bidding starts at $t = 1$ with all bidders bidding R, then all bidders have the same winning probability $1/n$ and bidders would stop bidding. However, if (out of equilibrium) bids differ, and for some bidder i, the probability of winning is below $1/n$, then in the next round bidder i sets his bid $b^*(b_{-i}^{t-1})$ so as to barely outbid the bidder with the lowest current bid in the event that i turns out to be the preferred supplier. Since the bidding is done in increments of ϵ, this implies for the bid of bidder i (recalling that B^{t-1} is defined as the lowest standing bid):

$$b^*(b_{-i}^{t-1}) \in (B^{t-1} + \overline{\alpha} - \epsilon, B^{t-1} + \overline{\alpha})$$

Equilibrium analysis

We claim that the bidding strategy β^c as defined above constitutes an equilibrium, depending on the reservation price R, the size of the buyer preference term $\overline{\alpha}$, and the distribution of costs $F(c_i)$.

We start the formal analysis by considering two bidders. Proposition 1 develops a sufficient condition for collusion to occur.

Proposition 1. *Assume there are two bidders and $R \geq \overline{c}$. The bidding strategy β^c describes a collusive equilibrium if*

$$\frac{R - \underline{c}}{2} \geq \max_{p \in [0, \overline{c} - \overline{\alpha}]} \left\{ \int_p^{\overline{c} - \overline{\alpha}} (x - \underline{c}) \cdot f(x + \overline{\alpha}) dx + \frac{p - \underline{c}}{2} \cdot F(p + \overline{\alpha}) \right\} \quad (2.2.1)$$

The proof is relegated to the Appendix. In the following, we provide the intuition. First, note that a supplier with lowest costs has the strongest incentive to deviate, i.e. we need to check whether he prefers to collude or not. If both suppliers follow the collusive bidding strategy β^c, they both bid R and win with a probability of 1/2 each. The resulting profit for a supplier with lowest costs is displayed in the left hand side of inequality (2.2.1). If one supplier deviates by placing a bid of b_i the other will respond by bidding $b_i + \overline{\alpha}$ as long as this bid is above his costs. If the deviator succeeds in outbidding his competitor he wins and he is paid a price equal to the costs of his competitor minus $\overline{\alpha}$. However, it might also be that at some point p he stops trying to underbid the competitor, if he has not been successful so far. In that case, both suppliers still have a winning probability of one half. The right hand side of inequality (2.2.1) describes the profit of a deviator with costs $c = \underline{c}$ who attempts to undercut his competitor and stops lowering the price at some level p.

Corollary 1. *A sufficient condition for a collusive perfect Bayesian equilibrium to exist is that the cost distribution function is concave.*

As we show in the Appendix, a concave cost distribution function guarantees that the right hand side of inequality (2.2.1) is maximized at $p = \overline{c} - \overline{\alpha}$, thus a deviator would stop lowering the price immediately. Sticking to the collusive outcome is then preferred. Furthermore, with a concave cost distribution function bidders always prefer collusion at current prices to lowering their bid even outside the equilibrium path. This ensures that the collusive bidding strategy β^c is sequentially rational.

Proposition 1 and Corollary 1 have interesting implications for the existence of a collusive equilibrium. Collusion is more likely if:

- The reservation price R is large, as this makes collusion profitable.[10]
- The probability of facing a high cost competitor is low (which is implied by a concave cost distribution function), as this makes deviation unattractive.
- The individual preference component $\overline{\alpha}$ is not too small, as this implies that anyone trying to undercut his competitor in order to gain a higher probability of winning must lower the price sufficiently, which makes this behavior unattractive. Additionally, if $\overline{\alpha}$ is very small, the buyer has little reason not to simply run a PB auction.

Next, consider a buyer-determined reverse auction with $n > 2$ bidders. Increasing the number of bidders has two opposing implications for the stability of collusion. On the one hand, having more bidders decreases the gain from sticking to high prices, as the probability of winning (which

[10] While a large reserve price R makes collusion more likely, collusion can also occur if R is small, depending on the distribution of costs.

is equal to $1/n$) is lowered. On the other hand, more bidders make it less likely that by lowering the price one will succeed in pricing the others out of the market. The analysis becomes difficult as the dynamics outside the equilibrium path can become very complex. If one of the bidders is 'outbid', i.e. if his cost is more than $\overline{\alpha}$ larger than the minimum bid, then an active bidder, who according to his collusive strategy β^c, stays within $\overline{\alpha}$ of the minimum bid, has still a chance of winning of $1/n$. However, by lowering his bid just below the minimum bid, he can increase his chance of winning to $2/n$. The probability $2/n$ can be obtained by conditioning on whether the bidder who was outbid was the preferred supplier: If that is the case (with probability $1/n$), the supplier who placed the lowest bid wins the auction with probability 1; otherwise (with probability $1 - 1/n$), the deviating supplier wins the auction if he is the preferred supplier (with probability $1/(n-1)$).

We will provide two examples where we determine the equilibrium explicitly. Example 1 has an interesting dynamic and shows some complexities, which arise in the general case. Example 2 deals with the parameterizations we used in our experiment.

EXAMPLE 1: In this example some bidders will, in equilibrium, lower their bids somewhat below the reservation price, and then start to collude. Suppose all bidders have costs of either 0 or 10, each with probability 1/2, the reserve price R is equal to 10 and $\overline{\alpha} = 0.5$. The minimum bid decrement is $\epsilon = 1$. Then a bidder with costs 0 might lower the price to 9 and stop there.[11] By doing this, he will avoid the competition of those bidders with costs of 10, but he will still collude with those with costs of 0. For example in the case of four bidders, collusion at 10 would give a profit of $10/4 = 2.5$. If a bidder with costs of 0 lowers the price to 9, his expected profit is given by

$$\left(\frac{1}{2}\right)^3 \cdot \frac{9}{4} + 3 \cdot \left(\frac{1}{2}\right)^3 \cdot \frac{9}{3} + 3 \cdot \left(\frac{1}{2}\right)^3 \cdot \frac{9}{2} + \left(\frac{1}{2}\right)^3 \cdot 9 = \frac{135}{32} \geq 2.5.$$

[11] If the reserve price were set at 9 or lower (i.e. $R < \bar{c}$, collusion would start immediately without further bidding.

EXAMPLE 2: : Table 2.1 lists six combinations for the number of bidder (n), the size of individual buyer preference ($\overline{\alpha}$), and the reserve price (R). These six combinations correspond to the six BDRA experimental treatments we conducted (see section 2.3.1 for more details).

Table 2.1: Parameters for BDRA experimental treatments.

Treatment number	Number of bidders (n)	Individual buyer preference ($\overline{\alpha}$)	Reserve price (R)
1	2	10	100
2	2	30	100
3	2	10	150
4	4	30	100
5	4	10	150
6	4	30	150

In all treatments costs are uniformly distributed on $[0, 100]$. The $n = 2$ cases (treatments 1, 2 and 3) are dealt with in Proposition 1. (Note that the uniform distribution is (weakly) concave, thus Corollary 1 applies.) The $n = 4$ cases (treatments 4, 5 and 6) are analyzed in Proposition 2.

Proposition 2. *Assume there are more than two bidders, costs are uniformly distributed on* $[0, 100]$ *and* $R \geq 100$. *The bidding strategy* β^c *describes a collusive equilibrium if* $\overline{\alpha} \geq 100 \cdot (n-4)/(n-2)$ *and*

$$\frac{R}{n} \geq \int_{\frac{\overline{\alpha}}{n-2}}^{100-\overline{\alpha}} x \cdot \frac{2}{n} \cdot \frac{n-1}{100} \cdot \left(\frac{x+\overline{\alpha}}{100}\right)^{n-2} dx + \frac{\overline{\alpha}}{n-2} \cdot \frac{1}{n} \cdot \left(\frac{\overline{\alpha} \cdot (n-1)}{100 \cdot (n-2)}\right)^{n-1} \tag{2.2.2}$$

The proof is relegated to the Appendix. Proposition 2 implies that collusion is an equilibrium for treatments 4, 5 and 6.

2.2.4 REVENUE COMPARISON

In cases where a BDRA leads to collusion and the buyer cannot fully reveal her preferences prior to the auction, there is a trade-off between using a PB auction or a BDRA. In the former case, price competition will be stronger, while in the latter case, the preferences can be better accommodated in the selection of the supplier. Formally, the total expected cost, including the horizontal quality component, of the buyer in a PB auction is given by:

$$E\left[(c_i)^{(n-1)}\right] + E\left[\alpha_i\right] = E\left[(c_i)^{(n-1)}\right] + \frac{n-1}{n} \cdot \overline{\alpha}. \qquad (2.2.3)$$

In the PB auction, bidders follow their dominant strategy. Consequently, the bidder with the lowest cost wins and is paid the second lowest cost. Due to the quality mismatch, the buyer looses on average $(n-1)/n \cdot \overline{\alpha}$. In the BDRA, all bidders bid R and the bidder for whom $\alpha_i = 0$ wins. Thus the expected cost for the buyer in a BDRA is R. Therefore, the expected difference between the two mechanisms is given by:

$$\frac{n-1}{n} \cdot \overline{\alpha} - \left(R - E\left[(c_i)^{(n-1)}\right]\right). \qquad (2.2.4)$$

A BDRA has the negative effect of higher prices that amounts to an average $R - E\left[(c_i)^{(n-1)}\right]$, but at the same time leads to better accommodating buyers' preferences, worth $(n-1)/n \cdot \overline{\alpha}$.

2.3 EXPERIMENTAL EVIDENCE

2.3.1 DESIGN OF THE EXPERIMENT

Like in the previous section, we work with binary individual buyer preferences, i.e. $\alpha_i \in \{0, \overline{\alpha}\}$, such that in each auction exactly one of the bidders is preferred. We vary $\overline{\alpha}$ so that in some treatments $\overline{\alpha} = 10$ and in other treatments $\overline{\alpha} = 30$. This variation captures the idea that the supplier specific buyer preferences can differ in importance compared to the overall project size. We also vary the reserve price at $R = 100$ and $R = 150$ as well as the number of bidders at $n = 2$ and $n = 4$. In all treatments $c_i \sim U[0, 100]$ for all suppliers i.

The focus of our design is on the influence of the buyer preferences, the reserve price, and the number of bidders on the performance of the BDRA. The six BDRA treatments we conducted are listed in Table 2.1. Additionally we conducted price-based auctions (PB) with 2 and 4 bidders ($n = 2$ and $n = 4$), which we use to calculate the buyer's total cost if the buyer does not take her supplier-specific preferences (α_i) into account. If bidders follow their dominant strategy the reserve price does not matter in PB auctions, so we used the reserve price of $R = 150$.

Comparing treatments 1 and 3 as well as treatments 4 and 6 allows us to test the prediction of the theory that collusion exists regardless of the reserve price. Comparing treatments 3 and 5 as well as treatments 2 and 4 allows us to test the prediction that collusion exists regardless of the number of bidders. Finally, comparing treatments 1 and 2 as well as treatments 5 and 6 tests the prediction of the theory that collusion is independent of $\overline{\alpha}$.

Expression (2.2.4) implies that in all six treatments, the expected buyer cost from the BDRA will be higher than the expected buyer cost in the PB auction. We will test this prediction by comparing the total expected cost of the buyer in each of our BDRA treatments to a corresponding expected total cost of the buyer in the PB treatment with the same number of bidders.

For each number of bidders ($n = 2$ and $n = 4$), we conducted each treatment with the same realizations of c_i and the same matching protocol, which we pregenerated prior to the start of the experiments.[12] This ensures that any differences in behavior we observe between the treatments with the same number of bidders are due to the factor we vary and not to different realizations of the parameters.

We used the between subjects design. Each BDRA treatment included 5 or 6 independent cohorts and both PB treatments had three cohorts. Each cohort included 6 participants in the $n = 2$ treatments and 12 participants in the $n = 4$ treatments. In total, 372 participants, all in the role of suppliers, were included in our study. We randomly assigned participants to one of the treatments. Each person participated only one time. We conducted all experimental sessions at a major university in the European Union. We recruited participants using the on-line recruitment system ORSEE Greiner (2015). Earning cash was the only incentive offered.

[12] Inadvertently, cost realizations in treatment 4 were also pregenerated but differed slightly from cost realizations in other four-bidder treatment. This had no effect on any of the analysis.

Upon arrival at the laboratory the participants were seated at computer terminals. We handed out written instructions to them and they read the instructions on their own. When all participants finished reading the instructions, we read the instructions to them aloud, to ensure public knowledge about the rules of the game.

After we finished reading the instructions, we started the game. In each session each participant bid in a sequence of 28 auctions; the first three auctions were practice periods to help participants better understand the setting. We used random matching, that we kept the same with-in each cohort. At the beginning of each round, the participants in a cohort were divided into three groups of bidders according to the prespecified profile matching protocol. Each group of bidders competed for the right to sell a single unit to a computerized buyer.

We programmed the experimental interface using the z-Tree system Fischbacher (2007a). The screen included information about the subject's cost c_i, the horizontal quality $\overline{\alpha}$, and the reserve price R. Bidders could also observe all bids placed in real time.

At the end of each round we revealed the same information in all treatments. This information included the bids of all bidders, the α_is, and the winner in that period's auction. The history of past winning prices and quality adjustment α_i in the session was also provided.

For each auction in each period the auction winners earned the difference between their price bids and their costs c_i, while the other bidders earned zero. We computed cash earnings for each participant by multiplying the total earnings from all rounds by a pre-determined exchange rate and adding it to a 2.50 Euro participation fee. Participants were paid their earnings from the auctions they won, in private and in cash, at the end of the session.

2.3.2 RESULTS: AVERAGE BUYER'S COST

Table 2.2 displays the buyer's average total cost and standard errors for the six conditions in our study under the BDRA and the PB auction. We also provide three theoretical benchmarks – collusive, price-based, and the binding auction with α included;[13] all statistics are based on cohort averages. In the PB auction this cost is given by the lowest price bid plus the average misfit cost of supplier specific misfit $(n-1)/n \cdot \overline{\alpha}$.

Table 2.2: Summary of average buyer's total cost compared to theoretical predictions.

		Buyer's total cost (observed)		Theroretical prediction		
Treatment	Description	BDRA	PB	BDRA (collusive benchmark)	PB	Binding auction with α included
1	$n=2$, $\overline{\alpha}=10$, $R=100$	74.05^{**} (1.08)	68.52^{++} (3.75)	100	68.19	68.13
2	$n=2$, $\overline{\alpha}=30$, $R=100$	89.30^{**} (1.16)	78.52^{+++} (3.75)	100	78.19	81.98
3	$n=2$, $\overline{\alpha}=10$, $R=150$	126.85^{**} (5.68)	68.52^{+++} (3.75)	150	68.19	68.56
4	$n=4$, $\overline{\alpha}=30$, $R=100$	71.49^{**} (3.96)	57.34^{++} (2.13)	100	59.71	59.86
5	$n=4$, $\overline{\alpha}=10$, $R=150$	56.38^{**} (5.10)	42.34^{+} (2.13)	150	44.70	45.43
6	$n=4$, $\overline{\alpha}=30$, $R=150$	100.63^{**} (6.50)	57.34^{+++} (2.13)	150	59.71	59.86

Notes: Comparison between observed and theoretical: ** $p \le 0.01$ (for the PB format none of the differences are significant). Comparisons between BDRA and PB: $^{+}$ $p \le 0.1$, $^{++}$ $p \le 0.05$, $^{+++}$ $p \le 0.01$.

We summarize the analysis in Table 2.2 as the following results:

[13] The binding auction with α included provides a benchmark for average buyer cost in the case in which the buyer is able to communicate the α information before the auction. It is a reasonable benchmark because we know enough about open-bid auctions to know that in such auctions people would bid approximately as theory predicts, and we include this for the purpose of providing a benchmark as to how much of a benefit providing α would. Note that the revenue maximizing auction would underweight the α component (see footnotes 5 and 18). Just including α might be worse than a price based auction Engelbrecht-Wiggans et al. (2007).

Result 1. *Average buyer's total cost is significantly below the collusive benchmark under the BDRA format (all p-values are below 0.001).*

Result 2. *Under the PB format, the average buyer's total cost is not significantly different from either the theoretical PB prediction or the binding auction with α included (none of the p-values are below 0.1).*

Result 3. *Average buyer's total cost is significantly higher under the BDRA format than under the PB format in all six conditions.*

Result 4. *If bidders were able to perfectly collude, the buyer's total cost would not have been affected by the number of bidders, but comparing treatments 3 and 5 as well as treatments 2 and 4 tells us that for $\overline{\alpha} = 10$, the average cost decreases by 70.68 (over 50%) when the number of bidders increased from 2 to 4 ($p < 0.001$). The difference (17.8 which is still nearly 20%) is smaller but still highly significant when $\overline{\alpha} = 30$.*[14]

Result 5. *Collusion implies that bidders should bid at the reserve, so buyer's total cost should decrease by 50 between treatments with $R = 150$ and $R = 100$. For the case of $n = 2$ we compare treatments 1 and 3, and observe that the cost decreased by 52.66, which is not significantly different from 50 ($p = 0.586$). But for the case of $n = 4$ we compare treatments 4 and 6, and observe that the cost decreased by only 29.14, which is significantly below 50 ($p < 0.001$).*

Result 6. *Collusion should not be affected by the magnitude of $\overline{\alpha}$, however the average buyer's total cost increased by 15.15 with two bidders when $\overline{\alpha}$ increased from 10 to 30 ($p < 0.001$ for comparing treatments 1 and 2) and by 45.34 with four bidders ($p = 0.0002$ when comparing treatments 4 and 5).*

Additionally, a *t*-test based on cohort averages tells us that the lowest bid increased by 14.79 with two bidders when $\overline{\alpha}$ increased from 10 to 30 ($p < 0.0001$) and by 36.93 with four bidders ($p = 0.0027$). That is, a higher

[14] The fact that collusion decreases with the number of bidders has also been pointed out in other contexts (see for example Huck et al., 2004).

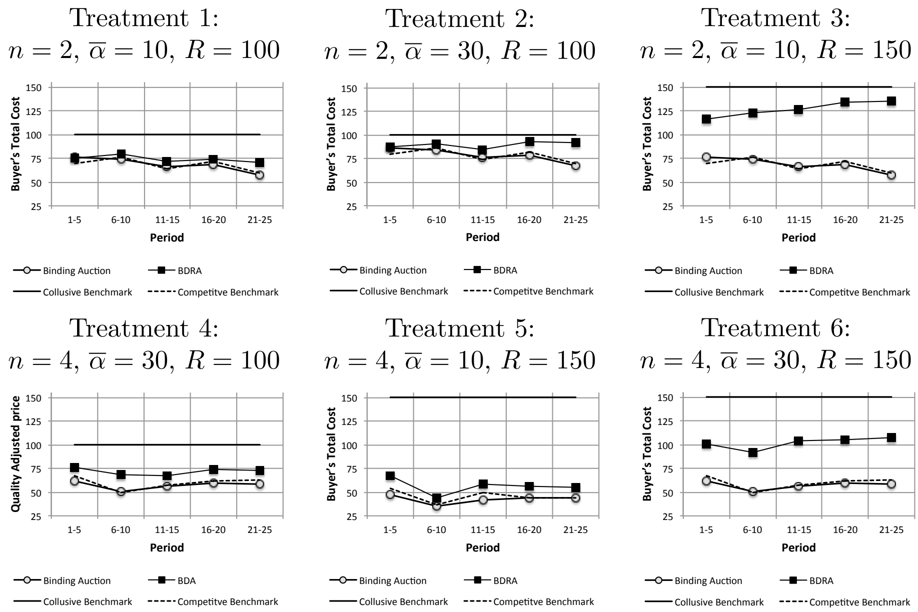


Figure 2.1: Average buyer's total cost over time, and theoretical benchmarks.

$\overline{\alpha}$ harms the buyer in two ways: it weakens competition and also sometimes results in a larger misfit.

In Figure 2.1 we plot, for each of the six conditions, average buyer's total cost over time (aggregated into 5-period blocks) under the BDRA and PB formats. Also for comparison we plot theoretical predictions: the collusive benchmark (R) is the benchmark for the BRDA format and the competitive benchmark is the expected buyer's total cost when the price ends up at the second lowest cost.

To formally analyze how the buyer's total cost in BDRA treatments is affected by the treatment variables (the number of bidders, the reserve price, the size of the $\overline{\alpha}$ parameter), as well as the bidder experience, we estimate a regression model (with random effects) in which the dependent variable is buyer's total cost, and independent variables, along with estimated coefficients, are listed in Table 2.3. This regression uses data from BDRA treatments only.

Table 2.3: Regression estimates for the effect of treatment variables and bidder experience on the expected cost of the buyer.

Dependent variable: Buyer's total cost	Description	Coefficient (standard errors)
β_0	Constant	74.86^{**} (2.934)
n-Dummy	1 when $n = 4$, 0 otherwise	-34.19^{**} (3.548)
R-Dummy	1 when $R = 150$, 0 otherwise	28.18^{**} (3.503)
$\overline{\alpha}$-Dummy	1 when $\overline{\alpha} = 30$, 0 otherwise	26.78^{**} (3.425)
Period	Period number 1-25	-0.21 (0.141)
Period × (R-Dummy)	Interaction variables between treatment variables and the period number.	0.74^{**} (0.178)
Period × (n-Dummy)		-0.723^{**} (0.177)
Period × ($\overline{\alpha}$-Dummy)		0.596^{**} (0.173)
R^2	0.289	
Observations (Groups)	2625 (318)	

The coefficients for the three treatment dummy variables echo Results 4-6. Coefficients of the Period variable and of the interaction variables between Period and the treatment variables tell us how the buyer's total cost is affected by bidder experience.

Result 7. *When the reserve price is low (100) and $\overline{\alpha}$ is low (10), buyer's cost decreases with experience (not significantly), but the decrease becomes strongly significant when the number of bidders is large. There is some collusion that is occurring even in treatments with low $\overline{\alpha}$ (treatment 1 and treatment 5) because buyer's cost is still significantly higher under the BDRA format than under the PB format; collusion may be decreasing over time.*

Result 8. *Higher reserve price reverses this learning trend, making collusion easier to sustain, as is evidenced by the positive and significant coefficient of Period$\times$(R-Dummy).*

Result 9. *Higher $\overline{\alpha}$ also makes collusion easier to sustain as is evidenced by the positive and significant coefficient of Period$\times$($\overline{\alpha}$-Dummy).*

2.3.3 RESULTS: BIDDING BEHAVIOR

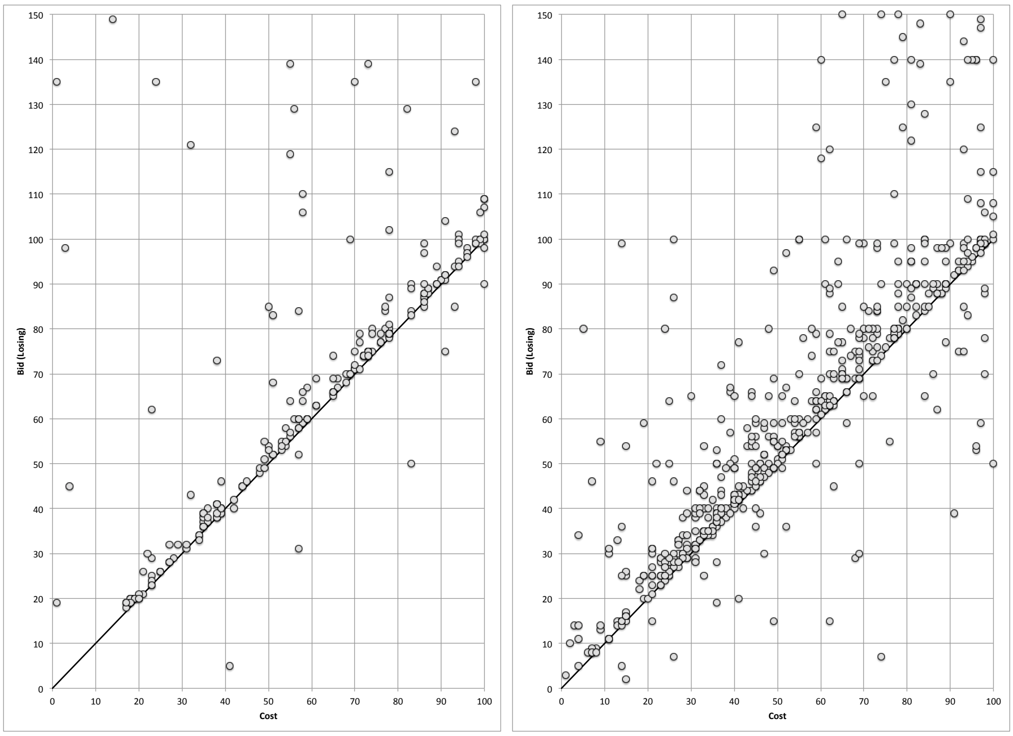
In this section we focus on the individual bidding behavior. First, we briefly describe bidding behavior in the PB auctions.

We plot bids as a function of cost (for losing bidders only) in Figure 2.2a for two bidders and in Figure 2.2b for four bidders. We also estimate a regression model (with random effects) using losing bids in PB auctions with the dependent variable *Bid* and independent variable *Cost*. The coefficient of cost is 0.964 (Std. Err = 0.025), which is not different from 1 at the 5% level of significance. There is also a small but significant constant term (9.52, Std. Err. = 1.78).[15]

Result 10. *The bidding in PB auctions is close to behavior implied by the dominant strategy; almost 80% of losing bidders drop out within 10 ECU of their cost, and the cost coefficient in regression is not significantly different from 1.*

To gain insight into how participants bid in our BDRA treatments we show distributions of bids for the six BDRA treatments in Figure 2.3. Figure 2.3 indicates that some, but not all, of the bidders in all of the BDRA treatments attempt to collude, because in all six treatments the modal bid is at the reserve. However, the proportion of collusive bids varies with our treatment variables. To formally analyze how bids are affected by treatment

[15] As is typical with open-bid auctions, we observe jump bidding in all our treatments. A consequence of jump bidding is that prices might drop quite fast, not giving high cost bidders an opportunity to lower their bid. Jump bidding explains some of the observations in the upper right corner of Figure 2(b). If we use only the second lowest bids in the $n = 4$ treatments in the regressions, the constant term is significantly lower (3.442, std. err = 0.052) and the cost coefficient remains almost unchanged.



(a) PB Auction $n = 2$ (b) PB Auction $n = 4$

Figure 2.2: Losers' bidding behavior in PB auctions.

variables, as well as by the bidders' cost and experience, we estimate a Tobit model (because as is clear from Figure 2.3, bids are censored by the reserve) with random effects, with the dependent variable *Bid*, and independent variables listed in Table 2.4.

To show robustness, we estimate four models, starting with *Cost* only (Model 1), then adding *Period* to control for bidder experience (Model 2), adding treatment variables (Model 3), and finally adding interaction effects between the treatment variables and *Cost*, as well as the treatment variables and *Period* (Model 4).

Result 11. *Contrary to theoretical predictions, BDRA bids are affected by cost. This relationship is weaker for high reserve and high* $\overline{\alpha}$ *(positive and significant Cost×(R-Dummy) and Cost×(*$\overline{\alpha}$*-Dummy)), and stronger for more bidders (positive and significant Cost×(n-Dummy)).*

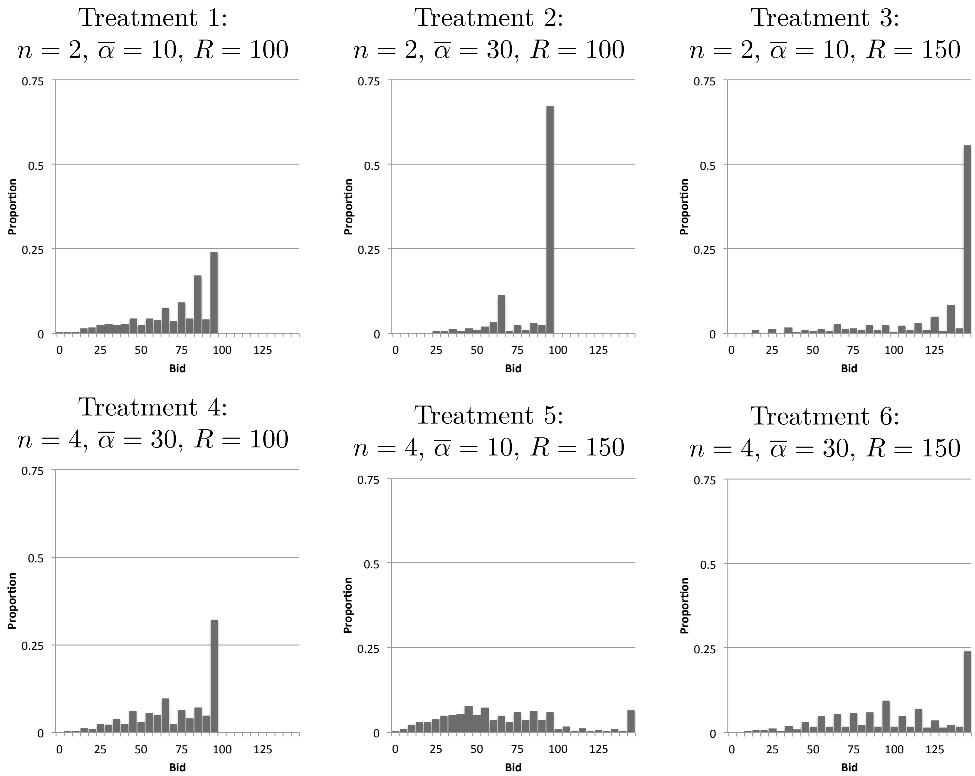


Figure 2.3: Distribution of bids in the BDRA treatments.

Result 12. *Bids slightly increase with experience in two bidder auctions (positive Period variable). This increase is higher for high reserve and high* $\overline{\alpha}$ *(positive and significant Period×(R-Dummy) and Period×(*$\overline{\alpha}$*-Dummy)), and lower for four bidder auctions (negative and significant Period×(n-Dummy)). Interestingly, this slight increase in average bids does not translate into higher buyer's total cost (Result 7).*

We can also see (Models 3 and 4) that the effect of treatment variables on bids is similar to the effect of treatment variables on the buyer's total cost.

Figure 2.4 displays bid-cost pairs of bidders that did not win in the six BDRA treatments. In contrast to the PB treatments the correlations between cost and bid are weaker which indicates less competition. We also observe, in all six BDRA treatments, a fair number of bids at the reserve.

Table 2.4: Estimates for the effect of treatment variables and bidders' experience on bids in the BDRA treatments.

Dependent variable: Bid	Model 1	Model 2	Model 3	Model 4
β_0	65.75^{**} (1.674)	60.47^{**} (1.807)	50.96^{**} (2.615)	46.61^{**} (3.203)
Cost	0.56^{**} (0.013)	0.56^{**} (0.013)	0.56^{**} (0.013)	0.61^{**} (0.028)
Period		0.39^{**} (0.050)	0.39^{**} (0.050)	0.52^{**} (0.110)
n-Dummy			-45.69^{**} (2.867)	-42.80^{**} (3.741)
R-Dummy			37.47^{**} (2.712)	35.41^{**} (3.46)
$\overline{\alpha}$-Dummy			35.49^{**} (2.672)	31.38^{**} (3.422)
Cost × (R-Dummy)				-0.19^{**} (0.031)
Cost × (n-Dummy)				0.31^{**} (0.034)
Cost × ($\overline{\alpha}$-Dummy)				-0.30^{**} (0.031)
Period × (R-Dummy)				0.85^{**} (0.120)
Period × (n-Dummy)				-1.38^{**} (0.132)
Period × ($\overline{\alpha}$-Dummy)				0.62^{**} (0.117)
Log Likelihood	-30,848.699	-30,817.496	-30,706.390	-30,580.866
Observations (Groups)	7,924 (318)			

Notes: * $p \leq 0.1$, ** $p \leq 0.01$

In Table 2.5 we show the proportion of BDRAs that ended in a collusive outcome. We classify an outcome as collusive if all suppliers have a positive probability of winning and all bids are above costs. Furthermore, we display

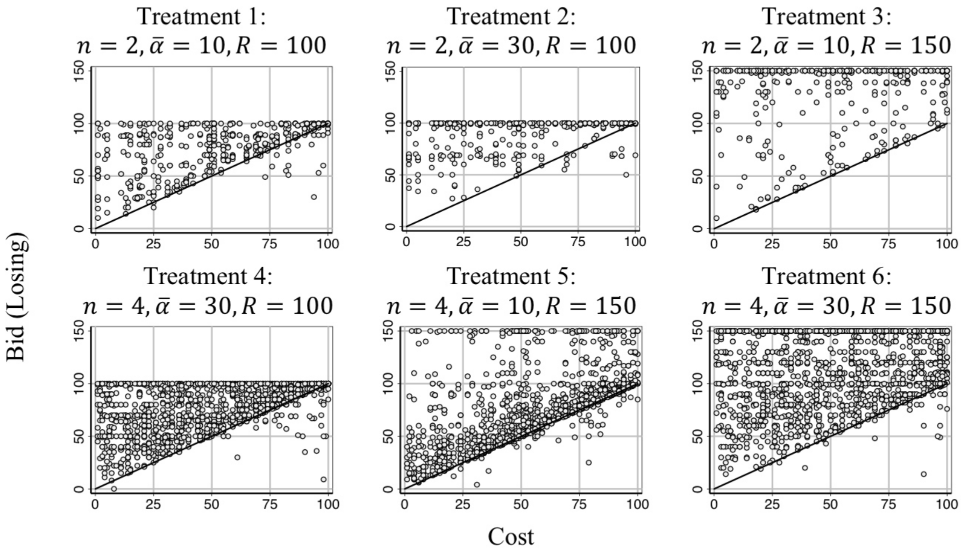


Figure 2.4: Bid as a function of cost of losing bidders for the BDRA treatments.

the average lowest bid given that the BDRA ended in with a collusive outcome.

Table 2.5: Proportion and characteristics of collusive outcomes in BDRA treatments.

Treatment	Proportion of collusive outcomes	Average lowest bid in collusive auctions (standard error)
1: $n = 2$, $\overline{\alpha} = 10$, $R = 100$	44.89%	80.81 (1.46)
2: $n = 2$, $\overline{\alpha} = 30$, $R = 100$	79.78%	90.89 (0.83)
3: $n = 2$, $\overline{\alpha} = 10$, $R = 150$	73.60%	136.641 (1.68)
4: $n = 4$, $\overline{\alpha} = 30$, $R = 100$	33.33%	80.61 (1.76)
5: $n = 4$, $\overline{\alpha} = 10$, $R = 150$	10.00%	112.91 (6.68)
6: $n = 4$, $\overline{\alpha} = 30$, $R = 150$	39.78%	122.80 (2.40)

Table 2.5 shows that there are two reasons why prices in the BDRA are lower than predicted for the collusive equilibrium. First, not all BDRAs end in a collusive outcome, and second, even if the outcome is collusive bids are, on average, below reserve.[16]

2.4 DISCUSSION AND CONCLUSIONS

We have shown that the common practice in procurement of using dynamic buyer-determined reverse auctions allows suppliers to collude on high prices. Collusion can be support-ed because of the uncertainty in the buyer's final decision taking process. Suppliers have a chance of winning at high prices, which might be more attractive than starting a price war and winning at a considerably lower price (with a possibly higher probability). This reasoning can be applied to other circumstances in which the uncertainty of the final decision allows firms to collude in the first place. For example, all private or public tenders in which prices and conditions are negotiated and offers are displayed are prone to the same form of collusion as described above. The reason is that participating firms can react to their opponents' offers and most importantly the final decision is uncertain.

There are several ways the buyer can counteract the problem of collusive behavior. Simple ones would be to precisely communicate α before the reverse auction starts or to conduct a PB auction. Both solutions resolve the uncertainty around the decision process and thus collusion would no longer be sustainable.[17] However, our practical experience showed us that the manager in charge of the procurement has not (at least not alone by herself) the final say on who will be awarded the contract. This is in particular true if she is using a non-binding auction. Consequently, she has no information

[16] BDRAs with four bidders sometimes ended in partial collusion, meaning that at least two of the bidders stop bidding above cost while still having a positive probability of winning. The proportion of BDRAs with four bidders that ended in partial collusion is 85% in treatment 4, 66% in treatment 5 and 87% in treatment 6. The average differences between the lowest bid and lowest cost in those BDRAs are 41.83 (28.36) in treatment 4, 35.11 (25.76) in treatment 5, and 73.78 (53.93) in treatment 6.

[17] Alternatively, the buyer could announce after each round a provisional winner, such that the suppliers can deduce α_i by themselves.

on the exact α_is and therefore cannot credibly communicate a clear decision rule. From a practical point of view, the best alternative would be to commit to a clear scoring rule that takes the non-price attributes of the different suppliers into account. However, this implies that all parties involved in the decision-making process - procurement, logistic, quality, management - have to become involved even before the auction is designed. For example, a supplier who offers a better quality such that the expected additional costs for recalls are expected to be lower by 3%, should be given a price preference of 3% in the auction. If all different dimensions are adequately quantified ex-ante, then a price auction will lead to the efficient outcome.[18] If the buyer, however, does not succeed in getting the uncertainty out of the process, then in a dynamic buyer-determined auction collusion can prevail.[19]

Our experimental results confirm the prediction that dynamic buyer-determined reverse auctions often result in high prices and are also more expensive in terms of buyer's total cost than binding auctions. Consistent with intuition, but in contrast to theoretical predictions, we found that collusion at high prices becomes less likely if the number of bidders increases, if the reserve prices decreases, and if the uncertainty about the decision criteria decreases.

The latter issue implies that buyers who use buyer-determined reverse auctions could re-duce collusion by reducing the uncertainty surrounding the decision making process. This includes providing the seller with information on the attributes, which enter the decision, such as quality, reliability, capacity, and reputation. To reduce the uncertainty further, buyers might also communicate to the suppliers the organizational procedure of the

[18]There exists an extensive literature on the optimal mechanism and auction design in a multidimensional framework (among others Che, 1993; Branco, 1997; Morand and Thomas, 2006; Rezende, 2009), once these different dimensions are quantified. As a general result it is advisable for the auctioneer to use a scoring rule where however the weight on the attributes different than the price should be somewhat lower than the true weight, as this fosters price competition between the suppliers.

[19]Collusion can also be prevented by the use of a static mechanism, e.g. a sealed bid auction, or a dynamic contest with a hard ending rule. If in the latter case the last-second bids are accepted for sure, then this mechanism becomes similar to a sealed bid format, i.e. a static auction. If the acceptance of last second bids is uncertain, high price equilibria can occur Ockenfels and Roth (2006).

decision taking process, e.g. whether a committee or the top management will take the final decision.

2.5 APPENDICES

2.5.1 THEORY

Proof of Proposition 1. If both bidders bid according to the collusive strategy β^c, then bidding ends after the first round and the expected profit of supplier i is given by

$$\pi_i^c(c_i) = \frac{R - c_i}{2}. \tag{2.5.1}$$

Now consider a deviation from the equilibrium strategy. Undercutting the opponent's bid by less than $\overline{\alpha}$ cannot be optimal as this reduces the profit in case of winning without affecting the probability of winning. Thus, the deviator has to lower his bid by more than $\overline{\alpha}$. If by doing so a deviator increases his probability of winning, this immediately implies that the other supplier has a zero probability of winning if the BDRA were to stop at this point. This supplier will, according to the collusive bidding strategy β^c, lower his bid as well. Consequently, a deviator can only increase his probability of winning if his bid is so low that the other will not follow suit anymore. This is the case if the bid b_i is smaller than $c_j - \overline{\alpha}$. The expected profit of a deviator that lowers his bid until his opponent dropped out or his bid is equal to some stopping price p is given by

$$\pi_i^d = \int_p^{\overline{c}-\overline{\alpha}} (x - c_i) \cdot f(x + \overline{\alpha}) dx + \frac{p - c_i}{2} \cdot F(p + \overline{\alpha}). \tag{2.5.2}$$

Comparing (2.5.1) and (2.5.2) shows that the incentive to deviate is largest for a supplier with lowest costs ($c_i = \underline{c}$). This leads to expression (2.2.1) in Proposition 1. □

Proof of Corollary 1. The first derivative of the expected deviation profit (2.5.2) with respect to the stopping price p is given by

$$\frac{\partial \pi_i^d}{\partial p} = \frac{F(p + \overline{\alpha}) - (p - c_i) \cdot f(p + \overline{\alpha})}{2} \tag{2.5.3}$$

Hence, the deviator wants to stop as early as possible if (2.5.3) is positive. This requirement is always fulfilled if F is concave, as then $F(x) \geq x \cdot f(x)$ holds. Note that in this case the collusive bidding strategies β^c indeed constitute a perfect Bayesian equilibrium. Even outside the equilibrium path, if someone is undercut, it is optimal to place the highest bid that is still in the range of $\overline{\alpha}$ of the other bid. Any higher bid would lead to a zero probability of winning. Any lower bid that is still in the range of $\overline{\alpha}$ of the other bid would also result in a winning probability of one half if the auction were to stop at this point but with a lower price in case of winning. Lastly, trying to outbid the deviator cannot be optimal since (2.5.3) is positive. □

Proof of Proposition 2. We show that if bidders behave according to the collusive strategy β^c then no one can make himself better off in the BDRA by deviating. Again we concentrate on a bidder with lowest costs. The expected profit of such a bidder from collusion is given by

$$\pi_i^c = \frac{R}{n} \tag{2.5.4}$$

If he instead tries to outbid one competitor by lowering his bid at most to p and then colludes with the remaining $n-1$ competitors his profit can be written as

$$\int_p^{100-\overline{\alpha}} x \cdot \frac{2}{n} \cdot \overbrace{\frac{n-1}{100} \cdot \left(\frac{x+\overline{\alpha}}{100}\right)^{n-2}}^{(n-1)\cdot f(x+\overline{\alpha})\cdot F(x+\overline{\alpha})^{n-2}} dx + p \cdot \frac{1}{n} \cdot \overbrace{\left(\frac{p+\overline{\alpha}}{100}\right)^{n-1}}^{F(p+\overline{\alpha})^{n-1}}. \tag{2.5.5}$$

Note that by outbidding one competitor the winning probability of the deviator increases to $2/n$, as he then wins not only if he is preferred but also if the outbid competitor is the preferred supplier. Optimizing expression (2.5.5) with respect to the stopping price p yields $p^* = \overline{\alpha}/(n-2)$ for $n > 2$. Hence, the profit from trying to outbid one of the $n-1$ competitors optimally is given by

$$\pi^d = \int_{\frac{\overline{\alpha}}{n-2}}^{100-\overline{\alpha}} x \cdot \frac{2}{n} \cdot \frac{n-1}{100} \cdot \left(\frac{x+\overline{\alpha}}{100}\right)^{n-2} dx + \frac{\overline{\alpha}}{n-2} \cdot \frac{1}{n} \cdot \left(\frac{\overline{\alpha}\cdot(n-1)}{100\cdot(n-2)}\right)^{n-1}. \tag{2.5.6}$$

Now it remains to be shown that the deviating bidder has no incentive to lower his bid further when the first competitor dropped out. To see this suppose that $m < n$ bidders are still active when the deviator reduced his bid to p_m, i.e. one (or more) competitors already dropped out. Then the expected profit from trying to outbid a further competitor by reducing the own bid at most to p_{m-1} can be expressed as

$$\int_{p_{m-1}}^{p_m} x \cdot \frac{n-m+2}{n} \cdot \overbrace{\frac{m-1}{100} \cdot \left(\frac{x+\overline{\alpha}}{100}\right)^{m-2}}^{(m-1)\cdot f(x+\overline{\alpha})\cdot F(x+\overline{\alpha})^{m-2}} dx + p_{m-1} \cdot \frac{n-m+1}{n} \cdot \overbrace{\left(\frac{p_{m-1}+\overline{\alpha}}{100}\right)^{m-1}}^{F(p_{m-1}+\overline{\alpha})^{m-1}} \tag{2.5.7}$$

Observe that by outbidding a further competitor the winning probability of the deviator increases to $(1-(m-2)/n)$, as he then wins as long as none of the surviving competitors is the preferred supplier. The first derivative of (2.5.7) with respect to the stopping price p_{m-1} is given by

$$\frac{(p_{m-1}+\overline{\alpha})^{m-2}}{n} \cdot [p_{m-1} \cdot (n-2m+2) + \overline{\alpha} \cdot (n-m+1)] \tag{2.5.8}$$

A bidder has no incentive to lower his bid as long as expression (2.5.8) is positive for all p_{m-1}. As expression (2.5.8) is decreasing in m it suffices to show that it is positive for $m = n-1$ in order to prove that it is positive for all $m \leq n-1$. At this point it is easy to see that it can never be optimal to outbid more than half of the competitors as expression (2.5.8) is always positive if $m \leq (n+2)/2$.

If we plug in $m = n-1$ in expression (2.5.8) we get a condition which guarantees that no bidder has an incentive to lower his bid further once a bidder dropped out.

$$\frac{(p_{n-2}+\overline{\alpha})^{n-3}}{n} \cdot [p_{n-2} \cdot (4-n) + 2 \cdot \overline{\alpha}] \geq 0 \tag{2.5.9}$$

For $n \leq 4$ this condition is always fulfilled. For $n > 4$ the term on the left reaches its minimum when the price reaches its maximum. As the price is bounded at $100 - \overline{\alpha}$ we can state a sufficient condition as

$$\overline{\alpha} \geq 100 \cdot \frac{n-4}{n-2}. \tag{2.5.10}$$

For these parameter values the collusive bidding strategies β^c constitute an equilibrium.

To prove that also in a perfect Bayesian equilibrium collusion is possible, we next show that the way bidders react to a deviating competitor as defined in β^c determines an upper bound for the deviation incentive for any sequentially rational strategy. Not following suit if a deviator bids more than $\overline{\alpha}$ below the own bid cannot be optimal, as this leads to a zero probability of winning. Hence, no bid higher than defined by our collusive bidding strategy can be a best response to a deviation. As a consequence the winning probability of a deviator and thereby also the expected profit from deviating cannot be larger when competitors behave sequentially rational than when they behave according to the collusive bidding strategy β^c. Thus, in any perfect Bayesian equilibrium, collusion remains to be an equilibrium outcome if it is an equilibrium given our collusive bidding strategy β^c. □

2.5.2 INSTRUCTIONS

This section provides the instructions in German (original) and English (translated) for Treatment 1 and for our price-based auction with two bidders.

Anleitung zum Experiment

Herzlichen Dank für Ihre Teilnahme am Experiment. Bitte sprechen Sie bis zum Ende des Experiments nicht mehr mit anderen Teilnehmern.

Dieses Experiment besteht aus **28 Runden**. In jeder dieser Runden befinden Sie sich in der gleichen Situation, die im Folgenden ausführlich erklärt wird. Die ersten **3 Runden** des Experiments sind Proberunden, in denen Sie nicht um Geld spielen. In den restlichen **25 Runden** können Sie Geld verdienen, das Ihnen am Ende des Experiments ausgezahlt wird. In jeder Runde spielen Sie mit einem anderen Teilnehmer aus diesem Raum.

Die Situation

In diesem Experiment sind Sie der Produzent eines Gutes und nehmen in jeder Runde als Bieter an einer Einkaufsaukion mit einem anderen Produzenten teil. In der Auktion möchte ein Käufer ein Gut kaufen. Um das Gut zu verkaufen, geben Sie und der andere Bieter **Gebote** ab, zu denen Sie bereit sind, das Gut zu verkaufen.
Die Bereitstellung des Gutes ist für Sie mit Kosten verbunden. Diese Kosten, die Ihnen nur entstehen, wenn Sie das Gut verkaufen, werden in jeder Runde zufällig und unabhängig für jeden Bieter ermittelt. Alle ganzzahligen Kosten zwischen **0** und **100** sind dabei gleich wahrscheinlich. Wählt der Käufer Ihr Gebot aus, so ist Ihr Gewinn aus der Auktion

Ihr Gewinn = Ihr Gebot – Ihre Kosten

Wählt der Käufer Ihr Gebot nicht aus, so machen Sie in dieser Runde einen Gewinn von 0.
Ob Sie die Auktion gewinnen oder nicht, hängt nicht nur von Ihrem Gebot ab, sondern auch von **Ihrer Qualität** und der Qualität des anderen Bieters. In jeder Auktion bevorzugt der Käufer zufällig einen der beiden Bieter und gibt diesem einen **Qualitätsvorteil** von **10**. Welcher Bieter den Qualitätsvorteil hat, ist während der Auktion nicht bekannt und wird erst veröffentlicht, nachdem die Bietzeit abgelaufen ist. Die Wahrscheinlichkeit bevorzugt zu werden ist für alle Bieter gleich. Der Käufer wählt den Bieter aus, der das niedrigste qualitätsangepasste Gebot (**QA Gebot**) abgegeben hat.

Ihr QA Gebot = Ihr Gebot – Ihre Qualität

Sollten beide Bieter ein qualitätsangepasstes Gebot (**QA Gebot**) in gleicher Höhe abgegeben haben, wird der Bieter mit der höheren Qualität ausgewählt.

Beispiel

Die Ungewissheit bezüglich des Qualitätsvorteils führt dazu, dass der Bieter, der das niedrigere Gebot abgegeben hat, nicht zwangsläufig die Auktion gewinnt. Betrachten Sie dazu das folgende Beispiel.

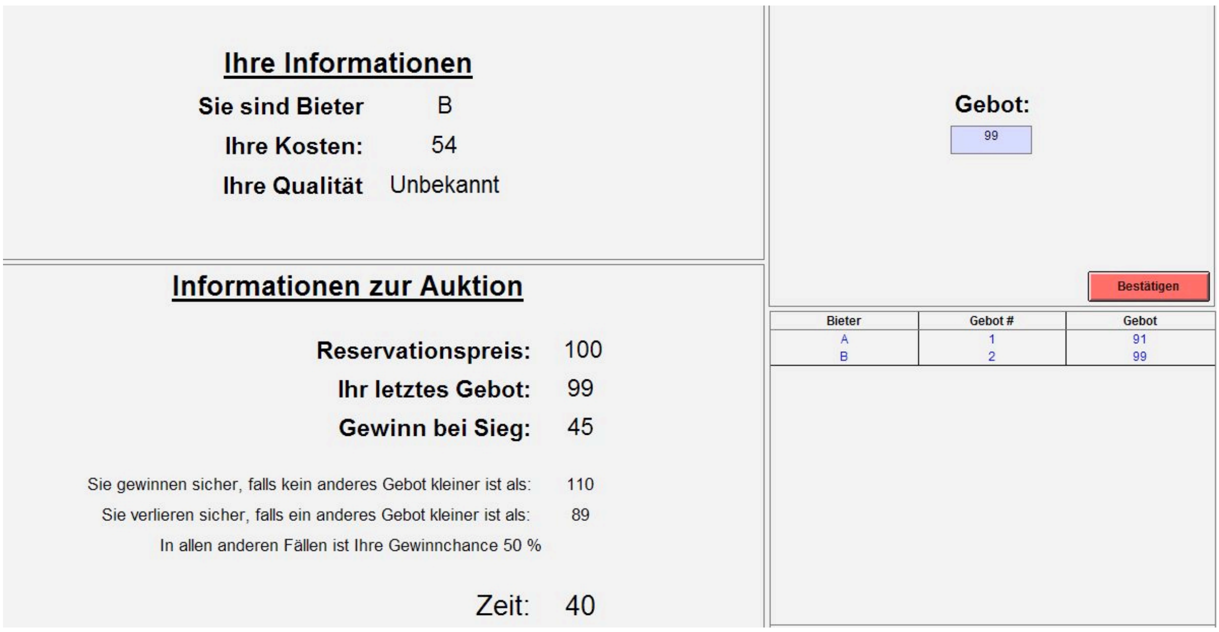
Nehmen Sie an, das letzte Gebot von **Bieter A** war 91 und das von **Bieter B** 99. Obwohl sie es während der Auktion nicht wussten, stellt sich nach der Auktion heraus, dass der Käufer **Bieter B** bevorzugt und ihm folglich den Qualitätsvorteil von 10 gibt. Daher sind die qualitätsangepassten Gebote

Bieter A's QA Gebot = 91 – 0 = 91
Bieter B's QA Gebot = 99 – 10 = 89

Daher wird der Käufer das Gut zu einem Preis von 99 ECU von **Bieter B** kaufen. Der nicht ausgewählte **Bieter A** macht einen Gewinn von 0. Bitte beachten Sie, dass die Auswahl des Käufers von den **QA Geboten** abhängt, Ihr Gewinn im Falle Ihrer Auswahl jedoch nur von Ihrem **Gebot**.

Die Auktion

Unten sehen Sie wie Ihr Bildschirm während der Auktion aussehen wird. Sie erfahren, ob Sie Bieter A oder B sind, wobei Sie in beiden Rollen mit gleicher Wahrscheinlichkeit der bevorzugte Bieter sind. Außerdem sehen Sie, zu welchen Kosten Sie das Gut bereitstellen können und wie hoch Ihr Gewinn wäre, wenn Sie die Auktion mit Ihrem aktuellen Gebot gewinnen würden.
Auf der rechten Seite des Bildschirms haben Sie eine Übersicht über Ihr aktuelles Gebot und das aktuelle Gebot des anderen Bieters. Mit dieser Information können Sie anhand der Anzeige auf der linken Seite bestimmen, ob Sie gegeben der aktuellen Gebote sicher gewinnen werden, sicher verlieren werden oder mit einer Wahrscheinlichkeit von 50% gewinnen werden.



Gebotsabgabe

Um ein Gebot abzugeben, tippen Sie das gewünschte Gebot in die Box ein und klicken anschließend auf “Bestätigen”. Bitte beachten Sie, dass Sie kein Gebot abgeben können, das größer als der Reservationspreis von 100 ECU ist. Ebenso können Sie kein Gebot abgeben, das größer ist als Ihr aktuelles Gebot in dieser Auktion. Sie können während der Auktion beliebig viele Gebote abgeben.
Die Auktionen in den **3** Proberunden werden eine Grundlaufzeit von **60 Sekunden** haben. Die restlichen **25** Auktionen haben eine Grundlaufzeit von **40 Sekunden**. Falls ein Bieter in den letzten **10 Sekunden** einer Auktion ein Gebot abgibt, so wird die Laufzeit auf **10 Sekunden** verlängert. Dies führt dazu, dass Sie keinen Vorteil haben, wenn Sie mit der Gebotsabgabe bis zur letzten Sekunde warten. Die Auktion endet, wenn der Timer bei 0 angekommen ist.

Ihre Gewinnchancen

Sie werden in einer Auktion nur sicher gewinnen, falls Ihr Gebot mindestens um 11 ECU kleiner ist als das Gebot des anderen Bieters. Andersrum bedeutet dies, dass Sie nur dann sicher verlieren, wenn der andere Bieter ein Gebot abgegeben hat, das um 11 oder mehr Einheiten unter Ihrem letzten Gebot liegt. In allen anderen Fällen haben Sie und der andere Bieter die gleiche Gewinnwahrscheinlichkeit von 50%.

Informationen die Sie nach Ende der Auktion erhalten

Am Ende jeder Auktion sehen Sie eine Liste mit den Geboten, Ihrer Qualität und der Qualität des anderen Bieters. Außerdem werden die qualitätsangepassten Gebote und Ihr Gewinn angezeigt.

Auszahlung

Am Ende des Experiments wird der Computer Ihre Auszahlung angeben und in Euro umrechnen. Dabei entsprechen 40 ECU einem Euro. Zusätzlich erhalten Sie ein Show Up Fee in Höhe von 2,50€. Bitte warten Sie auch nach Ablauf des Experiments ruhig an Ihrem Platz, bis Sie der Experimentator für die Auszahlung aufruft.

Vielen Dank für die Teilnahme an unserem Experiment.

Anleitung zum Experiment

Herzlichen Dank für Ihre Teilnahme am Experiment. Bitte sprechen Sie bis zum Ende des Experiments nicht mehr mit anderen Teilnehmern.

Dieses Experiment besteht aus **28 Runden**. In jeder dieser Runden befinden Sie sich in der gleichen Situation, die im Folgenden ausführlich erklärt wird. Die ersten **3 Runden** des Experiments sind Proberunden, in denen Sie nicht um Geld spielen. In den restlichen **25 Runden** können Sie Geld verdienen, das Ihnen am Ende des Experiments ausgezahlt wird. In jeder Runde spielen Sie mit einem anderen Teilnehmer aus diesem Raum.

Die Situation
In diesem Experiment sind Sie der Produzent eines Gutes und nehmen in jeder Runde als Bieter an einer Einkaufsaukion mit einem anderen Produzenten teil. In der Auktion möchte ein Käufer ein Gut kaufen. Um das Gut zu verkaufen, geben Sie und der andere Bieter **Gebote** ab, zu denen Sie bereit sind, das Gut zu verkaufen.
Die Bereitstellung des Gutes ist für Sie mit Kosten verbunden. Diese Kosten, die Ihnen nur entstehen, wenn Sie das Gut verkaufen, werden in jeder Runde zufällig und unabhängig für jeden Bieter ermittelt. Alle ganzzahligen Kosten zwischen **0** und **100** sind dabei gleich wahrscheinlich.
Wählt der Käufer Ihr Gebot aus, so ist Ihr Gewinn aus der Auktion

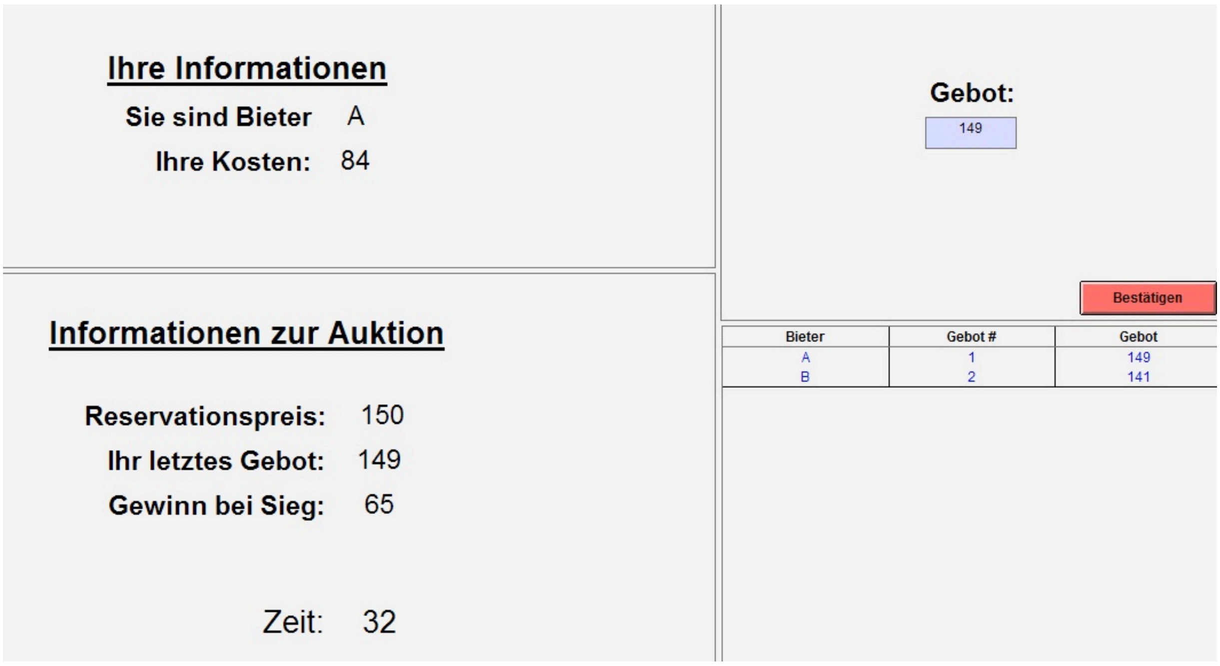
Ihr Gewinn = Ihr Gebot – Ihre Kosten

Wählt der Käufer Ihr Gebot nicht aus, so machen Sie in dieser Runde einen Gewinn von 0.
Ob Sie die Auktion gewinnen oder nicht, hängt nur von Ihrem Gebot ab.

Beispiel
Der Bieter, der das niedrigere Gebot abgegeben hat, gewinnt die Auktion. Betrachten Sie dazu das folgende Beispiel.

Nehmen Sie an, das letzte Gebot von **Bieter A** war 141 und das von **Bieter B** 149. Dann wird der Käufer das Gut zu einem Preis von 141 ECU von **Bieter A** kaufen. Der nicht ausgewählte **Bieter B** macht einen Gewinn von 0. Bitte beachten Sie, dass sowohl die Auswahl des Käufers als auch Ihr Gewinn im Falle Ihrer Auswahl nur von Ihrem **Gebot** abhängen.

Die Auktion
Unten sehen Sie wie Ihr Bildschirm während der Auktion aussehen wird. Sie erfahren, ob Sie Bieter A oder B sind. Außerdem sehen Sie, zu welchen Kosten Sie das Gut bereitstellen können und wie hoch Ihr Gewinn wäre, wenn Sie die Auktion mit Ihrem aktuellen Gebot gewinnen würden.
Auf der rechten Seite des Bildschirms haben Sie eine Übersicht über Ihr aktuelles Gebot und das aktuelle Gebot des anderen Bieters. Mit dieser Information können Sie bestimmen, ob Sie gegeben der aktuellen Gebote sicher gewinnen oder sicher verlieren werden.



Gebotsabgabe
Um ein Gebot abzugeben, tippen Sie das gewünschte Gebot in die Box ein und klicken anschließend auf “Bestätigen”. Bitte beachten Sie, dass Sie kein Gebot abgeben können, das größer als der Reservationspreis von 150 ECU ist. Ebenso können Sie nur Gebote abgeben, die kleiner als das niedrigste Gebot in dieser Auktion sind. Sie können während der Auktion beliebig viele Gebote abgeben.
Die Auktionen in den **3** Proberunden werden eine Grundlaufzeit von **60 Sekunden** haben. Die restlichen **25** Auktionen haben eine Grundlaufzeit von **40 Sekunden**. Falls ein Bieter in den letzten **10 Sekunden** einer Auktion ein Gebot abgibt, so wird die Laufzeit auf **10 Sekunden** verlängert. Dies führt dazu, dass Sie keinen Vorteil haben, wenn Sie mit der Gebotsabgabe bis zur letzten Sekunde warten. Die Auktion endet, wenn der Timer bei 0 angekommen ist.

Ihre Gewinnchancen
Sie werden in einer Auktion sicher gewinnen, falls Ihr Gebot kleiner ist als das Gebot des anderen Bieters. Andersrum bedeutet dies, dass Sie sicher verlieren, wenn der andere Bieter ein Gebot abgegeben hat, das unter Ihrem letzten Gebot liegt.

Informationen die Sie nach Ende der Auktion erhalten
Am Ende jeder Auktion sehen Sie eine Liste mit den Geboten und Ihrem Gewinn.

Auszahlung
Am Ende des Experiments wird der Computer Ihre Auszahlung angeben und in Euro umrechnen. Dabei entsprechen 35 ECU einem Euro. Zusätzlich erhalten Sie ein Show Up Fee in Höhe von 2,50€. Bitte warten Sie auch nach Ablauf des Experiments ruhig an Ihrem Platz, bis Sie der Experimentator für die Auszahlung aufruft.

Vielen Dank für die Teilnahme an unserem Experiment.

Instructions

Thank you for participating in this experiment. Please do not talk to other participants until the end of this experiment.

This experiment consists of **28 rounds**. In each of this rounds you are in the same situation that will be explained to you in detail. The first **3 rounds** of the experiment are practice rounds, in which you cannot earn money. In the remaining **25 rounds** you can earn money that will be paid out at the end of the experiment. In each round you play with another participant in this room.

The situation

In this experiment you are the producer of a good and you participate as a bidder in a procurement auction with one other producer in each round. In this auction a buyer wants to procure one good. In order to sell the good you and the other bidder place **bids** for which you want to sell the good.
Selling the good is costly. These costs, which only occur if you sell the good, are independently and randomly drawn for each bidder in each period. All integers between **0** and **100** are equally likely. If the buyer selects your bid your bid your profit is given by

Your Profit = Your Bid – Your Costs

If the buyer does not select your offer, you make a profit of 0 in that period. Whether you win the auction or not does not only depend on your bid, it also depends on **Your Quality** and the quality of the other bidder. In each auction the buyer randomly prefers one of the two bidders and assigns a **Quality Advantage** of **10** to this bidder. Which of the bidder has the quality advantage is not known during the auction and is only published when the bidding time has expired. The probability of being the preferred bidder is the same for all bidders. The buyer selects the bidder who placed the lowest quality-adjusted bid **(QA Bid)**.

Your QA Bid = Your Bid – Your Quality

If both suppliers place the same quality-adjusted bid (**QA Bid**), the bidder with the higher quality will be selected.

Example

The uncertainty about the quality advantage implies that a bidder who placed the lowest bid will not win for sure. Consider the following example.

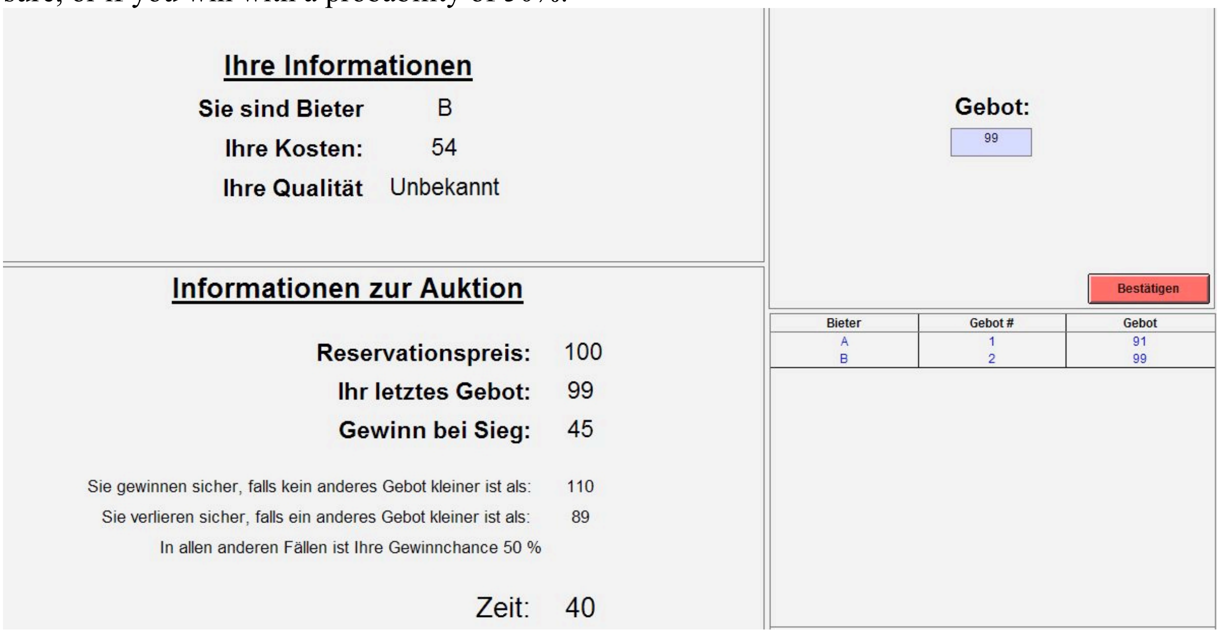
Suppose the last offer of **Bidder A** was 91 and that of **Bidder B** 99. Even though they did not know it during the auction it is revealed after the auction that the buyer prefers **Bidder B** and hence assigns a quality advantage of 10 to **Bidder B**. Then the quality-adjusted bids are

Bidder A's QA Bid = 91 – 0 = 91
Bidder B's QA Bid = 99 – 10 = 89

Hence the buyer will procure the good from **Bidder B** at a price of 99 ECU. The non-selected **Bidder A** makes a profit of 0. Please have in mind that the buyer's selection decision depends on the **QA Bids**, but your profit in case of selection only depends on your **bid**.

The auction

Below you can see how your screen looks like during the auction. You see if you are Bidder A or B. In both roles you have the same chance of being the preferred bidder. Furthermore, you learn at which costs you can provide the good and how large your profit would be if you won the auction with your current bid.
On the right hand side of the screen you have an overview of your current bid and the current bid of the other bidder. With this information you can calculate, if you win for sure, if you lose for sure, or if you win with a probability of 50%.



Bidding

To place a bid you have to type it into the box and click confirm. Please have in mind that you cannot place a bid that is larger than the reservation price of 100 ECU. You cannot place a bid that is larger than your current bid in the auction. You can place as many bids in the auction as you want.
The auctions in the **3** practice periods have a minimum duration of **60 seconds**. The remaining **25** auctions have a minimum duration of **40 seconds**. If a bidder places a bid within the last **10 seconds** the counter is reset to **10 seconds**. This implies that you have no advantage if you wait for the last second to place your bid. The auction ends if the timer reaches 0.

Your winning probability

You will only win an auction for sure if your bid is at least 11 ECU smaller than the bid of the other bidder. This also means that you only lose for sure if the other bidder placed a bid that is 11 or more units smaller than your last bid. In all other cases you and the other bidder have both a winning probability of 50%.

Information you receive at the end of the auction

At the end of the auction you see a list containing the bids, your quality, and the quality of the other bidder. Furthermore, you the quality-adjusted bids and your profit.

Payment

At the end of the experiment the computer will calculate your profit and display it in Euros. 40 ECU are equivalent to one Euro. Additionally, you get a Show Up Fee of 2,50€. Please wait at your seat until you are called for your payment.

Thank you for participating in our experiment.

Instructions

Thank you for participating in this experiment. Please do not talk to other participants until the end of this experiment.

This experiment consists of **28 rounds**. In each of this rounds you are in the same situation that will be explained to you in detail. The first **3 rounds** of the experiment are practice rounds, in which you cannot earn money. In the remaining **25 rounds** you can earn money that will be paid out at the end of the experiment. In each round you play with another participant in this room.

The situation

In this experiment you are the producer of a good and you participate as a bidder in a procurement auction with one other producer in each round. In this auction a buyer wants to procure one good. In order to sell the good you and the other bidder place **bids** for which you want to sell the good.
Selling the good is costly. These costs, which only occur if you sell the good, are independently and randomly drawn for each bidder in each period. All integers between **0** and **100** are equally likely. If the buyer selects your bid your bid your profit is given by

Your Profit = Your Bid – Your Costs

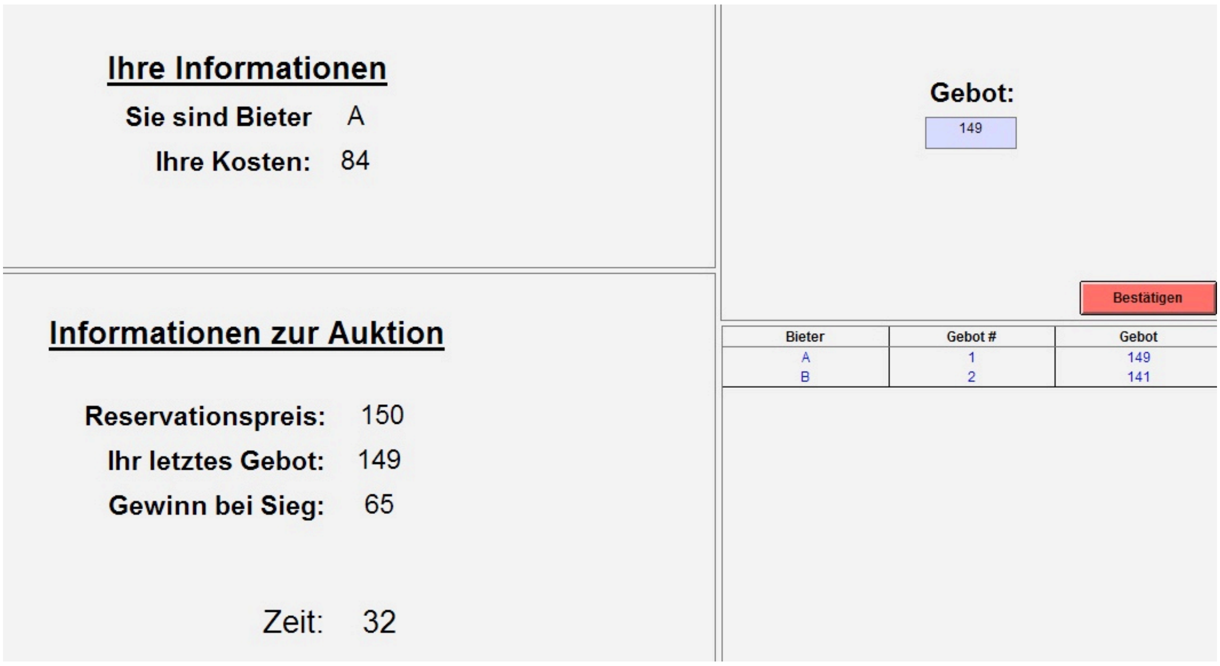
If the buyer does not select your offer, you make a profit of 0 in that period. Whether you win the auction or not does only depend on your bid.

Example

The bidder who placed the lower bid wins the auction. Consider the following example.

Suppose the last bid of **Bidder A** was 141 and that of **Bidder B** 149. Then the buyer will procure the good at a price of 141 ECU from **Bidder A**. The non-selected **Bidder A** makes a profit of 0. Please have in mind that the buyer's selection decision depends on the **QA Bids**, but your profit in case of selection only depends on your **bid**. Please have in mind that the buyer's selection decision and your profit in case of selection only depend on your **bid**.

The auction
Below you can see how your screen looks like during the auction. You see if you are Bidder A or B. In both roles you have the same chance of being the preferred bidder. Furthermore, you learn at which costs you can provide the good and how large your profit would be if you won the auction with your current bid.
On the right hand side of the screen you have an overview of your current bid and the current bid of the other bidder. With this information you can calculate, if you win for sure or if you lose for sure.



Bidding
To place a bid you have to type it into the box and click confirm. Please have in mind that you cannot place a bid that is larger than the reservation price of 150 ECU. You cannot place a bid that is larger than your current bid in the auction. You can place as many bids in the auction as you want.
The auctions in the **3** practice periods have a minimum duration of **60 seconds**. The remaining **25** auctions have a minimum duration of **40 seconds**. If a bidder places a bid within the last **10 seconds** the counter is reset to **10 seconds**. This implies that you have no advantage if you wait for the last second to place your bid. The auction ends if the timer reaches 0.

Your winning probability
You will win an auction for sure if your bid is smaller than the bid of the other bidder. This also means that you lose for sure if the other bidder placed a bid that is smaller than your last bid.

Information you receive at the end of the auction
At the end of the auction you see a list containing the bids and your profit.

Payment
At the end of the experiment the computer will calculate your profit and display it in Euros. 35 ECU are equivalent to one Euro. Additionally, you get a Show Up Fee of 2,50€. Please wait at your seat until you are called for your payment.

Thank you for participating in our experiment.

CHAPTER 3

TRUST IN PROCUREMENT INTERACTIONS

Abstract

We investigate the observation that auctions in procurement can be detrimental to the buyer-seller relationship. Poor relationship can result in a decrease in trust by the buyer during the sourcing and an increase in opportunistic behavior by the supplier after the sourcing. We consider a setting in which the winning supplier decides on the level of costly quality to provide to the buyer, and compare a standard reverse auction and a buyer-determined reverse auction in the laboratory. We find that buyer-determined auctions result in higher prices but also improve cooperation between the buyer and the selected supplier. In the buyer-determined auction it can be optimal for the buyer to choose the supplier who submitted a higher bid. The standard auctions, on the other hand, yield lower prices but reduce cooperation to a minimum. The degree of trust reflected by a larger number of trades and higher efficiency in case of trade are significantly higher in the buyer-determined auction. Theoretical reasoning based on other-regarding preferences helps to organize the results.

3.1 INTRODUCTION

Reverse auctions, and in particular non-binding reverse auctions are commonly used in procurement Elmaghraby (2007).[1] However, an often-heard

[1] In buyer-determined reverse auctions, bidders compete against each other like in a standard reverse auction, but the winner is not necessarily the supplier with the lowest bid. Rather, buyers decide based on the final quotes and further information on the suppliers, who will be awarded the contract. In a recent survey, Elmaghraby (2007) notes that "The exact manner in which the buyer makes her final selection still remains unclear. With either an on-line auction or a RFP, the buyer may still leave some terms of trade unspecified." (p. 411).

argument against procurement auctions is that reverse auctions can have a negative effect on the relationship between the buyer and the supplier (Smeltzer and Carr, 2003; Jap, 2002, 2003, 2007). This relationship is particularly important if there is some uncertainty about the exact specifications of the delivered product and the buyer has to trust the supplier.[2]

In this paper we investigate the observation that the mechanism used for procurement can influence the degree of cooperation between the buyer and the seller once trade takes place and the amount of trust that is necessary for trade to take place. For this purpose we compare a binding first-price reverse auction and a non-binding buyer-determined auction in a setting in which after the sourcing the seller decides on the quality of the product she delivers. We show that the buyer-determined auction induces a significantly higher degree of trust and cooperation, but at the same time leads to higher prices. Interestingly, it can be worthwhile for the buyer in a buyer-determined auction to choose the higher offer instead of the lower one.

To organize our results, we discuss a model based on other-regarding preferences. While standard reasoning implies that both mechanisms should lead to the same allocation, allowing for other-regarding preferences helps to explain the results of the experiment.

In the experiment, both in the binding auction as well as in the buyer-determined auction, potential suppliers place a sealed bid (or offer). In the binding auction, the buyer can only accept the lowest offer or refuse to trade, whereas he can also accept a higher offer in a buyer-determined auction. Once the winning supplier and price are determined, the selected supplier decides on the quality of the good to be delivered. A higher quality is more valuable to the buyer, but also more costly to the seller.

Now, with standard preferences, the seller would deliver lowest quality in all cases, as quality is not part of the contract. Since there is competition between suppliers, both mechanisms thus lead to prices equal to costs of the

[2] Mayer et al. (1995) define trust as "the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party".

lowest quality. With other-regarding preferences both suppliers and buyers might care about the profit the others obtain. In this case, individuals have two objectives. On the one hand they still want to maximize their monetary payoff, but on the other hand they care about the gap between their own and others' monetary payoffs. Thus, when prices are high there can be a trade-off. Increasing quality decreases supplier's own monetary payoff but also, depending on the price, may result in more equitable outcomes. Therefore, quality is no longer independent of prices and high prices might induce high quality if the supplier has other-regarding preferences and gains from cooperation are high. As a consequence, the equilibrium outcomes of price-based and buyer-determined auctions can differ greatly. We derive properties of buyer's beliefs that imply that the same subjects who coordinate on a high-price high-quality equilibrium in the buyer-determined auction will compete down to their lowest costs and provide minimum quality in price-based auctions.

This paper contributes to the literature on buyer-determined auctions. Engelbrecht-Wiggans et al. (2007) compare a price-based and a buyer-determined mechanism in a setting in which costs and qualities are correlated. They show theoretically that buyer-determined auctions are more profitable for the buyer if the correlation between costs and quality is high and the number of bidders is not too low. They also provide experimental evidence for their predictions. In contrast to our study, they assume that quality is exogenously given; in our setting, the supplier decides on the quality level after the selection. In Fugger et al. (2016) we analyze a setting in which suppliers are uncertain about buyer's exact preferences during the competitive bidding and suppliers bid either in a dynamic buyer-determined or a binding reverse auction. In such a setting, there is a trade-off for the buyer between binding price-based auctions and buyer-determined auctions. Price-based auctions induce low prices but might force the buyer to select a non-preferred supplier. On the other hand, buyer-determined auctions allow the buyer to choose the best offer but can also enable tacit collusion that results in high prices, especially when the number of bidders is small.

The work in the procurement literature closest to ours is Brosig-Koch and Heinrich (2012). In an experimental study, they find that price-based auctions are less profitable for buyers than buyer-determined mechanisms, when buyers can base their selection on suppliers' past performances. Like us, they also consider a setting with incomplete contracts, in which payments cannot be conditioned on the provided quality. However their approach differs from ours in two major aspects. First, their explanation of differences between auctions and buyer-determined auctions is based on reputation building. In their setting reputation building can only be profitable in the buyer-determined mechanism. While the buyer has to select the lowest bid in the price-based auction, he is free to make his selection based on bids and suppliers' reputation in buyer-determined auctions. This gives suppliers an incentive to provide high quality and thus results in more efficient outcomes with higher prices but also higher profits for buyers in buyer-determined auctions. In contrast to their set-up, we rule out reputation building as a possible explanation. As a consequence of the anonymity in our setting, other-regarding preferences rather than reputation can explain differences between the price-based and the buyer-determined mechanisms. Second, all their procurement mechanisms are binding in the sense that trade always takes place. Furthermore, trade is guaranteed to be profitable for the buyer. In our approach buyers can be at risk of making losses and are free to refuse trade. This specification gives us the opportunity to analyze the influence of the procurement mechanism on buyers' trust.

The paper is structured as follows: In the next section we describe our experimental setup and analyze the basic model with standard preferences. The results of the experiments are shown in Section 3.3. In Section 3.4 we use a model with other-regarding preferences to organize the results. In Section 3.5 we conclude the paper.

3.2 EXPERIMENTAL DESIGN AND MODEL SETUP

In the laboratory experiment, we focus on a procurement interaction in which one buyer faces two potential suppliers. The buyer's valuation for the good depends on the quality $q_i \in \{q^1, q^2, \cdots, q^7\}$ the selected supplier i provides. While the buyer benefits from higher quality, a higher level of quality is associated with higher costs $c(q_i)$ for the supplier, which for simplicity we assume to be the same across suppliers. We further assume that the provision of quality is welfare increasing, i.e. $\forall q' > q : \; q' - c(q') > q - c(q)$, and that suppliers' costs of second lowest quality are higher than buyer's valuation for lowest quality, i.e. $c(q^2) > q^1$.

In the procurement stage, participants take part either in a buyer-determined auction or a binding price-based auction depending on the treatment. In the buyer-determined auction (BDRA) treatment, each supplier places a sealed offer. The buyer observes both offers and decides whether to accept one of the offers or to reject both. If he accepts one offer, the selected supplier observes both offers and then chooses which quality level to provide. The binding price-based auction treatment (Auction) is similar to the buyer-determined auction. The only difference is that the buyer cannot choose between the two offers. He can only decide whether to accept or reject the lowest bid in the Auction. After the buyer decided from which supplier to buy, this supplier chooses the quality she wants to provide.

In the experiment we had a total of 108 participants and used the between-subjects design. There were six independent cohorts for each treatment. Each cohort included nine participants. In each session two cohorts of the same treatment were in the lab at the same time. Two thirds of our participants were given the role of suppliers, one third the role of buyers. These roles were not changed during the experiment. Each subject participated only one time and was randomly assigned to one of the two treatments. All experimental sessions were conducted in the Cologne Laboratory for Economic Research at the University of Cologne. We recruited participants using the online recruitment system ORSEE (Greiner, 2015) and earning cash was the only incentive offered.

Upon arrival at the laboratory, the participants were seated at computer terminals. We handed out written instructions to them and they read the instructions on their own. When all participants finished reading, we read the instructions to them aloud, in order to ensure public knowledge about the rules of the game. After we finished reading the instructions to the participants, we started the actual game. In each session, each participant took part in a sequence of 30 procurement interactions. We used random matching and the participants had no possibility to identify each other. At the beginning of each round, the nine participants in a cohort were divided into three groups consisting of one buyer and two suppliers. We programmed the experimental interface using the zTree system (Fischbacher, 2007a). The first two lines of Table 3.1, describing the quality levels and their costs, were displayed on every screen.

Table 3.1: Parameter values

Costs	10	20	30	40	50	60	70
Quality	15	80	130	180	220	250	270
Welfare	5	60	100	140	170	190	200

For each interaction in each period, the selected supplier earned the difference between the price and her costs and the buyer earned the difference between his valuation for the good given the quality the winning supplier provided, and the price. The supplier who was not selected earned zero. If no trade took place, buyer and suppliers earned zero. We computed cash earnings for each participant by multiplying the total earnings from all rounds by a predetermined exchange rate of 50 ECU per Euro and adding it to an initial endowment of 7.50 Euro, the endowment was included to prevent losses for the buyer. Furthermore each participant received a show-up fee of 2.50 Euro. Participants were paid their earnings in private and cash at the end of the session. Sessions lasted about 60 minutes and participants made an average profit of 16.71 Euro.

BENCHMARK

In order to establish a benchmark for the further analysis, we will first formally describe the two different procurement mechanisms and derive predicitions in the framework of standard economic theory.

In both mechanisms two suppliers face one buyer and each supplier places a bid $b_i \in \mathbb{R}^+$ and decides what quality q_i to provide in case of selection. The set of possible qualities is $\mathcal{Q} = \{q^1, q^2, \cdots, q^7\}$. The buyer observes suppliers' bids $\mathbf{b} = (b_1, b_2)$ and makes his selection decision. Let b^1 denote the lowest offer and b^2 the second lowest offers. In the Auction the buyer's set of actions $\mathcal{A}^{\text{Auction}}$ contains two elements, he can either refuse to trade a^0 or select the lowest bid b^1 by taking action a^1. In the BDRA the buyer's set of actions is given by $\mathcal{A}^{\text{BDRA}} = \{a^0, a^1, a^2\}$ as he also has the option to accept the second lowest bid b^2 by taking action a^2. Finally, let μ_b be the buyer's belief about the type distribution of a supplier who places a bid b. This belief determines buyer's expectations about the quality he will receive $\mathbb{E}[q|b]$ when he accepts a bid b and is hence important for his selection decision.

Applying the concept of backward induction, the analysis starts in the last stage where the selected supplier i decides what quality to provide. At this stage, the price for the product is already decided. Given the assumption that individuals only seek to maximize their own monetary payoff, the selected supplier faces the following problem

$$\max_{q_i \in \mathcal{Q}} b_i - c(q_i). \tag{3.2.1}$$

Hence, the selected supplier provides minimum quality $q_i = q^1$ independent of her bid b_i and the procurement mechanism. In the selection stage the buyer takes the action that maximizes his expected profit. Anticipating suppliers' behavior, the buyer only accepts bids that are not higher than q^1. Furthermore he always selects the lower bid as long as it is sufficiently low. For these reasons suppliers know that they only have a positive probability of winning the contract if their own bid is neither larger than q^1 nor larger than their competitor's bid. As a consequence, equilibrium prices in the BDRA and the Auction will be the same according to standard economic theory, namely $c(q^1)$. We summarize conclusions based on the standard theory with the following four hypotheses:

Hypothesis 1. *In both procurement mechanisms contract prices will be equal to lowest cost* $c(q^1) = 10$.

This hypothesis implies that buyers and sellers will make the same profit under the two mechanisms, and moreover, sellers will compete away all their profit, earning zero, while buyers will earn $q^1 - c(q^1) = 5$.

Hypothesis 2. *In both procurement mechanisms suppliers will provide the minimum quality $q^1 = 15$ regardless of their bid.*

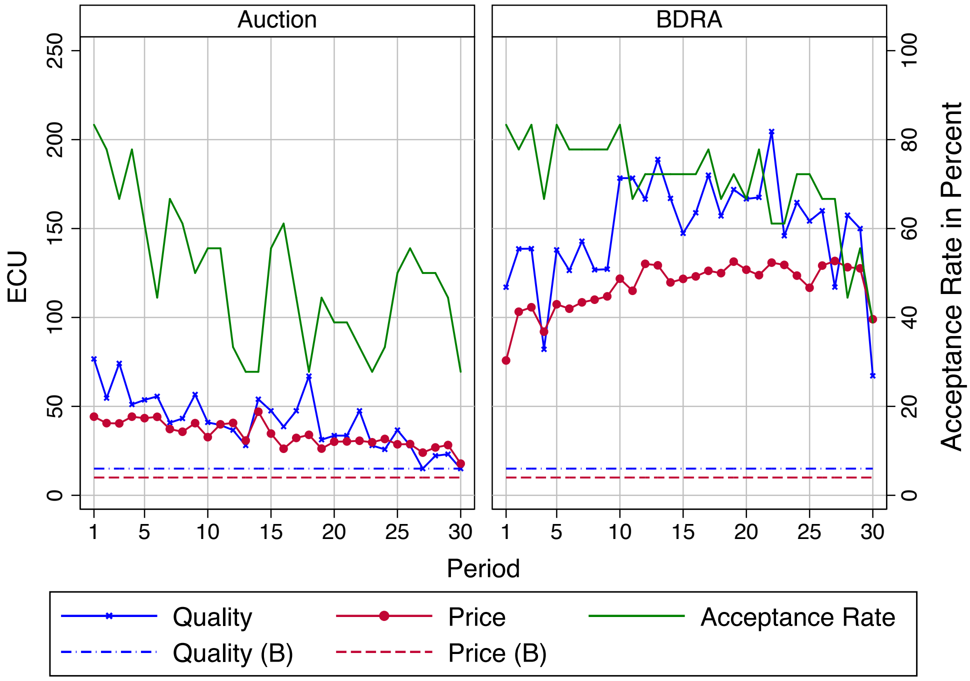
This hypothesis implies that the quality will be q^1, the same under the two mechanisms, resulting in the same (low) efficiency. Also, the quality provided will be uncorrelated with the auction price, and buyers will not accept any offer $b_i > q^1$under either procurement mechanism, because such an offer will result in a loss.

Hypothesis 3. *Under the BDRA if the buyer accepts an offer, it will be the lowest of the submitted offers.*

3.3 EXPERIMENTAL RESULTS

Figure 3.1 provides a concise summary of our results. It shows the average accepted prices, provided quality, and acceptance rates for each period, aggregated across all six cohorts (we present the same information by cohort in Figure 3.6). The dashed benchmark lines display standard theoretical benchmarks for price (H1) and quality (H2), and it is apparent from the figure that we can reject both H1 and H2. In both treatments observed prices and qualities are substantially higher than predicted. The average of accepted prices in the Auction was 35.0 ECU and in the BDRA it was 117.2 (vs. the prediction of $c(q^1) = 10$) . The average quality in the Auction was 43.7 ECU and in the BDRA it was 150.3 ECU (vs. the prediction of $q^1 = 15$). We can also see from the figure that behavior in the two treatments evolves differently over time. While accepted prices decrease in the Auction, they tend to increase in the BDRA. The acceptance rates also indicate that buyers were more likely to trade in the BDRA even though prices were higher . The acceptance rate declines over time, although more in the Auction treatment than in the BDRA treatment. Average quality is

Figure 3.1: Average accepted prices and provided values.



Notes: Displayed are the average accepted price and average provided quality of all trades that took place in a period over time. Furthermore, Figure 3.1 illustrates the price and quality benchmarks (B) and the evolution of the proportion of successful trades.

equal to minimum quality of 15 in the last period in the Auction treatment, but remains above 15 in the BDRA treatment ($p = 0.0897$).

Table 3.2 shows formally that accepted prices and provided qualities were significantly higher in the BDRA than in the Auction. In this setting higher quality implies higher efficiency if trade takes place, in addition the BDRA also had a higher acceptance rate, which increases its efficiency advantage further.

Contrary to the standard theory, that predicts that the buyer extracts the entire surplus, the profit of the selected supplier was on average higher than the buyer's profit in both treatments. According to the non-parametric Wilcoxon matched-pairs signed-rank test the profit of the buyer is sig-

Table 3.2: Averages and standard deviations based on session averages.

	Quality	Price	Costs	Buyer's profit	Selected supplier's profit	Acceptance rate
Auction	43.57* (12.06)	35.24* (4.31)	14.64* (2.09)	4.29 (6.04)	9.98* (1.62)	0.49 (0.07)
BDRA	141.20* (60.77)	114.23* (29.21)	34.76* (13.19)	23.41 (29.39)	28.37* (12.07)	0.71 (0.21)
p-Value	0.0065	0.0039	0.0039	0.3367	0.0039	0.0538

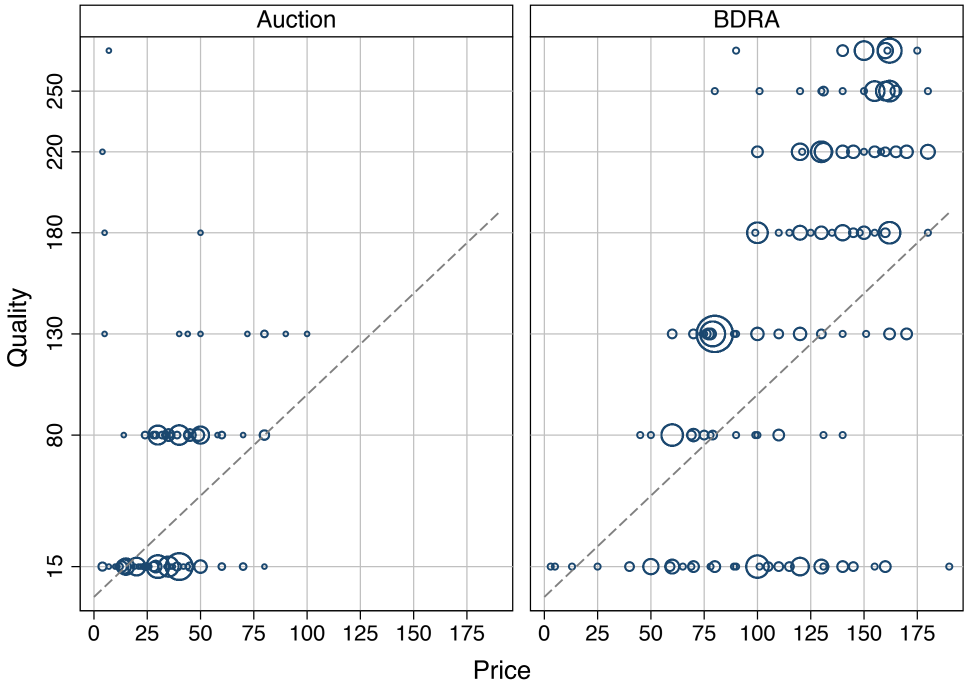
Notes: Displayed are the averages of the key parameters for Auction and BDRA based on cohort averages. * Indicates that the average is significantly different from theoretical prediction at the 0.05 level Furthermore Table 3.2 provides the p-values based on the non-parametric Wilcoxon-Mann-Whitney test comparing the two treatments taking each cohort as one independent observation.

nificantly lower than the selected supplier's profit ($p^{\text{Auction}} = 0.0464$ and $p^{\text{BDRA}} = 0.0277$). Suppliers were significantly better off in the BDRA than in the Auction. Also buyers earned, on average, higher profits in the BDRA. However, this difference was not significant and accepting the high bids in the BDRA was also a risky choice as the possible loss was substantial.[3]

Figure 3.2 displays price-quality combinations for each trade. Contrary to H2, there is a significant positive correlation between the auction price and provided quality. Each point above the dashed line is associated with a positive profit for the buyer. In the Auction nearly all accepted prices were smaller than 60 ECU and in more than 61.5 percent of trades the provided quality was $q^1 = 15$. In another 33.6 percent of trades the quality was $q^2 = 80$, the number of trades with even higher quality was negligible. The share of trades that were profitable for the buyer was only 41.9 percent. The BDRA results quite different. Only 5 percent of accepted prices were below

[3]The numbers reported in Table 3.2 differ slightly from those depicted in Figure 3.1. In Figure 3.1 we display the average over all trades that took place in a period, hence cohorts that traded more than other groups in the same treatment have more weight. In Table 3.2 we take the average of each cohort as the unit of analysis and thereby guarantee that each cohort has the same weight.

Figure 3.2: Observed price-quality combinations in Auction and BDRA.

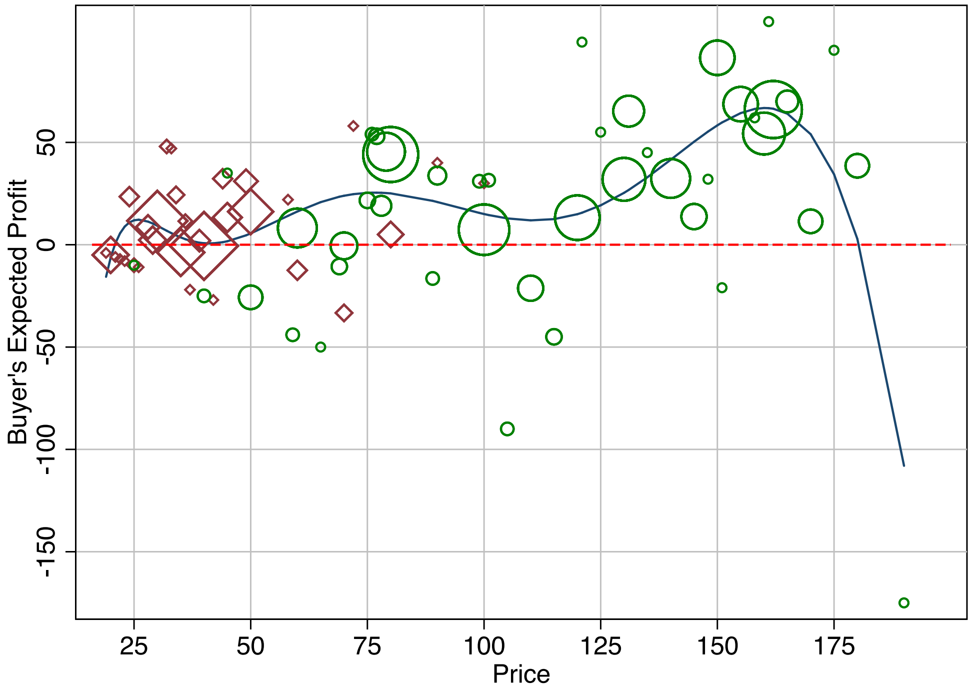


Notes: Displayed are all price-quality pairs in the Auction and the BDRA. Each pair above the dashed line represents a trade that was profitable for the buyer. The size of a circle corresponds to the number of observations of a price-quality pair.

60 ECU and most prices were between 80 and 155 ECU. Minimum quality of 15 was provided in less than 20 percent of trades. The share of trades that were profitable for the buyer was 75.8 percent. However, due to higher prices, realized losses were also larger in the BDRA. Contrary to H3, 46 percent of the time the buyer selected a higher offer in the BDRA, although selecting the higher offer did not result in higher quality. According to a random-effects panel regression, the quality provided by suppliers that were selected even though they placed the higher bid does not differ from the quality provision of suppliers that placed the smaller bid ($p = 0.223$).

Figure 3.3 illustrates the expected profit of a buyer as a function of the accepted price, considering all observations in the Auction and the BDRA

Figure 3.3: Expected buyer's profit depending on accepted price.



Notes: Figure 3.3 displays buyer's expected profit as a function of the price. Circles (for the BDRA) and diamonds (for the Auction) represent buyer's average profit given a price. The more frequently a price was accepted the larger the corresponding marker. The estimate is the result of a fractional polynomial regression of dimension six taking into account each trade in the Auction and BDRA.

treatment. Circles represent buyer's average profit given a price in the BDRA and diamonds represent the average profit given a price in the Auction. The more frequently a price was accepted the larger the corresponding marker. To get a better idea of the form of the expected profit function we fit a fractional polynomial of dimension six through the observed price-profit combinations. For a detailed description of the fitting method see Royston and Altman (1994). The figure displays a positive correlation between accepted price and buyer's (average) profit. This correlation was similar in both treatments. Hence, accepting a high bid was often profitable because it resulted in higher quality. Interestingly the expected profit is not monotonically increasing or decreasing in the accepted price. On the one hand accepting prices around 80 and 160 was profitable, but on the other hand accepting prices that were either substantially higher or lower was unprofitable.

So far we focused our analysis on successful trades. To better understand the buyer's decision of which offers to accept, we conduct random-effects ordered logit regressions with the dependent variable being the buyer's acceptance decision, and independent variables listed in the first column of Table 3.3. The first two regressions estimate buyer's acceptance decision taking the lowest offered price and the current period into account. For both formats the coefficient of Period is negative and significant reflecting a decreasing acceptance rate. Columns three and four of Table 3.3 present the results of regressions that also take into account the price the buyer paid and the quality he received in the previous period. In both treatments the quality level that the buyer received in the previous period influences the buyer's acceptance decision. The price paid in the previous period has a slightly negative effect on the likelihood of acceptance in the Auction treatment, but has no effect in the BDRA treatment. Because buyers who traded in the BDRA selected the higher bid 46 percent of the time, we also ran the same regressions as in Table 3 with the higher instead of the lower bid as an explanatory variable for the BDRA treatment and found that none of the coefficients differ much. Results are reported in Table 3.5.

Table 3.4 shows the results of a random-effects panel regression of suppliers' bidding behavior over time. Her bid is positively influenced by the bid her former competitor placed in the previous period. A supplier who traded in the last period does not change her bid in the Auction but increases it significantly in the BDRA. And average bid amounts go down over time in the Auction but not in the BDRA.

Table 3.3: Logit panel regression of acceptance probability.

	Log acceptance probability			
	Auction	BDRA	Auction	BDRA
Lowest bid	-0.00135	-0.00113	0.0232*	-0.00690
	(0.00731)	(0.00569)	(0.0127)	(0.00867)
Period	-0.0540***	-0.0875***	-0.0000514	-0.0389
	(0.0124)	(0.0177)	(0.0187)	(0.0242)
Quality_{t-1}			0.0297***	0.00788***
			(0.00535)	(0.00279)
Price_{t-1}			-0.0241*	0.00955
			(0.0127)	(0.00827)
Constant	0.841*	2.848***	-0.827	1.102
	(0.430)	(0.816)	(0.678)	(0.882)
Observations	540	540	260	374

Notes: Standard errors in parentheses. $^{*}p < 0.1$, $^{***}p < 0.01$ Regressions reported in the first two columns estimate the influence of the value of the lowest bid and the current period on buyer's acceptance probability taking all interactions into account. Regressions in the last two columns take also the quality the buyer received and the price he paid in the former period into account. The number of observations in these regressions is smaller because only those acceptance decisions are considered where the buyer traded in the period before.

Table 3.4: Panel regression of suppliers' bidding behavior.

	Bid	
	Auction	BDRA
Competitor's bid$_{t-1}$	0.139***	0.199***
	(0.0406)	(0.0412)
Trade$_{t-1}$	-0.734	6.237**
	(1.611)	(2.843)
Period	-0.772***	0.519**
	(0.144)	(0.235)
Constant	50.21***	81.53***
	(3.672)	(6.645)
Observations	1044	1044
R^2	0.0976	0.2128

Notes: Standard errors in parentheses. $^{**}p < 0.05$, $^{***}p < 0.01$ Regressions show how suppliers adjust their bidding behavior over time in response to the competitor's bid and the buyer's selection in the Auction and the BDRA. Trade$_{t-1}$ is a dummy variable that is 1 if the supplier traded in the previous period and 0 otherwise. Its coefficient indicates how a supplier adjusts her bid if she traded in the former period.

3.4 BEHAVIORAL MODEL

In contrast to the assumptions of standard theory, many observations in experimental economics suggest that many individuals are not solely motivated by profit maximization but also affected by fairness considerations. In this section we rationalize our experimental observations by applying the model of Fehr and Schmidt (1999) which incorporates inequity aversion. The modeling approach of Bolton and Ockenfels (2000) leads to similar results. A detailed equilibrium analysis is relegated to the Appendix 3.6.1.

Inequity aversion implies that an individual's utility is not only affected by her own payoff but also by the payoffs of other individuals in her reference group. In our case such a reference group consists of one buyer and two suppliers.[4] The individual's utility is hence given by

$$u_i = w_i - \frac{\beta_i}{2} \cdot \sum_{j \neq i} \max\{w_i - w_j, 0\} - \frac{\lambda \beta_i}{2} \cdot \sum_{j \neq i} \max\{w_j - w_i, 0\}. \quad (3.4.1)$$

Here w_i denotes the own payoff, the inequity aversion parameter β_i expresses how much the individual suffers from advantageous inequality and $\lambda \geq 1$ how much more individuals suffer from disadvantageous inequality compared to other members of the reference group. The own inequity aversion is private information, which cannot be revealed.[5]

[4]One might argue that suppliers compete anonymously in the bidding stage and that buyer's selection initiates a fundamental transformation in the sense of Williamson (1985). For example, Hart and Moore (2008) argue in this direction. In this case only the buyer and the selected supplier compare their profits with each other. Under this assumption suppliers can guarantee themselves non-negative expected utility because they do not suffer if they are not selected. As a consequence, low-price equilibria are affected since inequity averse suppliers prefer not to trade rather than selling at very low prices. However, specifying the reference group differently does not change the results for high-price equilibria qualitatively.

[5]Estimates for the share of inequity averse individuals and the amplitude of inequity aversion differ. Fehr and Schmidt (1999) assume that 30 percent of the suppliers are not affected by inequity aversion, another 30 percent have $\beta = 1/4$, and 40 percent have $\beta = 3/5$. Blanco et al. (2011) report that 29 percent of their subjects had $\beta < 0.235$, 15 percent between 0.235 and 0.4, and 56 percent larger than 0.5. Yang et al. (2012) observed that about 70 percent of their subjects have β smaller 0.125, 20 percent between 0.125 and 0.375, and 10 percent larger than 0.375. Andreoni and Vesterlund (2001) report that 44 percent of their subjects showed completely selfish behavior in a similar setting. The exact parameterization of λ has only little effect on the possible equi-

3.4.1 QUALITY PROVISION

Given that individuals only seek to maximize their profit as assumed by standard economic theory suppliers will always provide minimum quality independent of the price they are paid. In contrast to this prediction our experiment shows a strong positive correlation between price and quality.

Observation 1. *There is a strong positive correlation between price paid and quality provided in both the Auction and the BDRA.*

Inequity averse suppliers have two goals. On the one hand, they seek to maximize their profit and on the other hand, they try to reduce payoff differences between them and other members of their reference group. The weight a supplier assigns to each of these goals depends on her degree of inequity aversion. If prices are low, suppliers can reach both goals by providing minimum quality. In this case quality provision is independent of inequity aversion. However, if prices are high, the provision of higher quality reduces payoff inequality whereas provision of lower quality increases profits. As a consequence, an inequity averse supplier faces a trade off and her quality provision depends on her inequity aversion (β_i, λ) and her bid b_i but not on the procurement mechanism. A high price and aversion against advantageous inequality have a positive influence on the provided quality, whereas stronger aversion to disadvantageous inequality decreases quality. The relationship is illustrated in Figure 3.4.

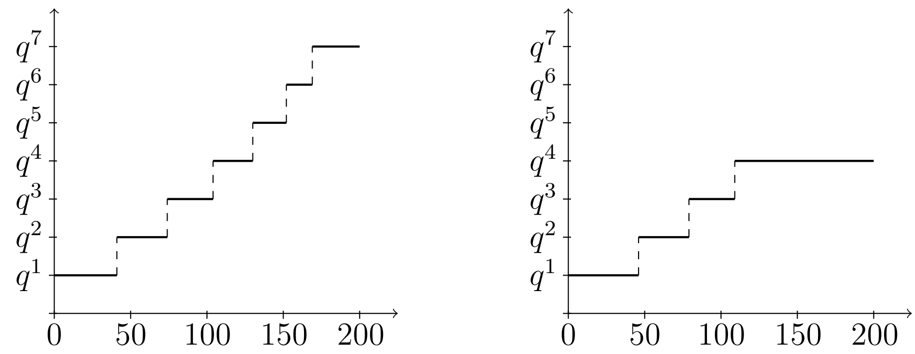
3.4.2 ACCEPTANCE DECISION

If suppliers only seek to maximize their profit and always provide lowest quality, the buyer should anticipate this and never accept bids that are higher than his valuation for minimum quality. If he accepts a bid in the BDRA, he should accept the lower bid. However, our experimental data shows that bids larger than the valuation for minimum quality are accepted and often result in positive profits. Furthermore, buyers select the higher

librium outcomes, because the effects are mainly driven by suppliers' aversion towards advantageous inequality.

Figure 3.4: Relationship between price, quality, and inequity aversion.

(a) $\beta_i = 1/3$, $\lambda = 2$ (b) $\beta_i = 1/6$, $\lambda = 2$



Notes: Displayed is supplier's optimal quality decision in our experiment as a function of the price and different degrees of inequity aversion. The higher her inequity aversion β_i the higher is the maximum quality she provides and the lower is the minimum price that induces a certain quality.

bid in the BDRA nearly as frequently as the lower bid and some buyers reject bids that are accepted by other buyers.

Observation 2. *Buyers frequently accept bids that are higher than their valuation for minimum quality.*

Observation 3. *Buyers frequently select the higher bid in the BDRA.*

Observation 4. *Some buyers accept bids at levels at which other buyers reject bids.*

Inequity averse suppliers provide higher than minimum quality if they are paid a sufficiently high price. This implies a positive correlation between price and quality and can explain why the buyer accepts bids that are higher than his valuation for minimum quality. A strong positive correlation between price and quality can also explain why buyers sometimes selects the higher of the two bids in the BDRA.

In order to explain buyers' rejection behavior we have to take into account their heterogeneity in terms of their inequity aversion. A buyer's inequity aversion influences his risk attitude. Intuitively, an inequity averse buyer suffers twice when he pays a high price but receives low quality. First, he makes a monetary loss like a purely selfish buyer. Second, he faces disadvantageous inequalities compared to the suppliers, that reduces his utility further. As a consequence, a buyer with the lowest degree of inequity aversion is the one who is willing to take the greatest risk and the one who derives the highest utility from accepting. Hence, some high bids will only be accepted by buyers that are not too inequity averse, which can explain positive rejection rates.

Figure 3.5 displays a buyer's expected utility as a function of the price under the assumptions that bids do not contain information about suppliers' types and that their inequity aversion parameters β_i are uniformly distributed between $[0, 3/5]$. Furthermore, it is assumed that suppliers suffer twice as much from disadvantageous inequality than from advantageous inequality, i.e. $\lambda = 2$. The solid line with $\beta^B = 0$ is a counterpart to Figure 3.3 that illustrates the buyer's expected profit in our experiment. It also illustrates the expected utility of inequity averse buyers and shows that a buyer who is more inequity averse prefers lower prices and has a smaller expected utility from accepting a bid.

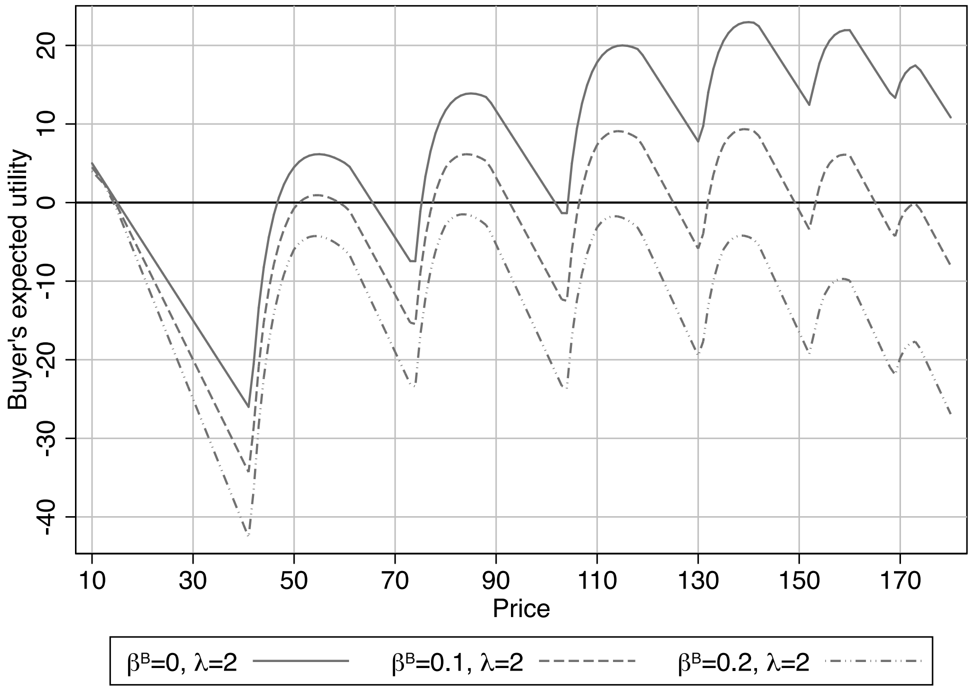
3.4.3 BIDDING BEHAVIOR

The analysis in Section 3.2 shows that both Auction and BDRA have the same unique low-price equilibrium outcome if suppliers are purely selfish. In contrast to that the experiment shows that prices remain substantially higher than predicted in the BDRA. Even though prices in the Auction are also higher than predicted they are substantially lower than prices in the BDRA and decrease over time.

Observation 5. *Bids are substantially higher in the BDRA than in the Auction.*

The main difference between the Auction and the BDRA is that a buyer who wants to trade selects the most attractive bid in the BDRA but has to choose the lowest bid in the Auction. As a consequence, suppliers in the

Figure 3.5: Buyer's expected utility.



Notes: Displayed is the buyer's expected utility depending on his inequity aversion as a function of the accepted bid. It is assumed that suppliers' inequity aversion parameter β_i^S are uniformly distributed between 0 and 3/5 and that all participants suffer twice as much from disadvantageous inequality than from advantageous inequality, i.e. $\lambda = 2$.

Auction have an incentive to marginally undercut their competitor as long as the lower bid is still accepted by the buyer. In contrast, no supplier has an incentive to undercut nor to overbid in the BDRA if her competitor places the buyer's preferred bid, because any other bid would not be selected.

Without restrictions on beliefs, however, the set of possible equilibria in the Auction and BDRA tends to be large and contains a low-price equilibrium as well as high-price equilibria when individuals are inequity averse. See Propositions 3 and 4. For example, if the buyer believes that every bid different from some bid $b' > q^1$ is made by purely selfish suppliers, then both suppliers bidding b' and providing quality depending on their inequity aversion can be an equilibrium both in the BDRA and in the Auction. The game theoretic concept of a perfect Bayesian equilibrium has the only requirement for beliefs that the expectations following the equilibrium bid(s) are correct. There is thus much leeway in specifying the beliefs off the equilibrium path, which can stabilize many high-price equilibria in both mechanisms. This implies that our inequity aversion model can explain our observations but has – at least in its full generality – no predictive power with respect to differences in bidding behavior in the two mechanisms.

In order to derive testable predictions we need to impose an additional assumption on the buyer's belief. The above example has the property that his belief function has a jump at the equilibrium price and suppliers are aware of this jump. It seems to be more realistic, and that is what we will assume in the following, that buyer's beliefs are continuous in the bids. This means that his belief about a supplier's type and consequently his expectations about the quality do not change drastically if her bid changes only marginally. This assumption reduces the set of possible equilibria of the Auction strongly but has no influence on the predictions for the BDRA.

In the Auction suppliers typically have an incentive to place a bid marginally smaller than their competitor. Only if this bid is rejected or decreases the selection probability substantially, such a deviation incentive does not exist. The consequences are easiest to observe when we consider a situation in which it is commonly known that the buyer is purely selfish. Assume that both suppliers are supposed to place a high bid that is connected with a strictly positive expected profit for the buyer and hence would be accepted. Then a supplier in the Auction has an incentive to undercut marginally, because due to the continuity of buyer's expected utility the buyer will accept the smaller bid rather than refusing to trade. This implies that the deviating supplier increases her selection probability from one half to one and reduces her utility in case of selection only marginally, which makes lowering the bid attractive in the first place. This incentive to undercut is present for all high prices that correspond to a strictly positive expected profit for the buyer. Hence, if the buyer is known to be purely selfish, the only high-price equilibrium candidates are prices that are connected to an expected profit of zero for the buyer.

If there is uncertainty about the buyer's inequity aversion even those high-price equilibria cannot exist in the Auction and there is a unique low-price equilibrium in the Auction as shown in Proposition 5. The reasoning is as follows: Given that the competitor places a high bid that would be accepted if the buyer's level of inequity aversion is below some threshold, then the supplier can almost double her own selection probability by undercutting in the Auction. Undercutting decreases the probability that trade takes place marginally, but if the buyer wants to trade he has to select the lowest bid. Furthermore, the supplier's profit in case of selection is only marginally smaller than without undercutting. Hence, suppliers have an incentive to undercut each other as long as the buyer's acceptance probability is strictly positive. At some point in this undercutting process it will be more attractive for suppliers to place a low bid and to aim at those buyer types who do not accept high bids, because trade probability becomes too small. Hence, only low-price equilibria exist in the Auction when the buyer's beliefs are continuous and the type distribution has no mass points.[6]

In contrast to the Auction the set of equilibria of the BDRA does not change if only continuous beliefs are considered. A buyer who wants to trade selects the most attractive bid and suppliers have a clear incentive to make their bid more attractive if this increases their expected utility in case of selection. As a consequence, equilibrium bids in the BDRA have the property that they are at least as high as the price that maximizes the expected utility of the most inequity averse buyer type.

Even though different buyer types might prefer different bids, their belief function might be such that the expected utility functions of all buyer types have the same local maximizers. Here the term local maximizer denotes a

[6]A mass point in the buyer's type distribution implies that decreasing a bid marginally can reduce the probability of trade substantially. This can in principal stabilize high-price equilibria in the Auction, because it makes undercutting less attractive for suppliers.

Such a high-price equilibrium would have two interesting properties. First, a buyer that cares more about inequity than the mass point type does not trade. Second, the buyer's expected utility from accepting is zero if he is the mass point type.

price that corresponds to a local maximizer of a buyer's expected utility. If this is the case, equilibrium bids are local maximizers. The same reasoning as above rules out that bids slightly smaller than a local maximizer can be equilibrium bids. Bids slightly larger than a local maximizer can also not be equilibrium bids, because a supplier would then have an incentive to place a marginally lower bid. Such a bid would be more attractive for all buyer types and the utility in case of selection only marginally smaller.

Summing up, the inequity aversion model predicts that high-price equilibria might exist in the BDRA whereas only low-price equilibria exist in the Auction if beliefs are continuous. Even if high-price equilibria exist in the Auction suppliers bid less than in high-price equilibria of the BDRA, which is in line with our observation in the experiment.

3.5 CONCLUSION

In this paper we investigated the possibility that binding price-based reverse auctions have a negative influence on the buyer-seller relationship. We compare them to buyer-determined reverse auctions in an incomplete contracts procurement interaction, in which the quality of the product to procure cannot be specified in the contract.

While standard theory predicts that both procurement mechanisms yield the same results, our data shows substantial differences between the binding auction and the buyer-determined reverse auction. We observe that the buyer-determined reverse auction results in high prices, high quality and more frequent trade. In contrast to that prices, quality, and trade frequency are significantly smaller in the binding auction, which implies clear ranking in terms of efficiency favoring the buyer-determined reverse auction. Also with regard to profits, the BDRA was on average more profitable for both buyers and suppliers. However, this difference is not significant because the BDRA was also more risky for buyers. Due to high accepted bids, some trades result in large losses when low quality was provided whereas others are very profitable.

We find that our observations are in agreement with theory based on other-regarding preferences. This theory can rationalize the price and quality differences between the two procurement formats and also explains that the share of accepted bids is smaller in the binding auction than in the buyer-determined reverse auction. The intuition is that buyer's commitment to only consider the lowest bid in a binding auction can hinder the implementation of the buyer's optimal price and decreases efficiency.

3.6 APPENDICES

3.6.1 THEORY

In this section we analyze the Auction and the BDRA under the assumption that the buyer and suppliers are inequity averse. If no trade takes place both suppliers and the buyer have a utility of zero. Expression (3.6.1) corresponds to the utility of the selected supplier S and (3.6.2) to that of her competitor $\neg S$ who is not selected. The first lines in the utility functions reflect the utility suppliers derive from their profits. The second lines express how much they suffer from the inequality compared to the buyer and the third lines express how much they suffer from the inequality compared to the other supplier. Expression (3.6.3) gives the utility of the buyer. The first line corresponds to his profit, the second line to the utility he derives from the comparison to the selected supplier, and the third line corresponds to the utility he derives from the comparison to the supplier who is not selected. Recall that the parameters β_i reflect how much an individual suffers from advantageous inequality and $\lambda > 1$ how much more they suffer from disadvantageous inequality.

$$\begin{aligned}
u_S =& b_S - c(q_S) \\
&- \tfrac{1}{2}\left[\lambda\beta_S \cdot \max\{q_S + c(q_S) - 2b_S, 0\} + \beta_S \cdot \max\{2b_S - q_S - c(q_S), 0\}\right] \\
&- \tfrac{1}{2}\left[\lambda\beta_S \cdot \max\{c(q_S) - b_S, 0\} + \beta_S \cdot \max\{b_S - c(q_S), 0\}\right],
\end{aligned} \tag{3.6.1}$$

$$\begin{aligned}
u_{\neg S} =& 0 \\
&- \frac{1}{2}\left[\lambda\beta_{\neg S} \cdot \max\{q_S - b_S, 0\}) + \beta_{\neg S} \cdot \max\{b_S - q_S, 0\}\right] \\
&- \frac{1}{2}\left[\lambda\beta_{\neg S} \cdot \max\{b_S - c(q_S), 0\} + \beta_{\neg S} \cdot \max\{c(q_S) - b_S, 0\}\right],
\end{aligned} \tag{3.6.2}$$

$$\begin{aligned}
v_B =& q_S - b_S \\
&- \frac{1}{2}\left[\lambda\beta_B \cdot \max\{b_S - q_S, 0\}) + \beta_B \cdot \max\{q_S - b_S, 0\}\right] \\
&- \frac{1}{2}\left[\lambda\beta_B \cdot \max\{0 - q_S, 0\} + \beta_B \cdot \max\{q_S, 0\}\right].
\end{aligned} \tag{3.6.3}$$

To account for heterogeneity among individuals we assume that the β_i are independently and identically distributed according to a continuous distribution function $F : [0, 3/5] \to [0, 1]$ without mass points and that an individual's type is her private information that cannot be revealed. Let $U_i[\mathbf{b}, (\beta_i, \lambda)] = \Pr\{\text{selected}\} \cdot u_S + \Pr\{\text{not selected}\} \cdot u_{\neg S}$ denote the expected utility of supplier i.

The expected utility of the buyer from accepting a bid b_S is given by $V_B[b_S, (\beta_i, \lambda)] = \sum_{k=1}^{7} e(q^k|b_S) \cdot v_B(b_S, q^k)$ where $e(q^k|b_S)$ corresponds to the buyer's expectations about the probability of receiving a quality q^k when accepting a bid b_S. These expectations are determined by his belief μ_{b_S}.

QUALITY PROVISION After defining the game we analyze the Auction and the BDRA via backward induction starting with the selected supplier's quality decision. The selected supplier S will provide the quality $q_S^*[b_S, (\beta_S, \lambda)]$ level that maximizes her utility given her bid and her inequity aversion, i.e.

$$q^*[b_S, (\beta_S, \lambda)] = \arg\max_{q_i \in \mathbf{Q}} u_S(q_i). \tag{3.6.4}$$

Obviously, higher prices and stronger aversion against advantageous inequality result in weakly higher quality whereas increasing aversion against disadvantageous inequality results in weakly lower quality.

SUPPLIER SELECTION In the second stage the buyer selects his preferred bid or refuses trade if all available bids are connected with a negative expected utility. In the Auction the buyer can only select the lower bid whereas he is free to select the higher bid in the BDRA. A buyer who expects to receive quality q^k with probability $e(q^k|b_S)$ when accepting a bid b_S has an expected profit of

$$V_B(b_S) = \sum_{k=1}^{7} e(q^k|b_S) \cdot v_B(b_S, q^k) \tag{3.6.5}$$

and makes the selection decision that maximizes his expected profit.

Given that the share of suppliers who provide high quality when receiving a high price is sufficiently large the buyer's selection crucially depends on his beliefs about suppliers' type distribution associated with a certain bid. In order to satisfy the equilibrium requirements his beliefs must correspond to the objective probabilities for all bids that are placed in equilibrium, however, there is substantial leeway in specifying his beliefs for bids that are not part of the equilibrium path.

One possible belief in an equilibrium in which all suppliers bid b^* is as follows: The buyer's belief given the equilibrium bid b^* is correct. This implies that his expectations about the quality are correct, i.e. $e(q^k|b^*) = \Pr\{q^k|b^*\}$ for all $q^k \in \mathcal{Q}$. For all other bids $b_j \neq b^*$ he believes to face a purely selfish supplier and hence expects to receive minimum quality q^1, i.e. $e(q^1|b_j) = 1$.

Equilibrium analysis

We focus on pooling strategies in which all suppliers place the same bid b^*. The idea is that selfish suppliers mimic their inequity averse competitors, which implies that bids do not reveal information about suppliers' types. Due to the mentioned leeway in specifying beliefs outside the equilibrium path, there can be a wide variety of perfect Bayesian equilibria in both procurement formats. We now characterize two types of possible pooling equilibria. The low-price equilibrium and the high-price equilibrium. In a low-price equilibrium all suppliers bid $c(q^1)$ and provide minimum quality q^1, the buyer accepts the lowest bid. In a high-price equilibrium all suppliers bid b^*, the buyer trades if his degree of inequity aversion is sufficiently low and the selected supplier provides the quality level that maximizes her utility.

Proposition 3. *A low-price equilibrium in which suppliers provide minimum quality and their bids are equal to their costs of providing minimum quality exists in the Auction and the BDRA.*

Proof. Consider the Auction first. Suppose that all suppliers place a low bid equal to $c(q^1)$. Then the selected supplier maximizes her utility by providing lowest quality q^1 and the buyer optimally accepts the bid. In this case no supplier has an incentive to deviate, because there is no offer she can make that would positively influence the payoff distribution, which proves the existence in the Auction.

Now turn to the BDRA and suppose that the buyer expects to receive lowest quality whenever accepting a bid $b' \neq c(q^1)$, i.e., $e(q^1|b') = 1$ for all $b' \neq c(q^1)$. Then the buyer will only consider the lowest bid and hence the same considerations as for the Auction apply to the BDRA. □

Given that the share of fair suppliers is sufficiently large also high-price equilibria exist in the Auction as well as in the BDRA.

Proposition 4. *In the Auction and in the BDRA a high-price equilibrium, in which all suppliers place the same bid $b^* > q^1$ can exist. Some prices are only equilibrium prices in the BDRA but not in the Auction.*

Proof. Consider a situation in which a high price $b^* > q^1$ exists that is connected with a positive expected profit for the buyer. Assume that all suppliers place this bid b^* and provide the quality that maximizes their utility in case of selection, which implies that they make strictly positive profits. The buyer's belief about supplier i's type is given by F if $b_i = b^*$ and he expects to face a purely selfish supplier if $b_i \neq b^*$. The buyer accepts the bid b^* if his level of inequity aversion is low and rejects it if he has a high level of inequity aversion. Notice that given the belief only low bids between $c(q^1)$ and q^1 as well as the bid b^* have a positive selection probability.

In the Auction the situation described above constitutes an equilibrium if no supplier has an incentive to place a low bid. Because the buyer can only select the lowest bid, a supplier can increase her own selection probability by placing a low bid. However, a low bid reduces her profit in case of selection. Thus, equilibrum prices have to be sufficiently high such that undercutting to a low bid between $c(q^1)$ and q^1 is not profitable.

In the BDRA the conditions for the existence of a high-price equilibrium are less demanding. The main reason is that a supplier cannot rule out her competitor's selection by undercutting the competitors bid, because low bid will only be selected if it is more attractive than b^* for the buyer.

We now provide an example to illustrate that a high-price equilibrium as described above can exist with the parameterization of our experiment. All suppliers bid $b^* = 50$ and individuals' β_i are distributed between 0 and 1/4 such that 80 percent of the suppliers provide a quality of 80 and 20 percent a quality of 15 in case of selection.

If both the buyer and suppliers suffer twice as much from disadvantageous inequality than from advantageous inequality, i.e. $\lambda = 2$, the strategies constitute an equilibrium both in the Auction and the BDRA. However, if $\lambda = 3.1$ a supplier with a high level of inequity aversion has an incentive to place a low bid in the Auction, but prefers to bid b^* in the BDRA.

□

Continuous beliefs

In this section we impose a restriction on beliefs, namely that the buyer's beliefs are continuous in the bids. Let $G_b(x)$ be the distribution function of supplier's type that corresponds to the buyer's belief μ_b when he observes a bid b.

Definition (Continuous beliefs)**.** *Buyer's beliefs μ_b are called continuous in b if* $\lim_{\epsilon \to 0} |G_b(x) - G_{b+\epsilon}(x)| = 0$ *for all x.*

In combination with a type distribution without mass points buyer's continuous beliefs imply that his expectations about the quality and hence also his expected utility are continuous in the price. This refinement has no influence on the set of equilibria in the BDRA, but shrinks the set of equilibria of the Auction strongly.

Proposition 5. *In the Auction a high-price equilibrium, in which the buyer's beliefs are continuous cannot exist. There is a unique low-price equilibrium with a price $c(q^1)$.*

Proof. Consider a situation in which a high price $b' > q^1$ exists which would yield a positive expected profit for the buyer if the suppliers' type distribution is the ex-ante distribution,. Assume that all suppliers place this bid b' and provide the quality that maximizes their utility in case of selection.

We start with a simplified setting in which it is commonly known that the buyer is purely selfish. In this case the buyer would always accept the bid b' and both suppliers would have a selection probability of one half. Due to the continuity of buyer's beliefs the bid b' can only be an equilibrium bid if it has the property that buyer's expected profit from accepting is zero for b' and negative for all bids marginally smaller.

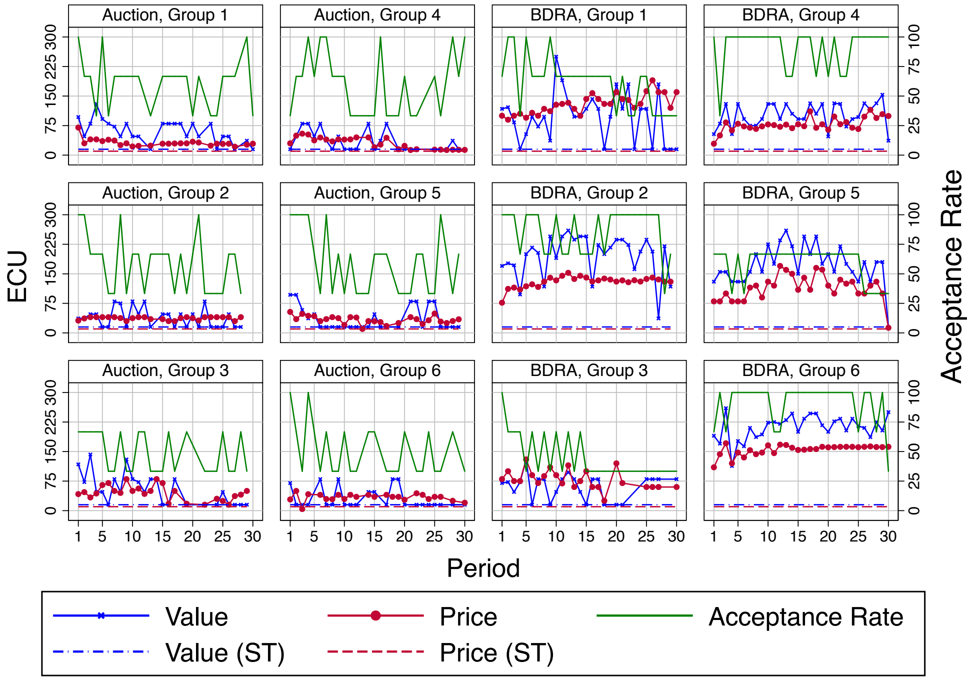
To see this suppose that the buyer expects a strictly positive profit when accepting b', then the continuity of buyer's beliefs implies that there also exists a price slightly below b' the buyer would accept, because he still expects a strictly positive profit. Hence, a supplier could make herself strictly better off by marginally undercutting b'. This deviating supplier doubles her selection probability to one. Moreover, she avoids the negative utility connected with the selection of her competitor and decreases her utility in case of selection only marginally. Only a high-price equilibrium with an expected profit of zero for the buyer can exist, because in that case a marginally lower bid will not be accepted.

If there is uncertainty about the buyer's inequity aversion, even such a high-price equilibrium cannot exist if the continuous type distribution function has no mass points. Suppose a high-price equilibrium exists in which all suppliers place a high bid b'. A bid that is only selected if the buyer is purely selfish cannot be an equilibrium bid, because it is has a selection probability of zero. However, a high bid that is accepted by a continuum of buyer types cannot be an equilibrium bid neither, because suppliers have an incentive to undercut. By slightly undercutting the deviating supplier reduces the acceptance probability and her utility in case of selection only marginally but decreases her competitor's selection probability to zero.

The continuity of the buyer's beliefs in connection with the continuous type distribution without mass points guarantees that also the probability of trade is continuous in the bid. For this reason there is always a deviation incentive, which proves that a high-price equilibrium cannot exist. □

3.6.2 GRAPHS AND TABLES

Figure 3.6: Evolution of prices, values and acceptance rates by groups.



Notes: Displayed are the average accepted price, average provided quality, and the average acceptance rate in the Auction and the BDRA over time. Additionally standard theory predictions for price and quality are provided.

Table 3.5: Logit panel regression of acceptance probability.

	Acceptance probability	
	BDRA	BDRA
Highest bid	-0.00751	-0.00680
	(0.00468)	(0.00604)
Period	-0.0870***	-0.0413*
	(0.0175)	(0.0237)
Quality_{t-1}		0.00784***
		(0.00280)
Price_{t-1}		0.00893
		(0.00772)
Constant	3.732***	1.390
	(0.892)	(0.974)
Observations	540	374

Notes: Standard errors in parentheses. $^{*}p < 0.1$, $^{***}p < 0.01$
The regression reported in the first column estimates the influence of the value of the highest bid and the current period on buyer's acceptance probability taking all interactions into account. The regression in the second column takes also the quality the buyer received and the price he paid in the former period. The number of observations in this regression is smaller because only those acceptance decisions are considered where the buyer traded in the period before.

3.6.3 INSTRUCTIONS

This section provides the instructions in German (original) and English (translated).

ANLEITUNG ZUM EXPERIMENT

Herzlichen Dank für Ihre Teilnahme am Experiment. Bitte sprechen Sie bis zum Ende des Experiments nicht mehr mit anderen Teilnehmern.

Dieses Experiment besteht aus **30 Runden**, die jeweils die gleiche Abfolge an Entscheidungen haben. Die Abfolge der Entscheidungen wird unten ausführlich erklärt. Es gibt im Experiment 2 Rollen: **Käufer** und **Zulieferer**. Zu Beginn des Experiments bekommen Sie eine dieser Rollen zufällig zugelost und behalten diese Rolle für das gesamte Experiment. Auf dem ersten Bildschirm des Experiments sehen Sie, welche Rolle Sie haben. Unabhängig von Ihrer Rolle erhalten Sie eine Anfangsausstattung von 250 ECU.

Überblick über die Entscheidungen in einer Runde
Zu Beginn jeder Periode werden zufällig Gruppen bestehend aus einem Käufer und zwei Zulieferern gebildet. Anschließend macht jeder **Zulieferer** ein Preisangebot, zu dem er bereit ist, das Gut zur Verfügung zu stellen.
[Treatment 1: "Der Zulieferer mit dem **kleinsten Preisangebot** gewinnt die Auktion. Der **Käufer** sieht nun dieses Preisangebot und kann darüber entscheiden, ob er das Angebot annimmt oder ablehnt."]
[Treatment 2: "Der **Käufer** sieht nun diese Preisangebote und kann darüber entscheiden, ob er eines der Angebote annimmt oder beide ablehnt."]
Das angenommene Preisangebot ist der **Preis.** Der **ausgewählte Zulieferer** entscheidet abschließend über die **Qualität** des Gutes, das er dem Käufer bereitstellt.

Der Gewinn des Käufers
Der Gewinn des Käufers hängt von dessen Wertschätzung für das Gut und dem Preis von diesem ab. Der Wert des Gutes wird durch seine Qualität bestimmt. Je höher die Qualität, desto größer der Wert. Den genauen Zusammenhang zwischen Qualität und Wert finden Sie in der folgenden Tabelle

Qualität	1	2	3	4	5	6	7
Wert in ECU	15	80	130	180	220	250	270

Gewinn des Käufers = Wert des Gutes - Preis

Der Gewinn der Zulieferer
Nur der ausgewählte Zulieferer macht Gewinn. Der andere Zulieferer macht einen Gewinn von 0. Der Gewinn des ausgewählten Zulieferers wird bestimmt durch den Preis und die Qualitätsentscheidung des Zulieferers. Je höher die Qualität, desto größer die Produktionskosten. Den genauen Zusammenhang zwischen Qualität und Kosten finden Sie in der folgenden Tabelle

Qualität	1	2	3	4	5	6	7
Kosten in ECU	10	20	30	40	50	60	70

Gewinn des ausgewählten Zulieferers = Preis - Kosten

Auszahlung
Am Ende des Experiments wird die Summe aus Ihren Gewinnen in den einzelnen Perioden gebildet und zu Ihrer Anfangsausstattung von 250 ECU hinzuaddiert. Anschließend wird dieser Gewinn in Euro umgerechnet, dabei entsprechen 50 ECU einem Euro. Bitte beachten Sie, dass auch negative Gewinne, also Verluste, möglich sind und diese bei der Auszahlung berücksichtigt werden.

Sollten Sie Fragen zum Ablauf des Experiments haben, signalisieren Sie dies bitte dem Experimentator durch Handzeichen.

INSTRUCTIONS

Thank you for participating in this experiment. Please do not talk to other participants until the end of this experiment.

This experiment consists of **30 rounds**. In each of this round you are in the same situation. The situation will be explained to you in detail. There are two roles in this experiment: **Buyer** and **Supplier**. At the beginning of the experiment one of these roles is randomly assigned to you and you keep the role during the experiment. You see your role on the first screen of the experiment. Independent of your role you will receive an initial endownment of 250 ECU.

Overview of the decisions in one round
At the beginning of each round groups consisting of one buyer and two suppliers are randomly determined. Then each supplier places a bid at which he is willing to provide the good.
[Treatment 1: "The supplier who placed the **lowest bid** wins the auction. The **buyer** observes this bid and can decide whether he wants to accept or reject the offer."]
[Treatment 2: "The **buyer** observes the bids and decides whether he wants to accept one of the bids or to rejects both. "]
The accepted bid determines the **price**. The **selected supplier** then decides about the quality of the good he provides to the buyer.

Buyer's profit
The buyer's profit depends on his valuation for the good and its price. The valuation is determined by its quality. The higher the quality the higher the valuation. The exact correlation between quality and valuation is given in the following table

Quality	1	2	3	4	5	6	7
Value in ECU	15	80	130	180	220	250	270

Buyer's profit = Value - Price

Supplier's profit
Only the selected supplier makes a profit. The other supplier makes a profit of 0. The profit of the selected supplier is determined by the price and the supplier's quality decision. The higher the quality the higher the cost of production. The exact correlation between quality and cost is given in the following table

Quality	1	2	3	4	5	6	7
Cost in ECU	10	20	30	40	50	60	70

Selected supplier's profit = Price - Cost

Payment
At the end of the experiment the sum of your profits in each round is added to your initial endownment of 250 ECU. Then your profit will be displayed in Euros. 50 ECU are equivalent to 1 Euro. Please have in mind that negative profits, i.e. losses, are possible and will be considered for the payment.

If you have questions, please raise your hand.

CHAPTER 4

PREFERENCES AND DECISION SUPPORT IN COMPETITIVE BIDDING

Abstract

We examine bidding behavior in first-price sealed-bid and Dutch auctions, which are strategically equivalent under standard preferences. We investigate whether the empirical breakdown of this equivalence is due to (non-standard) preferences or due to the different complexity of the two formats (i.e., a different level of mathematical/individual sophistication needed to derive the optimal bidding strategy). We first elicit measures of individual preferences and then manipulate the degree of complexity by offering various levels of decision support. Our results show that the equivalence of the two auction formats only breaks down in the absence of decision support. This indicates that the empirical breakdown is caused by differing complexity between the two formats rather than non-standard preferences.

4.1 INTRODUCTION

The first-price sealed-bid auction (FSPBA) and the Dutch auction (DA) are two of the most frequently used auction formats. With slight variations, both the FPSBA and the DA generate billions of dollars in revenue each year.[1] Governments and private firms frequently use the FPSBA for procurement in construction and to subcontract with suppliers. Federal banks and firms use variants of the DA to sell securities and refinance credit. The

[1] In an FPSBA, bidders simultaneously submit "sealed" bids to the seller and the highest bidder receives the object and pays his bid. In a DA, the seller starts at a high initial ask price and gradually decreases the ask price until the first bidder stops the auction, receives the item, and pays the stop price.

DA is also used in initial public offerings (e.g., Google Inc.) as an alternative to classic valuation by investment banks.[2] Furthermore, the DA can be found on fish and fresh-produce markets (e.g., Cassady, 1967).

Theory suggests that the FPSBA and the DA yield the same revenue as both formats are strategically equivalent. However, this strong theoretical result breaks down empirically. Previous research suggests three possible explanations: opportunity costs (Carare and Rothkopf, 2005; Katok and Kwasnica, 2007), preferences (Weber, 1982; Nakajima, 2011; Lange and Ratan, 2010; Belica and Ehrhart, 2013; Ehrhart and Ott, 2014), and complexity of the decision (Cox et al., 1983). We analyze the role of preferences and complexity while controlling for opportunity costs. Our results indicate that the non-equivalence is driven by the difference in complexity of competitive bidding in the two auction formats rather than by individual (non-standard) preferences.

The empirical breakdown of this equivalence is a robust observation in experimental settings both in the laboratory and in the field. However, the direction of the deviation is non-conclusive. On the one hand, Coppinger et al. (1980) and Cox et al. (1982a) find that the FPSBA yields higher revenue than the DA in a controlled laboratory setting. On the other hand, in a field experiment on an Internet auction platform, Lucking-Reiley (1999) finds that the DA generates higher revenue than the FPSBA.

Differences in opportunity costs can explain these differences. In a DA, bidders have an incentive to accept a high price and stop the auction early, because they have to frequently monitor the price clock or even have to physically return to the auction site to check for updates in prices as long as the auction is running. Such costs do not occur in the (static) FPSBA which ends immediately after the (simultaneous) submission of bids.

Carare and Rothkopf (2005) show theoretically that such increased opportunity costs increase the optimal bid. In a DA, Cox et al. (1983) and Katok and Kwasnica (2007) analyze the trade-off between opportunity costs

[2] Note, however, that these examples typically auction off multiple units and that the auctions are then modified such that they usually do not discriminate between different bidders but apply a uniform-pricing rule.

and additional utility from suspense, i.e., from a joy of gambling. Both articles provide evidence that increasing opportunity costs by increasing payoffs or by decreasing the clock speed, respectively, increases bids in a DA. In contrast to their approach, our goal is to assess the predictive power of different preference-based theories for observed bidding and to analyze the effect of complexity. Hence, we eliminate confounding differences in opportunity costs by holding the time per auction format and thus the opportunity costs from participation constant. In addition, we hold the action set, i.e., the set of feasible bids, constant across the two formats which allows a direct comparison of the two auctions.

In the absence of opportunity costs, the strategic-equivalence result rests on the assumption that bidders have standard preferences, i.e., they derive utility only from realized personal payoffs. In addition, the utility function is global in the sense that the effect of wealth changes does not depend on whether such changes occur in the gain or loss domain or whether they are certain or generated by a lottery. With regard to the departures from standard preferences, we study expectations-based reference-dependent and Allais-type preferences. We focus on these two specifications because they are frequently used to explain decision making under uncertainty.[3]

Under reference dependence, the bidder compares gains and losses in wealth relative to a reference point (Kahneman and Tversky, 1979). In this comparison, the bidder is assumed to be loss averse and puts more weight on negative deviations from this reference point (losses) than on equivalent positive deviations (gains). Loss aversion contradicts the global-utility assumption of standard preferences because the bidder considers changes in wealth with respect to a local reference point. The specification of the reference point is subject to debate. Köszegi and Rabin (2006, KR) propose expectations-based reference dependence, i.e., the reference point is stochastic and given by the rational expectations that the individual holds

[3]Reference dependence as proposed by Kahneman and Tversky (1979) is the most cited theory on risky decision making (Kim et al., 2006). Allais-type preferences are an early critique of expected utility theory (EUT) (Allais, 1953) and are empirically very robust in explaining deviations from predictions under standard preferences (Kahneman and Tversky, 1979; Camerer, 1989; Weber, 2007).

over the outcomes of a risky decision. In the following, we will denote expectations-based reference-dependent preferences as *KR preferences*.

Individuals with *Allais-type (AT) preferences* prefer outcomes that are generated with certainty to the same outcomes that are generated by a risky lottery (e.g., Andreoni and Sprenger, 2010). This difference is most prevalent in the Allais paradox (Allais, 1953). Here, subjects prefer a degenerate lottery over a risky one with a higher expected value but reverse their choice if both lotteries are monotonically transformed and become both risky (the so-called common-ratio effect, CRE). This reversal is inconsistent with standard preferences as it violates the crucial independence axiom of EUT (Savage, 1954; Anscombe and Aumann, 1963). According to this axiom, decisions between lotteries should not depend on consequences that do not differ between the lotteries.

We make use of data from a two-stage experiment in which we first elicit the preferences of all subjects that participate in our experiment. In this first stage, we utilize the procedure of Abdellaoui et al. (2007) and elicit individual preferences in a fully non-parametric procedure, i.e., without imposing any assumption on the functional form of utility. Furthermore we measure to what extent participants exhibit Allais-type preferences by utilizing a metric version of the CRE (e.g., Beattie and Loomes, 1997; Dean and Ortoleva, 2014; Schmidt and Seidl, 2014).

Preference theories assume Bayesian rationality in the sense that bidders derive and process probabilities correctly. However, bidding in auctions can be a demanding problem. In deriving the optimal bid, the bidder faces a trade-off between increasing his winning probability by submitting a higher bid and increasing his winning profit by submitting a lower bid. Individual preferences determine the optimal bid that balances these diametric effects. However, this optimization requires a certain level of mathematical sophistication. It is thus possible that the observed differences between bidding behavior is due to different levels of complexity of the two auction formats. In other words, bidders can make mistakes, e.g., in deriving the winning probability associated with their bid, and these mistakes might differ between the two formats.

We design a decision support system (DSS) to reduce the complexity and assist bidders in deriving the optimal bid that corresponds to their individual preferences. We vary the auction format within-subjects and the level of decision support between-subjects. Subjects either have no decision support (No DSS treatment) or they have medium (Medium DSS treatment) or full support (Full DSS treatment) to assist bidding. The decision support system is a computerized overlay displaying additional information. Medium DSS shows the winning probability whereas Full DSS additionally provides expected profits. Although this information is redundant for fully rational decision makers, it is non-trivial to derive and providing such information greatly reduces the complexity of optimal bidding.

The increase in the use of auctions has led to a rise in the demand for expert services. While our implementation of decision support is primarily a mean to analyze the role of complexity in competitive bidding, the design of such DSS is also of interest in itself. Several patents have been filed for (automated) bid-advising systems that account for, e.g., the auction structure and risk attitudes of rival bidders based on historical data.[4] Our DSS implementation resembles such automated bidding advice that estimates competitors' bidding behavior in a given auction format. In addition, there is an increasing number of consulting firms specializing in auctions (e.g., Market Design Inc.) and major economic consulting companies offer services regarding auctions and bidding (e.g., The Brattle Group, NERA). These services typically include all aspects relevant for setting up and participating in auctions (e.g., bid tracking, bidding strategy, auction rules and design, training, provision of input to regulators).

Our results highlight the role of decision support systems. In line with the literature, we find significant differences between auction formats if bidders do not receive decision support. However, differences vanish between participants once we provide decision support. This indicates that the observed differences in bidding behavior between the FPSBA and the DA are due to different levels of complexity rather than non-standard preferences. In addition, our tests show that bidding behavior strongly depends

[4]See, for example, Guler et al. (2002, 2003, 2009); Zhang and Guler (2013).

on participants' risk aversion. The influence of individual loss aversion and Allais-type preferences is not significant and cannot explain differences in bidding behavior. Our results thus highlight that from a consulting perspective, it seems to be more important to support decision makers in the derivation of optimal bidding strategies than to focus on the choice of the auction format.

The paper proceeds as follows. The next section introduces the model environment and theoretically analyzes the effect of different preference specifications on optimal bidding in the FPSBA and the DA. Section 4.3 presents our experimental design and our implementation of decision support. We report our results in Section 4.4. Section 4.5 concludes.

4.2 THEORY

In this section, we first describe the two auction mechanisms. We then characterize the equilibria in both auction formats for standard preferences (SP), Köszegi-Rabin (KR) preferences, and Allais-type (AT) preferences. We analyze the optimal bidding behavior of one bidder given a bidding strategy of the competitor.

In both auction formats, two bidders compete for one indivisible item and the highest bidder wins. Let $P = \{p_1, \ldots, p_n\}$ be a discrete price grid. In the FPSBA, each bidder places a *bid* $b \in P$ at which he is willing to buy the item. In the DA, each bidder decides for every *ask* $a \in P$ whether to accept it or not. In the FPSBA, the *price* corresponds to the highest bid, whereas in the DA, it corresponds to the highest accepted ask. The winning bidder receives the item and pays the price. If the bidder does not win the auction, he does not receive the item and does not pay anything.[5] In both auction formats bidders face a trade-off between improving their probability of winning and increasing their profit in case of winning.

To derive the equilibrium bidding strategy in the discrete FPSBA, we follow Cai et al. (2010). For the dynamic course of the DA, we adopt the modeling approach of Bose and Daripa (2009). In the DA, the seller starts

[5] Ties are broken at random with equal probability to receive the item.

the auction with the highest ask p_n. She then approaches each bidder sequentially asking whether or not the bidder accepts that ask. Which bidder is asked first is randomly determined at the beginning of each offer. Each bidder has the same chance to be asked first. In case that the bidder who is asked first rejects the offer, the seller offers the same ask to the other bidder.

4.2.1 STANDARD PREFERENCES

The term standard preferences covers all preferences that are purely outcome-based and only consider the own payoff. This means an individual has standard preferences if the utility function is global and only depends on one's own payoff (DellaVigna, 2009).

Proposition 6 (Standard Preferences)**.** *The FPSBA and the DA are strategically equivalent, which implies that they yield the same revenue (Vickrey, 1961).*

The crucial observation to this result is that the information revealed during the descending of the price clock in the DA does not change the trade-off between a bidder's winning probability and his profit in case of winning. Suppose a bidder bids $b = p_k$ in an FPSBA. This bidder enters a DA with the plan to accept the ask $a = p_k$, because the ex-ante problem is identical for the two formats. As the price clock is approaching p_k, two things may happen. First, the competitor accepts an ask greater than p_k. In this case, the auction ends and the bidder cannot react to this information. Second, the price continues to fall which increases the probability to win. However, the marginal trade-off stays the same. This is due to the fact that a bidder derives his optimal bidding strategy under the assumption that he has the highest valuation. Hence, the bidder sticks to his plan and waits for the ask p_k.

4.2.2 EXPECTATIONS-BASED REFERENCE POINTS

In contrast to individuals with standard preferences, an individual with reference-dependent preferences does not only care about his absolute payoff, but also compares the outcome to a reference point. Therefore, the utility function of such a bidder consists of two parts. First, the term $u(x)$ corresponds to utility derived from payoff x as under standard preferences. Second, the term $n(x, r)$ corresponds to gain-loss utility that evaluates the outcome x against a reference level r (Kahneman and Tversky, 1979). Following the approach of Köszegi and Rabin (2006) the gain-loss utility is defined piece-wise as

$$n(x, r) = \mu\left(u(x) - u(r)\right),$$

where

$$\mu(z) := \begin{cases} \eta z & \text{if } z > 0 \\ \eta\lambda z & \text{if } z \leq 0. \end{cases}$$

Here $\eta > 0$ determines how important the relative component is compared to the absolute payoff. Furthermore, λ represents the level of loss aversion which weighs negative deviation from the reference point (losses) relative to positive deviations (gains). If $\lambda > 1$, the bidder is loss averse, i.e., losses hurt him more than equally sized gains please him. If $\lambda = 1$, the agent is loss-neutral, and if $\lambda < 1$, the agent is gain-seeking. Total utility is the sum of both parts and given by $u^{\text{KR}}(x, r) = u(x) + n(x, r)$. We follow the literature and focus on the effect of loss aversion by assuming that utility of payoff $u(x)$ is linear. Hence, gain-loss utility $n(x, r)$ is a two-piece linear function.

Köszegi and Rabin (2006) assume that the reference point is stochastic and formed by the rational expectations of the bidder. They introduce the concept of a *personal equilibrium* which requires that the bidder has rational expectations about his own behavior and behaves consistently with his plans. Specifically, they propose that the bidder evaluates each possible outcome x under the winning probability $\Pr(x|b)$ against all other possible outcomes under this distribution. This modification has recently been successful in describing various empirical observations from laboratory endowment effects to labor supply in the field (e.g., Sprenger, 2010; Ericson and Fuster, 2011; Crawford and Meng, 2011).

Proposition 7 (Expectations-based reference point)**.** *A revenue ranking of the FPSBA and the Dutch auction is not possible.*

In the FPSBA, loss aversion implies that bidders want to reduce the difference between the payoff in case of winning and in case of losing the auction. As a consequence, subjects with a higher degree of loss aversion place higher bids than less loss-averse subjects. In the FPSBA, there exists an almost everywhere unique optimal bidding strategy (Eisenhuth and Ewers, 2012).

In contrast to the FPSBA, there might be several consistent bidding strategies in the DA. For example, it may be optimal for a subject to accept a high offer p if it planned to do so, whereas it is optimal for the same subject to wait for a smaller offer p' if her initial plan was to accept only a small offer p'. Different plans induce different reference points and thereby different optimal bidding strategies. Since several reasonable reference points can exist in the DA, we do not get a unique bidding prediction but a set of optimal bidding strategies. Applying a refinement and identifying the bidding strategy with the highest expected utility might not be possible as the optimality of a bidding strategy can change during the dynamic course of the auction (Ehrhart and Ott, 2014).

As shown in the Appendix 4.6.2, it may well be the case that for a given valuation the lowest optimal bid in the DA is lower than the optimal bid in the FPA, whereas the highest optimal bid in the DA is higher than the optimal bid in the FPA. As a consequence, a revenue ranking is not possible in general.

4.2.3 ALLAIS-TYPE PREFERENCES

Allais-type preferences violate the independence (or substitution) axiom, which is essential for EUT (Allais, 1953; Savage, 1954; Anscombe and Aumann, 1963). The independence axiom states that an individual who is indifferent between two lotteries should also be indifferent between these lotteries if the probabilities of both lotteries are multiplied by $\rho \in (0, 1]$. That is, if one scales the probabilities of both lotteries by a common ratio, the preference ordering is not affected under EUT. Grimm and Schmidt (2000) show that this independence requirement is a necessary and sufficient condition for strategic equivalence between the FPSBA and the DA.

Kahneman and Tversky (1979) report that subjects have a preference for certainty, i.e., outcomes in a degenerate lottery. In their experiment, a majority of individuals reveals that they prefer a degenerate lottery over a risky one but reverse this choice if both lotteries are scaled by ρ such that both now become risky. Thus, participants violate the independence requirement. This so-called "Allais paradox" (Allais, 1953) is empirically very robust, although reverse Allais-type preferences (i.e., a preference for risky outcomes if a certain outcome is available) have also been observed experimentally (Camerer, 1989; Weber, 2007).

Proposition 8 (Allais-type preferences)**.** *The DA yields higher revenue than the FPSBA if bidders have Allais-type preferences. The FPSBA generates higher revenue if bidders have reverse Allais-type preferences (Weber, 1982; Nakajima, 2011).*

The intuition is that the current price in the DA is augmented by a psychological premium for certainty for individuals with Allais-type preferences. This premium makes it more attractive to accept a high price in the DA than in the FPSBA in which all bids imply uncertainty. In other words, the DA offers a certain payoff in the given round against a risky lottery (prices in future rounds), whereas the FPSBA only offers a risky lottery.[6]

[6] We note that this overbidding only works given our organization of the DA, because we resolve the order in which the seller approaches the two bidders at the beginning of each period. If we had broken ties at random after each round, which is frequently done in DA implementations, the current price would actually be risky as well and Allais-type preferences would coincide with standard preferences.

4.3 EXPERIMENT

In this section, we first introduce our experimental design and then review previous research that examines the equivalence of the first-price sealed-bid auction and the Dutch auction experimentally.

4.3.1 DESIGN

Each subject participated in 18 FPSBA and 18 DA. Each auction consists of one participant and one bidding robot as bidders. The valuations of the participant are drawn from the set $\{6, 10, 14, 18, 22, 26, 30, 34, 38\}$ EUR. In each format, every participant is assigned each valuation twice in order to make participants' bidding behavior as comparable as possible. The bidding robot draws one price from $P = \{0, 1, \ldots, 21\}$ EUR according to a uniform distribution. This realization is the robot's bid in the FPSBA and its stopping price in the DA. We use a bidding robot as the competitor for three reasons. First, we do not want our results to be confounded by other-regarding preferences that are not considered in any of the models presented in Section 4.2. Second, we effectively reduce the strategic problem to a decision problem by fixing the strategy of the competitor. This makes it easier for subjects to focus on their optimal strategy by breaking the dynamics of higher-order beliefs.[7] Third, we are able to precisely calculate the winning probability and the expected profit. The provision of this information depends on the DSS treatment status.

Auction formats

In our experiment, we analyze the following two auction formats:

- **FPSBA** In the FPSBA, the computer screen informs the participants about their valuation and features a testing area. In this area, participants can explore the consequences of a particular bid on their

[7] Note that most work that analyzes strategic interaction in auctions assumes that subjects' preferences are common knowledge and that only valuations are private information. However, one cannot ensure common knowledge in reality.

profit and, depending on the DSS treatment, on the winning probability and the expected profit (see below). Participants are further informed about the remaining time of the current round. Finally, they enter their actual bid and submit this bid by pressing a button. After submitting their bid, participants are immediately informed whether they have won the auction and about the remaining time the current auction lasts. When the round has timed out, a feedback screen informs the subjects about their valuations, the winning bid, whether or not they received the item, and their profit for the this round.

- **DA** In the DA, the computer screen informs participants about their valuation and displays the current price, the time until the next price, and the next price. As in the FPSBA, participants are informed about their profit given both the current and the next price. Depending on the DSS treatment, participants are also informed about the probability to be offered the current price and the next price as well as the associated expected profits (see below). Finally, participants can accept the current price by pressing a button. After either the participant or the computer bidder has accepted the current price, participants are immediately informed whether they have won the auction and about the remaining time the current auction lasts. When the round has timed out, participants receive the same feedback as in the FPSBA.

Decision support system

The theoretical analysis on the role of preferences in Section 4.2 highlights the fact that deriving the optimal bid depends on the following aspects: (i) the profit from winning with the chosen bid, $v^i - b^i$, (ii) the probability to win with the chosen bid, $\Pr(\text{win}|b^i)$, and (iii) the expected utility derived from the combination of the former two. The latter depends on the individual preferences whereas the former two are identical across all theories. Hence, we design a DSS that assists the bidder by providing (i) the profit from winning, (ii) the winning probability, and (iii) the expected profit which is the product of (i) and (ii).

Any deviation from bidding predictions can result from two sources: an omitted preference specification or problems in deriving the optimal bid. Our DSS allows us to disentangle the role of preferences from the impact of a lack of mathematical sophistication (complexity). This is because in the experiment, we fix the bidding strategy of the competitor and hence reduce the strategic problem of finding mutual best responses to the problem of finding a one-sided best response (i.e., an optimization or decision problem). We can thus objectively state expected profits and winning probabilities that should help participants derive the bid that maximizes the expected utility based on their actual preference specification. In other words, we implement the DSS to analyze whether observed bids are due to the underlying preferences or the complexity of the auction.

Specifically, the DSS varies between participants regarding the information a bidder receives during an auction. There are three nested levels of DSS: No, Medium, and Full DSS. In the FPSBA, the information is given for the current test bid. In the DA, the information is given for both the current and the next price. We vary the information content of the DSS between participants. The information content in each condition is as follows:

- **No DSS** In the FPSBA, subjects see the *profit if bid is successful* which is the profit their test bid would generate given that they won the auction. In the DA, subjects see the *profit at given price* which is the profit they would make if they accept the current price or if they now decide to accept the next price.
- **Medium DSS** Subjects have the same information as in No DSS. In addition, in the FPSBA, they also see the *winning probability* of their test bid which is the probability of having a higher bid than the competitor plus the probability of having the same bid and being selected as winner by the tie-breaking rule. In the DA, subjects receive the *probability to be offered the given price* for both the current and the next price. The probability to receive the current price p_k is trivially

given by 1. However, the probability to be offered the next ask, H_k^i, is highly non-trivial to derive (see Section 4.6.2 for details).

- **Full DSS** Subjects have the same information as in Medium DSS. In addition, in the FPSBA, they also see the expected profit of their test bid. In the DA, subjects see the expected profit of the next price. In the FPSBA, the expected profit is the product of the winning probability and the profit if the bid is successful. In the DA, the expected profit is the product of the probability to be offered the given price and the profit at the given price.

We are not aware of any other work that incorporates decision support in auctions. Armantier and Treich (2009) elicit both subjective probabilities and risk preferences in an attempt to find an explanation for overbidding in experimental first-price auctions. The authors report that participants underestimate their winning probability and overbid. Furthermore, they investigate the effect of a feedback system regarding winning probabilities. The feedback is implemented as follows. Participants are asked to predict their winning probability and they are given feedback regarding the precision of their prediction at the end of each round. As such, their feedback system is designed to induce learning whereas learning is not necessary in our setup as participants are given support before (FPSBA) or during (DA) the auction. They show that overbidding is reduced if their feedback system is in place.

Subjects

Table 4.1 provides an overview of participants characteristics in the different treatments.

Risk aversion is measured as the are under the curve on the gain domain, i.e. the integral of the estimated utility function on the gain domain. We normalize the domain of utility to [0,1] by dividing each elicited gain by the maximum gain. We interpolate linearly between the elicited points and use a geometric approach to calculate the area. In case of risk aversion the measure is smaller 0.5. A risk seeking individual has a measure larger than 0.5 and a risk neutral subject has a measure equal to 0.5.

Loss aversion relates the slope of utility in the gain domain to its slope in the loss domain. Kahneman and Tversky (1979) define loss aversion by $-u(-x) > u(x)$ for every $x > 0$. We measure the coefficient of loss aversion as the mean of $-u(-x)/u(x)$ for all elicited values x.

Allais-type preferences are measured by metric measure of the common-ratio effect (CRE) to assess the preference reversal due to violations of the independence axiom. Participants exhibiting the common-ratio effect show a preference reversal such that, they have a preference for certain outcomes. Participants with a CRE of 0 are consistent with expected utility theory, a CRE larger zero indicates Allais-type preferences and subjects with a CRE smaller zero have reverse Allais-type preferences.

Subjects' numeracy is rated according to a combination of the Schwartz et al. (1997) and the *Berlin Numercy Test* that assess the understanding of fundamental concepts of probability. Subjects have to answer seven questions and the variable numeracy reflects how many of these questions were answered correctly.

Table 4.1: Summary statistics by treatment

Treatment	No DSS		Medium DSS		Full DSS		
First format	FPSBA	DA	FPSBA	DA	FPSBA	DA	p-value
Risk aversion	0.461	0.466	0.499	0.528	0.441	0.526	0.52
	(0.167)	(0.105)	(0.106)	(0.140)	(0.143)	(0.103)	
Loss aversion	1.842	1.396	1.673	1.352	2.088	1.407	0.08
	(0.860)	(0.474)	(0.713)	(0.506)	(0.842)	(0.450)	
Allais-type	2	2.714	3.857	3.667	4.333	2.267	0.90
	(13.90)	(2.301)	(4.605)	(6.199)	(9.566)	(18.25)	
Numeracy	4.333	4.714	3.929	4.833	4.167	4.867	0.24
	(1.291)	(2.199)	(1.141)	(1.267)	(1.403)	(0.990)	
Participants	15	14	14	12	12	15	

Notes: Reported are means of each variable with standard deviation in parentheses. The last column presents the results of a Kruskal-Wallis tests for the equality of populations.

Organization

The auctions were the second stage of the experiment. In the first stage, which was conducted one week before the second, participants' preferences were elicited. Detailed results are reported in Zeppenfeld (2015).[8] Both stages of the experiment were conducted in the Cologne Laboratory for Economic Research (CLER) at the University of Cologne, Germany.[9] Using the recruiting system *ORSEE* (Greiner, 2015), we invited a random sample of the CLER's subject pool via email. The whole experiment was computerized using the programming environment *z-tree* (Fischbacher, 2007b).

In both stages, payoffs were stated in Euros (EUR). Participants were paid out in private for the entire course of experimentation after the completion of the second stage. In the second stage, one auction of each auction format was randomly chosen to be payoff-relevant. All 82 participants were paid their total net earnings, i.e., their earnings from the auctions and their earnings from first stage of the experiment. The average payoff for the entire experiment was 36.63 EUR corresponding to approx. 45.54 USD at the time of the payment.[10]

4.3.2 OPPORTUNITY COSTS AND ACTION SETS

Previous research argues that differences between the two mechanisms come from the heterogeneous organization of the two auctions. The FPSBA is faster, as it only requires to place simultaneous bids and the winner can be announced immediately after all bids are collected. The DA, on the other hand, requires a certain time interval for the clock to reach the desired price level of an individual bidder. Hence, a bidder in a DA faces substantial waiting costs. Carare and Rothkopf (2005) analyze the effect of transaction

[8]The first stage of the experiment was the same for all participants and participants only learned their earnings of the first part until the very end of the entire experiment, i.e., after they completed the second stage.

[9]See `www.lab.uni-koeln.de`.

[10]The first stage elicited preference parameters across gains and losses. Total net payoffs across the entire experiment range from −3.00 EUR (−3.73 USD) to 98.45 EUR (122.41 USD). The one subject who accumulated negative payoffs paid in cash at the end of experiment.

costs that accrue from the necessity to return to the auction site to check whether the desired price level has been reached. Not surprisingly, facing these additional costs, a bidder is willing to stop the auction at a higher price to avoid the need to return to the auction site.

Cox et al. (1983) and Katok and Kwasnica (2007) analyze the following trade-off experimentally. Despite the fact that bidders face transaction and/or opportunity costs from slow DA's, they also enjoy the "waiting game", as it implies a certain level of suspense. Cox et al. (1983) do not find that tripling payoffs, and therewith increasing the opportunity costs of playing the waiting game, significantly increases bids in a DA. Hence, they reject the hypothesis of "suspense utility". Katok and Kwasnica (2007) find that increasing the clock time, i.e., the time between consecutive price ticks, significantly increases bids in a DA. Slow clocks increase opportunity costs which have to be paid no matter if the bidder wins the auction or not. Katok and Kwasnica (2007) note that in the laboratory, these opportunity costs correspond most likely to participants' value of leaving the laboratory earlier. Hence, a bidder is willing to accept a higher ask to reduce the time to complete the experiment and save opportunity costs.

We account for opportunity costs in two ways. First, we hold opportunity costs constant across treatments. We follow Turocy et al. (2007) and keep the time per mechanism constant. This means that we fix the absolute time per mechanism irrespective of how fast participants decide (FPSBA) or how early they stop (DA). One round of bidding in the FPSBA always lasts 60 seconds.[11] One round of bidding in the DA always lasts 220 seconds, i.e., ten seconds per price tick (see below for a motivation). If a participant accepts a current ask, he wins the auction, but the next round does not start before the 220 seconds are over.[12] Second, all subjects play both the FPSBA and the DA.

[11]If participants do not enter a valid bid by the end of this time limit, they do not participate in the auction in that round.

[12]In both mechanisms, after the auction has ended, participants see a screen showing the remaining time until the round is completed and whether or not they have won the auction.

Katok and Kwasnica (2007) show that the clock speed has great impact on the bids in a DA due to the implied differences in opportunity costs. Because we hold opportunity costs constant, this is not an argument in our experiment. Participants in the FPSBA have 60 seconds to arrive at a bid that balances the trade-off between the winning probability and the profit in case of winning. We determine the clock speed in the DA based on two considerations. On the one hand, the trade-off between two consecutive price ticks in a DA is easier to compute and participants should need less time. On the other hand, we have to provide some time for the reference point to form. We therefore decide on a clock speed of ten seconds. This is the same clock speed as in the middle treatment in Katok and Kwasnica (2007). However, in contrast to their experiment subjects cannot reduce the duration of the DA in our experiment, as each DA lasts for 220 seconds.

In addition to controlling opportunity costs, we also hold action sets constant across the two mechanisms. In Cox et al. (1983), participants' bids are rounded to the next feasible bid in the DA. Participants can then either confirm or alter this rounded bid. In Katok and Kwasnica (2007), participants can bid integers in the FPSBA, whereas price decrements in the DA were five tokens. In contrast, in our design, participants in the FPSBA face the same set of possible prices as in the DA. This is a direct transfer of our model environment to the laboratory and ensures strict comparability between the two mechanisms.

4.4 RESULTS

In this section, we report the results of the second stage of our laboratory experiment and focus on the comparison of the FPSBA and the DA. We only consider winning bids, because we only observe a participant's bid in the DA if a participant stopped the auction and won. In order to derive a one-dimensional measure of individual bidding behavior, we first conduct OLS regressions without constants for each participant. Regressing without a constant corresponds to the assumption that a bidder with a valuation of zero behaves rational and places a bid of zero. This gives us the average slope of a subjects bidding function. The steeper the slope the more aggressive is the subject's bidding behavior. Each participant represents one independent observation, because there was no interaction between participants. We report results of non-parametric Wilcoxon signed rank (SR), Mann-Whitney-Wilcoxon (MWW), or Kruskal-Wallis (KW) tests.

In line with the observations by Coppinger et al. (1980) and Cox et al. (1982a), we find that individuals place higher bids in the FPSBA than in the DA (MWW: $p = 0.0183$). However, a closer look reveals that bidders only place higher bids in the FPSBA than in the DA if they get no decision support (MWW: $p = 0.0046$). The No DSS treatment is comparable to standard experimental auction designs. If bidders get (some) decision support, the differences vanish (MWW: Medium DSS $p = 0.1498$ and Full DSS $p = 0.6256$). Table 4.4 complements these tests controlling for bidder characteristics. It confirms the observation that bids in the DA are substantially lower than in the FPSBA in absence of decision support ($p < 0.001$) and that this differences vanish once support is provided (Medium DSS $p = 0.1628$, Full DSS $p = 0.8044$).

In the FPSBA, the provision of decision support changes the bidding behavior significantly (KW: $p = 0.0704$). Bidders who receive decision support (Medium DSS, Full DSS) place lower bids than bidders without decision support (No DSS; MWW: $p = 0.0214$). In contrast, the influence of decision support is overall not significant in the DA (KW: $p = 0.1224$). However, we find some evidence that the effect of decision support works in the opposite direction compared to the FPSBA, i.e., bidders who only receive limited decision support (No DSS, Medium DSS) place smaller bids than those bidders who get full decision support (Full DSS; MWW: $p = 0.0424$).

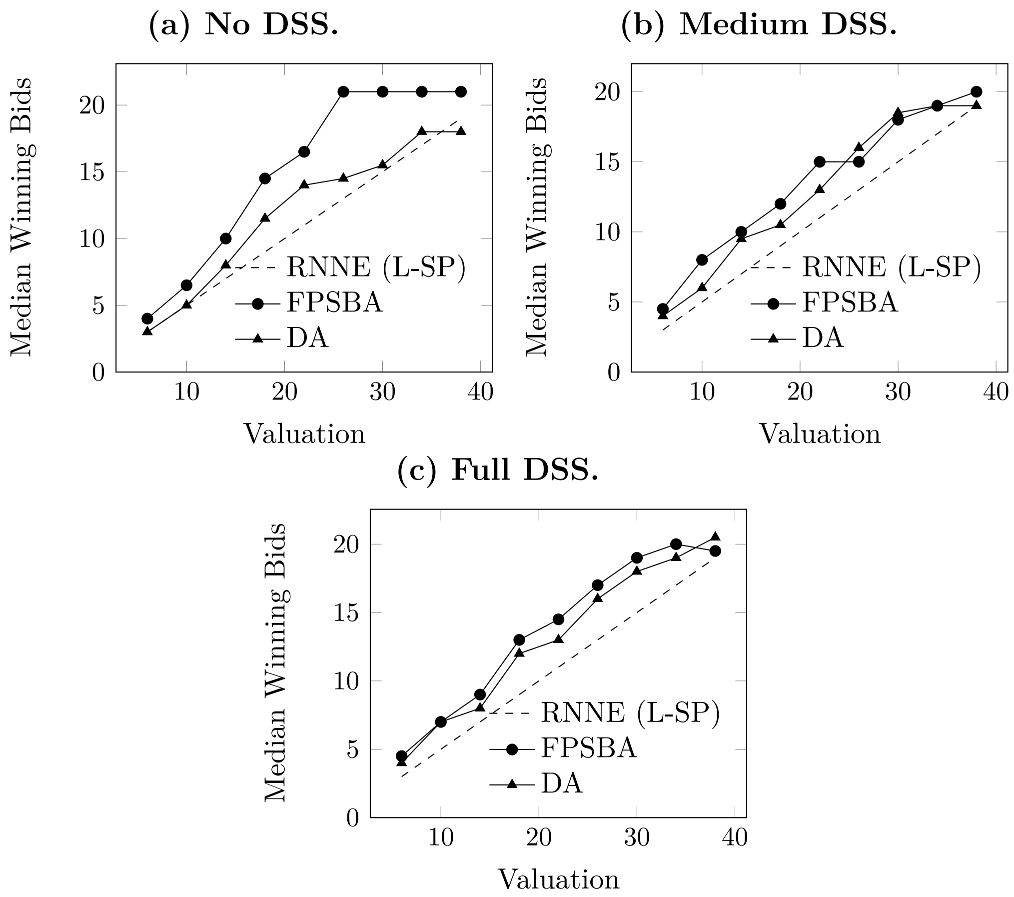
Figure 4.1 illustrates the bidding behavior and Table 4.2 presents the results of Tobit panel regressions analyzing the influence of elicited preferences and of decision support in the FPSBA and the DA. Controlling for individual characteristics, the regressions support the results of our non-parametric tests. The provision of decision support (Medium DSS, Full DSS) decreases bids in the FPSBA. In contrast to that, in the DA the provision of Medium DSS does not influence bidding behavior ($p = 0.679$) and the influence of Full DSS is also not significant ($p = 0.106$).

The regressions further show that risk-averse bidders place higher bids, whereas loss aversion and Allais-type preferences have no or only marginal influence on bidding behavior. Theories based on Allais-type preferences predict higher bids in the DA than in the FPSBA, something we do not observe. In the DA we find some indication that subjects with a higher numeracy score place lower bids. However, the significance vanishes if we do not control for risk aversion.

Table 4.3 complements Table 4.2 and examines if the elicited preferences (risk aversion, loss aversion, Allais-tpye preferences) and characteristics (numeracy) have different effects on bidding behavior in the two auction formats. We only find weak evidence that a higher numeracy score leads ceteris paribus to lower bids in the DA than in the FPSBA, but no indication that any of the elicited preferences can explain differences in bidding behavior. Cox et al. (1983) argue that differences between the two mechanisms result from violations of Bayes' rule and indirectly test this conjecture by tripling individual payoffs which increases opportunity costs from miscalculations. In contrast, our design is a direct test of the impact of cognitive limitations and we find additional evidence for this conjecture.

Similar to the other experimental papers that compare bidding behavior in the FPSBA to bidding behavior in the DA (Cox et al., 1983; Katok and Kwasnica, 2007), participants in our experiment first played 18 rounds in the DA and then another 18 rounds in the FPSBA.[13] In contrast to the findings of Cox et al. (1983); Katok and Kwasnica (2007), we find that neither subjects who first participate in the FPSBA nor subjects who start in the DA change their bidding behavior when the auction format changes (SR: FPSBA $\rightarrow$ DA, $p = 0.3888$; DA $\rightarrow$ FPSBA, $p = 0.1973$). This within-participant consistency is in contrast to the literature and we relate this finding to the strict comparability of the two formats in our experiment. Hence, our bidding data indicates that a constant action set and fixed op-

[13] In order to control for order effects, about half of the participants played in reverse order.



Notes: Depicted are medians of the winning bids for each valuation and format separated by decision support. The reference line is the risk-neutral Nash equilibrium (RNNE) given by Linear SP (L-SP). Participants in No DSS do not receive additional information. In treatment Medium DSS, participants receive information about the winning probability (FPSBA) or the probability to receive the next price (DA). In treatment Full DSS, participants receive the same information as in Medium DSS and, in addition, the expected profit associated with their bid.

Figure 4.1: Median winning bids across decision support.

portunity costs are necessary for consistency between the two formats.[14] The other cited experiments that also vary the order of the two formats do not find a similar consistency in bidding even in absence of decision support. We think that the consistency in our data stems from the direct comparability of the two formats in our design by using the same price grid and

[14]Opportunity costs include, e.g., monitoring costs (Carare and Rothkopf, 2005) or costs from participating in the experiment (Katok and Kwasnica, 2007).

Table 4.2: Tobit panel regressions of the influence of preferences on winning bids in periods 1 to 18.

	Winning bid			
	(1)	(2)	(3)	(4)
	FPSBA	DA	FPSBA	DA
Valuation	0.523***	0.479***	0.524***	0.479***
	(0.0134)	(0.0154)	(0.0134)	(0.0154)
Allais-type	-0.0222	0.00507	-0.0156	0.00747
	(0.0374)	(0.0289)	(0.0347)	(0.0275)
Risk aversion	6.101**	10.02***	6.202**	9.533***
	(2.974)	(2.983)	(2.754)	(2.928)
Loss aversion	0.488	-0.468	0.441	-0.536
	(0.508)	(0.745)	(0.475)	(0.709)
Numeracy	0.200	-0.469**	0.115	-0.472**
	(0.300)	(0.233)	(0.280)	(0.222)
midDSS			-2.007**	-0.329
			(0.786)	(0.795)
fullDSS			-1.670**	1.218
			(0.812)	(0.753)
Period	0.0865***	0.0336	0.0859***	0.0338
	(0.0237)	(0.0267)	(0.0237)	(0.0267)
Constant	-2.553	-0.00274	-1.005	0.00709
	(2.652)	(2.199)	(2.520)	(2.096)
Observations	443	448	443	448
Participants	41	41	41	41

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: Reported are results of tobit panel regressions with an upper limit at the highest possible bid of 21.

holding opportunity costs constant. Only bidders in the No DSS treatment who start bidding in the FPSBA change their bidding behavior and place lower bids when the auction format changes to a DA (SR: $p = 0.0995$). This observation might indicate that, in absence of decision support, the FPSBA is more complex than the DA.

4.5 CONCLUSION

We examine the role of decision support and preferences in first-price sealed-bid and Dutch auctions. In a laboratory experiment, we elicit participants' preferences and vary the degree of decision support to account for the complexity in deriving the optimal bid. We confirm the frequently observed non-equivalence of the first-price and Dutch auction under the absence of decision support. In addition, we observe that any differences in bidding behavior between the two mechanisms vanish once we provide decision support, which indicates that differences in bidding behavior are due to different levels of complexity. Differences between the two auction formats based on preferences should be independent of the level of decision support. We use the elicited individual preferences of all participants to explain bidding behavior. We find no indication that non-standard preferences explain the empirical differences. Our results thus indicate that the empirical breakdown of equivalence is primarily caused by the complexity of the bidding decision rather than by bidders' preferences. This observation should be taken into account in real-world business interactions involving auctions.

In the experiment, the implemented DSS is perfect in the sense that we can precisely calculate the respective probabilities and expected values due to the fixed bidding strategy of a bidding robot. Obviously, this is not directly implementable in real auctions. However, the availability of historical bid data promotes the design of decision support systems similar to our implementation. Thus, our findings on the differences in auction formats indicate that the higher revenue in the FPSBA is less relevant in real auctions in which bidders are likely to have such support.

4.6 APPENDICES

4.6.1 TABLES

Table 4.3: Tobit panel regression of the influence of preferences and numeracy on differences between winning bids in the FPBSA and the DA in periods 1 to 18.

	Winning Bid
Valuation	0.501***
	(0.0103)
Period	0.0577***
	(0.0181)
Constant	-1.730
	(2.548)
Risk aversion	6.053**
	(2.873)
Loss aversion	0.490
	(0.490)
Allais-type	-0.0225
	(0.0360)
Numeracy	0.216
	(0.290)
DA	0.843
	(3.358)
DA × Risk aversion	3.914
	(4.217)
DA × Loss aversion	-0.937
	(0.913)
DA × Allais	0.0280
	(0.0469)
DA × Numeracy	-0.672*
	(0.377)
Observations	891
Participants	82

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: The upper limit in the Tobit regression is the maximum bid of 21. It was placed in 174 out of 891 observations. DA is a dummy variable that is zero if the auction format is a FPSBA and is one in case of a DA.

Table 4.4: Tobit panel regression of the influence of decision support in the FPSBA and the DA in periods 1 to 18.

	Winning bid
Valuation	0.502***
	(0.0103)
Period	0.0581***
	(0.0181)
Constant	1.417
	(1.682)
Allais-type	-0.00370
	(0.0220)
Risk aversion	6.498***
	(1.973)
Loss aversion	0.169
	(0.388)
Numeracy	-0.159
	(0.172)
midDSS	-2.245***
	(0.786)
fullDSS	-1.729**
	(0.815)
DA	-3.251***
	(0.794)
DA × midDSS	2.088*
	(1.131)
DA × fullDSS	3.041***
	(1.130)
Observations	891
Participants	82

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Notes: The upper limit in the Tobit regression is the maximum bid of 21. It was placed in 174 out of 891 observations. DA is a dummy variable that is zero if the auction format is a FPSBA and is one in case of a DA.

Table 4.5: Average winning bids for periods 1 to 18.

	No DSS			Medium DSS			Full DSS			KW test	
Valuation	FPSBA	DA	p-value	FPSBA	DA	p-value	FPSBA	DA	p-value	p-value FPSBA	p-value DA
6	4.25	7.42	0.8710	4.25	4.00	0.5541	4.25	3.67	0.4450	0.9905	0.9191
10	6.67	6.00	0.3417	7.31	5.93	0.1234	7.38	6.57	0.6310	0.5114	0.6148
14	10.20	8.35	0.0397	10.38	10.50	0.9575	8.67	8.55	0.7575	0.1396	0.1450
18	14.39	11.04	0.0042	12.57	10.91	0.1105	11.25	11.80	0.1498	0.2347	0.7103
22	15.29	12.05	0.0740	14.54	13.83	0.5108	14.67	13.42	0.2008	0.7910	0.6215
26	18.88	14.50	0.0022	15.18	15.71	0.6428	17.09	17.15	0.8142	0.0150	0.0878
30	19.71	16.14	0.0019	17.96	15.73	0.3084	18.00	18.20	0.786	0.0189	0.1328
34	20.20	17.65	0.0062	18.68	17.04	0.1268	18.83	19.17	0.6750	0.0219	0.1285
38	20.20	17.86	0.0190	19.35	18.42	0.4404	18.50	19.77	0.1287	0.0265	0.1372
Average	15.87	13.33	-	14.57	13.86	-	14.93	15.01	-	-	-

Notes: Reported are the average winning bids for periods 1 to 18 and the probability that bids in the different formats are drawn from the same distribution based on the Wilcoxon-Mann-Whitney U-test. The Kruskal-Wallis (KW) test reports whether there is any significant difference across decision support systems for a given auction format.

4.6.2 THEORY

We consider a situation in which the bidder faces one competitor either in a FPSBA or in a DA. Let $P = \{p_1, p_2, \cdots, p_n\}$ be the common price grid, i.e. the set of possible bids in the FPSBA and the set of possible offers in the DA. Let p_k denote the kth- smallest possible price in this price grid. Let the price grid be uniformly spaced, with $p_k - p_{k-1} = \delta$ for all k.

The probability that the competitor places a bid smaller or equal p_k in the FPSBA is given by $F(p_k)$. $F(p_k)$ also denotes the probability that the highest price offer the competitor is going to accept in a DA is smaller or equal p_k.

For large η and λ the utility of a bidder is mainly driven by the relative outcomes, i.e. by his gain loss utility, and not by absolute outcomes. Consequently, it may be the case that a bidder who has a strictly positive chance of making strictly positive profits and faces no risk of a loss prefers not to participate in the auction. In the following we assume that bidder's expected utility is increasing in his valuation, which rules out such implausible predictions and guarantees monotone bidding functions This assumption is referred to as *no dominance of gain-loss utility* in Herweg et al. (2010).

First-Price Sealed-Bid Auction

In the FPSBA both participants place a bid $b_i \in P$ and the participant who places the higher bid wins. In case of a tie both participants have a winning probability of one half. The expected profit of a bidder with valuation v bidding b_k is given by

$$\Pi(b_k, v) = \left[F(b_{k-1}) + \frac{F(b_k) - F(b_{k-1})}{2}\right] \cdot (v - b_k) \tag{4.6.1}$$

$$= \frac{F(b_k) + F(b_{k-1})}{2} \cdot (v - b_k) \tag{4.6.2}$$

$$=: P_\omega^k \cdot (v - b_k). \tag{4.6.3}$$

When relative outcomes are evaluated as

$$\mu(x) := \begin{cases} \eta x & x \geq 0 \\ \eta\lambda x & x < 0, \end{cases} \tag{4.6.4}$$

the expected utility of a bidder with KR preferences bidding b_k is given by

$$\begin{aligned} U(b_k, v) &= P_\omega^k \cdot (v - b_k) \\ &\quad + P_\omega^k \cdot (1 - P_\omega^k) \cdot \mu(v - b_k) \\ &\quad + P_\omega^k \cdot (1 - P_\omega^k) \cdot \mu(b_k - v) \end{aligned} \tag{4.6.5}$$

and optimal bids are given by

$$b^*_{FP}(v) = \arg\max_{b \in P} \{U(b, v)\}. \tag{4.6.6}$$

As the price grid starts at 0, bidders can always place bids smaller their valuation. For this reason the relevant part of the piece-wise defined utility function is given by

$$U(b_k, v) = P_\omega^k \cdot (v - b_k) - P_\omega^k \cdot (1 - P_\omega^k) \cdot (v - b_k) \cdot \eta(\lambda - 1). \tag{4.6.7}$$

Let v_k be the valuation for which a bidder is indifferent between bidding p_k and p_{k+1}. Given that these v_k are increasing in k the optimal bidding strategy $\beta_{FP}(v)$ is monotone and it is optimal for bidders to bid p_k for all bidders with a valuation between v_{k-1} and v_k. These indifference values are given by

$$U(b_k, v_k) \stackrel{!}{=} U(b_{k+1}, v_k) \tag{4.6.8}$$

$$\Leftrightarrow v_k = b_k + \delta \frac{\overbrace{P_\omega^{k+1} - P_\omega^{k+1}(1 - P_\omega^{k+1})\eta(\lambda - 1)}^{:=\Omega_{k+1}}}{\underbrace{P_\omega^{k+1} - P_\omega^k - \eta(\lambda - 1)\left(P_\omega^{k+1}(1 - P_\omega^{k+1}) - P_\omega^k(1 - P_\omega^k)\right)}_{:=\Lambda_k = \Omega_{k+1} - \Omega_k}} \tag{4.6.9}$$

The *no dominance of gain-loss utility* assumption implies a restriction on values for η and λ:

$$\begin{aligned} & \frac{\partial U(b,v)}{\partial v} = P_\omega^k - P_\omega^k \cdot (1-P_\omega^k)\eta(\lambda-1) \overset{!}{\geq} 0 \\ \Leftrightarrow \quad & \eta(\lambda-1) \overset{!}{\leq} \min_{k\in\{1,\dots,n\}} \left\{ \frac{1}{1-P_\omega^k} \right\} \\ \Leftrightarrow \quad & \eta(\lambda-1) \overset{!}{\leq} \frac{1}{1-P_\omega^1}, \end{aligned} \tag{4.6.10}$$

(4.6.10) implies that $\Omega_k \geq 0$ and $\Lambda_k \geq 0$ for all k and we get

$$\begin{aligned} v_k - v_{k-1} &= \overbrace{b_k - b_{k-1}}^{=\delta} + \delta \left[\frac{\Omega_{k+1}}{\Lambda_k} - \frac{\Omega_k}{\Lambda_{k-1}} \right] \\ &= \frac{\delta}{\Lambda_k \Lambda_{k-1}} \left[\Lambda_k \Lambda_{k-1} + \Omega_k \Lambda_k - \Omega_{k+1} \Lambda_{k-1} \right] \\ &= \frac{\delta}{\Lambda_k \Lambda_{k-1}} \left[\Lambda_{k-1}(\lambda_k - \Omega_{k+1}) + \Omega_k \Lambda_k \right] \\ &= \frac{\delta \Omega_k}{\Lambda_k \Lambda_{k-1}} \left[\Lambda_k - \Lambda_{k-1} \right] > 0. \end{aligned}$$

The bidding strategy is then given by

$$\beta_{FP}(v) = \begin{cases} 0 & \text{if } v \in [0, v_1] \\ b_k & \text{if } v \in (v_k, v_{k+1}], \end{cases} \tag{4.6.11}$$

with $v_{n+1} = 1$ if $v_k \leq 1$. Else if $v_k > 1$ for any k, β_{FP} is adjusted accordingly.

Dutch Auction

In the DA participants sequentially receive decreasing offers $a_j \in P$ starting with p_n. A participant who receives an offer can either accept or reject it. In case of acceptance the auction ends immediately. If the participant who receives the offer p_k first rejects, the other participant will also receive the offer p_k. If the other participant rejects p_k, too, the new offer will be p_{k-1}. Which participant receives the offer p_{k-1} first is randomly determined. This modeling approach is also used by Bose and Daripa (2009).

Every time the bidder receives an offer he has the choice between accepting or waiting for a lower offer. Let H_k be the probability that the bidder will receive an offer p_{k-1} given that he rejects offer p_k. The probability H_k can be split in two parts. First, ρ_k denotes the probability that the price step p_{k-1} is reached, i.e. the probability that the good is not sold at p_k. Second, ϕ_k denotes the probability that the bidder receives an offer p_{k-1} given that the price step p_{k-1} is reached. Consequently, $H_k = \rho_k \cdot \phi_k$.

COMPUTATION OF ρ_K In order to derive the probability ρ_k of reaching the next price step p_{k-1} we first determine how likely it is that the bidder receives the first offer at p_k given that he receives an offer p_k. First, denote by $\#_k^i \in \{1, 2\}$ the position of the bidder in period k. Second, denote by A_k the event that the bidder receives the offer p_k.

$$\Pr\{\#_k = 1|A_k\} = \frac{\Pr\{\#_k = 1\} \cdot \Pr\{A_k|\#_k = 1\}}{\Pr\{\#_k = 1\} \cdot \Pr\{A_k|\#_k = 1\} + \Pr\{\#_k = 2\} \cdot \Pr\{A_k|\#_k = 2\}} \tag{4.6.12}$$

$$= \frac{\frac{1}{2}}{\frac{1}{2} + \frac{1}{2} \cdot \frac{F(p_k)}{F(p_{k+1})}} \tag{4.6.13}$$

$$= \frac{F(p_{k+1})}{F(p_{k+1}) + F(p_k)}. \tag{4.6.14}$$

Consequently, the probability that the bidder is asked second at p_k given that he is asked at p_k is given by

$$\Pr\{\#_k = 2|A_k\} = 1 - \Pr\{\#_k = 1|A_k\} \tag{4.6.15}$$

$$= \frac{F(p_k)}{F(p_{k+1}) + F(p_k)}. \tag{4.6.16}$$

Given that the bidder is asked second, $\#_k = 2|A_k$, his rejection of the offer p_k directly implies that the price step p_{k-1} is reached. However, if the bidder is asked first, $\#_k = 1|A_k$, his rejection only implies that the price step p_{k-1} is reached if the competitor also rejects p_k given that she already rejected p_{k+1}, which happens with probability $F(p_k)/F(p_{k+1})$. Hence, the probability ρ_k that price step p_{k-1} will be reached given that the bidder rejects the offer p_k is given by

$$\rho_k = \Pr\{\#_k = 2|A_k\} \cdot 1 + \Pr\{\#_k = 1|A_k\} \cdot \frac{F(p_k)}{F(p_{k+1})} \tag{4.6.17}$$

$$= \frac{2 \cdot F(p_k)}{F(p_{k+1}) + F(p_k)}. \tag{4.6.18}$$

COMPUTATION OF ϕ_K Given that the price step p_{k-1} is reached the probability of being asked first is one half. In this case the bidder receives an offer with certainty. If the opponent is asked first, which also happens with a probability of one half, the bidder receives the item only if the competitor refuses the offer p_{k-1}. The probability that the competitor refuses the offer p_{k-1} given that she refused p_k is given by $F(p_{k-1})/F(p_k)$. Hence, the probability of receiving an offer p_{k-1} given that price step p_{k-1} is reached is given by

$$\phi_k = \frac{1}{2} + \frac{1}{2} \cdot \frac{F(p_{k-1})}{F(p_k)}. \tag{4.6.19}$$

COMPUTATION OF H_K Combining the probability ρ_k of reaching the next price step p_{k-1} with the probability ϕ_k of receiving an offer given that the price step p_{k-1} is reached, gives us the probability H_k of receiving another offer when rejecting p_k.

$$H_k = \rho_k \cdot \phi_k \tag{4.6.20}$$

$$= \frac{F(p_k) + F(p_{k-1})}{F(p_k) + F(p_{k+1})}. \tag{4.6.21}$$

BIDDING Let $\mathrm{R}\,(p_j|p_k)$ denote the probability that the bidder will be receive (or has received) an offer p_j given that he is currently offered p_k,

$$\mathrm{R}\,(p_j|p_k) := \begin{cases} \frac{F(p_j)+F(p_{j+1})}{F(p_k)+F(p_{k+1})} & j \leq k \\ 1 & j > k. \end{cases} \tag{4.6.22}$$

Note that for some $a < b < c$,

$$\mathrm{R}\,(a|b)\,\mathrm{R}\,(b|c) = \mathrm{R}\,(a|c)\,.$$

The expected profit of a bidder with valuation v planning to accept offer p_j who is currently offered $p_k \geq p_j$ is given by

$$\Pi(p_j, v|p_k) = \mathrm{R}\left(p_j|p_k\right) \cdot (v - p_j). \tag{4.6.23}$$

A bidder with KR preferences conceives a plan at the beginning of the auction, namely accepting the offer $r \in \{p_1, ..., p_m\}$ and evaluates his profit compared to a reference outcome determined by his plan. The utility of such a bidder with valuation v who planned to accept offer r from accepting the current offer p_k is given by

$$u_k = v - p_k + \left(1 - \mathrm{R}\left(r|p_k\right)\right) \cdot \mu\left(v - p_k\right) + \mathrm{R}\left(r|p_k\right) \cdot \mu\left(r - p_k\right). \tag{4.6.24}$$

Defining

$$u(x, r|y) = v - x + \left(1 - \mathrm{R}\left(r|y\right)\right) \cdot \mu\left(v - x\right) + \mathrm{R}\left(r|y\right) \cdot \mu\left(r - x\right), \tag{4.6.25}$$

We now analyze two cases:

1. $p_j < r < p_k$:

Then, the expected utility from waiting for an offer p_j is given by,

$$U(p_j, v, r|p_k) = R(r|p_k)\Big[(1 - \mathrm{R}(p_j|r))[\mu(r - v)] + R(p_j|r)\left[v - p_j + \mu(r - p_j)\right]\Big]. \tag{4.6.26}$$

2. $r < p_j < p_k$:

Then, the expected utility from waiting for an offer p_j is given by,

$$U(p_j, v, r|p_k) = R(p_j|p_k)\Big[(1 - \mathrm{R}(r|p_j))[v - p_j + \mu(v - p_j)] + R(r|p_j)\left[v - p_j + \mu(r - p_j)\right]\Big]. \tag{4.6.27}$$

The bidder prefers to accept now over waiting if and only if

$$u_{k,r} \geq \max_{p_j < p_k} \{U(p_j, v, r|p_k)\} \tag{4.6.28}$$

Determining the indifference values $v_{k,r}$ gives us the bidding function,

$$\beta_r(v) = \begin{cases} 0 & \text{if } \; v \in [0, v_1] \\ p_k & \text{if } \; v \in (v_k, v_{k+1}], \end{cases} \tag{4.6.29}$$

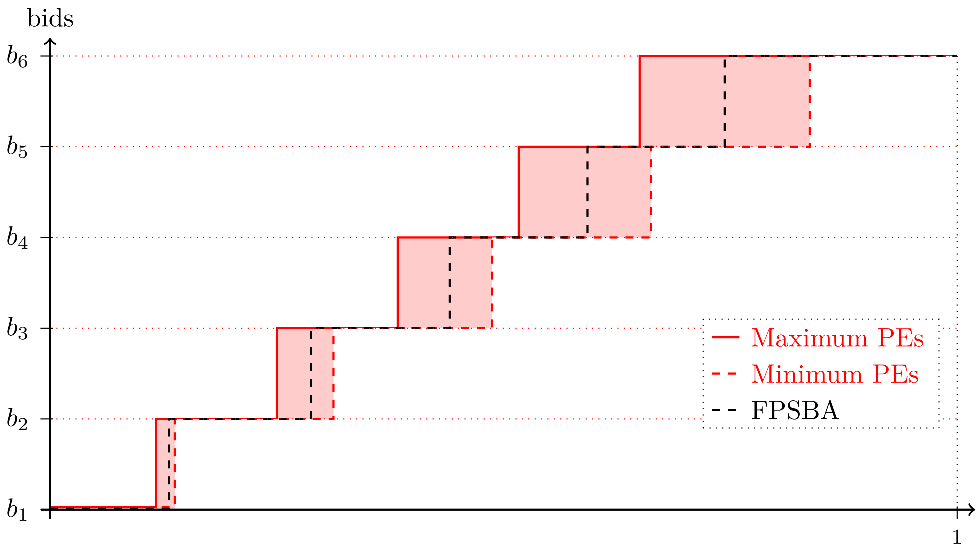
with $v_{m+1} = 1$.

These strategies define best responses to the distribution of competitor's bids $F(x)$. It is easy to see that bidding strategies depend on the reference point r, i.e. the bidders plan when to accept an offer. As a consequence multiple personal equilibria are possible.

First-Price Sealed-Bid Auction vs. Dutch Auction

For subjects with KR preferences it is not possible to make a general statement about the revenue ranking of the FPSBA and the Dutch auction. In the following we provide examples that prove this statement.

Figure 4.2: Equilibrium bids in Dutch auctions and FPSBA



Notes: This figure shows the lowest and the highest personal equilibrium bids in the DA and the unique equilibrium bidding strategy in the FPSBA for $\lambda = 2.5$ and $\eta = 0.5$. The revenue ranking of the two auction format depends on the equilibrium selection in the DA.

4.6.3 INSTRUCTIONS

This section provides the instruction in German (original) and English (translated) separated by parts 1 and 2. Each part consists of part A and part B. Part B was always distributed after part A had been conducted. Experiment 1 was identical for each participant. Experiment 2 was counterbalanced, i.e., half of the participants received the first-price sealed-bid auction in part A followed by the Dutch auction in part B. The other half faced the reversed order. We present the instructions for the full-DSS treatment where subjects had full information. The instructions for the other treatments are the same and only exclude parts of the decision support which is reported in parentheses within the instructions.

Übersicht

Dieser Teil des Experiments besteht aus 18 Runden, die jeweils die gleiche Abfolge an Entscheidungen haben. Am Ende wird eine der 18 Runden zufällig durch den Computer ausgewählt und ausgezahlt. Alle Runden haben dabei die gleiche Wahrscheinlichkeit ausgewählt zu werden.

Erstpreisauktion

Sie nehmen an einer Erstpreisauktion teil, in der Sie ein Produkt erwerben können. Zu Beginn jeder Runde erfahren Sie, welchen Wert das Produkt für Sie hat. Dieser Wert wird aus der Menge

{ 6 €, 10 €, 14 €, 18 €, 22 €, 26 €, 30 €, 34 €, 38 € }

gezogen. Jeder Wert kommt genau zweimal vor. Die Reihenfolge ist jedoch zufällig bestimmt.

Sie befinden sich in einer Gruppe mit einem anderen Bieter. Der andere Bieter ist ein Bietroboter.

In der Auktion kann ein ganzzahliges Gebot zwischen 0 € und 21 € abgegeben werden. Der andere Bieter wählt sein Gebot zufällig zwischen 0 € und 21 €. Jedes Gebot ist dabei gleich wahrscheinlich.

Der Bieter, der das höchste Gebot abgegeben hat, gewinnt die Auktion und erhält das Produkt. Der Preis des Produkts entspricht diesem höchsten Gebot. Falls Sie und der andere Bieter das gleiche Gebot abgeben, erhalten Sie das Produkt mit 50% Wahrscheinlichkeit.

Falls Sie die Auktion gewinnen, ist Ihr Gewinn gegeben durch:

Gewinn = Wert – Gebot.

Falls Sie die Auktion nicht gewinnen, beträgt Ihr Gewinn 0.

Entscheidungshilfe

Bevor Sie Ihr echtes Gebot eingeben, können Sie verschiedene Gebote testen, wofür Ihnen ein Testbereich zur Verfügung steht.

Im Testbereich sehen Sie:

[Treatments: No DSS, Medium DSS, Full DSS]

- **Gewinn, falls Gebot erfolgreich**
  Der Gewinn, falls das aktuelle Testgebot erfolgreich wäre. Dieser wird wie folgt berechnet:
  Gewinn = Wert – Gebot.

[Treatments: Medium DSS, Full DSS]

- **Gewinnwahrscheinlichkeit**
  Die Wahrscheinlichkeit, dass Sie mit einem Gebot in Höhe des Testgebots die Auktion gewinnen.

[Treatments: Full DSS]

- **Erwarteter Gewinn**
  Durchschnittlicher Gewinn, den Sie mit dem Gebot erwarten können. Dieser wird wie folgt berechnet:
  Erwarteter Gewinn = (Gewinnwahrscheinlichkeit) x (Gewinn, falls Gebot erfolgreich).

Gebotsabgabe

- Um Ihr finales Gebot abzugeben, tippen Sie eine Zahl aus der erlaubten Menge der Gebote in das vorgesehene Feld ein. Anschließend klicken Sie auf „Gebot abgeben".
- Sie haben in jeder Runde 60 Sekunden Zeit, Ihr finales Gebot abzugeben. Sollten Sie kein Gebot in den 60 Sekunden abgeben haben, nehmen Sie in dieser Runde nicht an der Auktion teil.

Hinweis

Eine Runde dauert immer 60 Sekunden, unabhängig davon zu welchem Zeitpunkt Sie Ihr Gebot abgegeben haben. Nachdem Sie und der andere Bieter ein finales Gebot abgegeben haben, ist die Auktion zwar beendet, aber die Runde endet erst, wenn die 60 Sekunden abgelaufen sind.

Ergebnis

Übersicht

Dieser Teil des Experiments besteht aus 18 Runden, die jeweils die gleiche Abfolge an Entscheidungen haben. Am Ende wird eine der 18 Runden zufällig durch den Computer ausgewählt und ausgezahlt. Alle Runden haben dabei die gleiche Wahrscheinlichkeit ausgewählt zu werden.

Tickerauktion

Sie nehmen an einer Tickerauktion teil, in der Sie ein Produkt erwerben können. Zu Beginn jeder Runde erfahren Sie, welchen Wert das Produkt für Sie hat. Dieser Wert wird aus der Menge

{ 6 €, 10 €, 14 €, 18 €, 22 €, 26 €, 30 €, 34 €, 38 € }

gezogen. Jeder Wert kommt genau zweimal vor. Die Reihenfolge ist jedoch zufällig bestimmt.

Sie befinden sich in einer Gruppe mit einem anderen Bieter. Der andere Bieter ist ein Bietroboter.

In der Auktion startet der Preis bei 21 € und wird alle 10 Sekunden um 1 € gesenkt. Bei jedem neuen Preis wird zufällig einer der Bieter zuerst gefragt, ob er diesen Preis annehmen möchte. Nimmt der gefragte Bieter den Preis an, so endet damit die Auktion. Lehnt der gefragte Bieter ab, so wird der gleiche Preis dem verbleibenden Bieter angeboten. Beide Bieter haben die gleiche Wahrscheinlichkeit zuerst gefragt zu werden.

Der andere Bieter wählt zufällig einen Preis zwischen 0 € und 21 € aus, zu dem er annehmen würde. Jeder mögliche Preis hat dabei die gleiche Wahrscheinlichkeit ausgewählt zu werden.

Sie gewinnen die Auktion und erhalten das Produkt, falls Sie vor dem anderen Bieter einen Preis annehmen.

Falls Sie die Auktion gewinnen, ist Ihr Gewinn gegeben durch:

Gewinn = Wert – Preis.

Falls Sie die Auktion nicht gewinnen, beträgt Ihr Gewinn 0.

Entscheidungshilfe

Sie sehen auf dem Bildschirm den aktuellen Preis, den nächsten Preis sowie die Zeit bis zum nächsten Preis.

Zusätzlich sehen Sie:

[Treatments: No DSS, Medium DSS, Full DSS]

- **Gewinn bei gegebenem Preis**
  Der Gewinn, falls Sie den Preis annehmen würden. Dieser wird wie folgt berechnet:
  Gewinn bei gegebenem Preis = Wert – Preis.

[Treatments: Medium DSS, Full DSS]

- **Wahrscheinlichkeit, Preis angeboten zu bekommen**
  Die Wahrscheinlichkeit, dass Sie den jeweiligen Preis annehmen können.

[Treatments: Full DSS]

- **Erwarteter Gewinn**
  Durchschnittlicher Gewinn, den Sie erwarten können, wenn Sie sich jetzt entscheiden den jeweiligen Preis anzunehmen. Dieser wird wie folgt berechnet:
  Erwarteter Gewinn = (Wahrscheinlichkeit, Preis angeboten zu bekommen) x (Gewinn, bei gegebenem Preis).

Hinweis

Eine Runde dauert immer 220 Sekunden, unabhängig davon welchen Preis Sie annehmen. Nachdem Sie oder der andere Bieter einen Preis angenommen haben, ist die Auktion zwar beendet, aber die Runde endet erst, wenn die 220 Sekunden abgelaufen sind.

Ergebnis

Nach jeder Runde sehen Sie das Ergebnis der Runde. Hier erfahren Sie den Preis, ob Sie das Produkt erhalten haben und wie hoch Ihr Gewinn ist.

Overview

This part of the experiment consists of 18 rounds which have the same course of decisions. At the end, one of the 18 rounds will be randomly selected by the computer and paid out. All rounds have the same probability to be selected.

First-Price Auction

You will participate in a first-price auction in which you can acquire a product. At the beginning of each round, you will learn which value this product has for you. The value will be drawn from the set

{6 €, 10 €, 14 €, 18 €, 22 €, 26 €, 30 €, 34 €, 38 €}.

Each value occurs exactly twice. The order, however, is random.

You are in a group with one other bidder. This other bidder is a bidding robot.

In the auction, you can enter an integer bid between 0 € and 21 €. The other bidder will choose his bid randomly between 0 € and 21 €. Every bid is equally likely.

The bidder with the highest bid wins the auction and receives the product. The price of the product is given by this highest bid. If you and the other bidder submit the same bid, you have a 50% chance to receive the product.

If you win the auction, your profit is given by:

Profit = Value – Bid.

If you do not win the auction, your profit is 0.

Decision Support

Before you enter your actual bid, you can test different bids for which a testing area is provided for you.

In the testing area, you will see:

[Treatments: No DSS, Medium DSS, Full DSS]

- **Profit if bid was successful**
  The profit if the actual profit was successful. It is calculated as follows:
  Profit = Value – Bid.

[Treatments: Medium DSS, Full DSS]

- **Winning Probability**
  The probability that you win the auction with a bid equal to the test bid.

[Treatments: Full DSS]

- **Expected Profit**
  Average profit that you can expect with the bid. It is calculated as follows:
  Expected Profit = (Winning Probability) x (Profit if bid is successful).

Bid Submission

- To submit your final bid, type in a number out of the feasible set of bids into the respective field. Then, click on "submit bid".
- In each round, you have 60 seconds to submit your final bid. If you do not submit a bid within these 60 seconds, you will not participate in the auction in this round.

Note

One round always lasts for 60 seconds, independently of when you submit your bid. After you and the other bidder submitted a final bid, the auction end but the round will only end after the 60 seconds have elapsed.

Result

After each round, you will see the result of that round. Here you learn the price, whether or not you received the product, and how large your profit is.

Overview

This part of the experiment consists of 18 rounds which have the same course of decisions. At the end, one of the 18 rounds will be randomly selected by the computer and paid out. All rounds have the same probability to be selected.

Ticker Auction

You will participate in a ticker auction in which you can acquire a product. At the beginning of each round, you will learn which value this product has for you. The value will be drawn from the set

{6 €, 10 €, 14 €, 18 €, 22 €, 26 €, 30 €, 34 €, 38 €}.

Each value occurs exactly twice. The order, however, is random.

You are in a group with one other bidder. This other bidder is a bidding robot.

In the auction, the price starts at 21 € and will decrease by 1 € every 10 seconds. At every new price, one of the bidders is randomly asked whether or not he wants to accept the price. If the bidder accepts the price, the auction ends. If the bidder rejects the price, the same price is offered to the remaining bidder. Both bidders have the same probability to be asked first.

The other bidder will randomly choose a price a price between 0 € and 21 € which he would accept. Each feasible price has the same probability to be chosen.

You will win the auction and receive the product if you accept a price before the other bidder does.

If you win the auction, your profit is given by:

Profit = Value – Bid.

If you do not win the auction, your profit is 0.

Decision Support

On your screen, you see the current price, the next price, and the time until the next price is shown.

In addition, you will see:

[Treatments: No DSS, Medium DSS, Full DSS]

- **Profit at given price**
  The profit if you accepted the current price. It is calculated as follows:
  Profit at given price = Value – price.

[Treatments: Medium DSS, Full DSS]

- **Probability to be offered the given price**
  The probability that you can accept the respective price.

[Treatments: Full DSS]

- **Expected Profit**
  Average profit that you can expect if you decide now to accept the respective price. It is calculated as follows:
  Expected Profit = (Probability to be offered this price) x (Profit at given price).

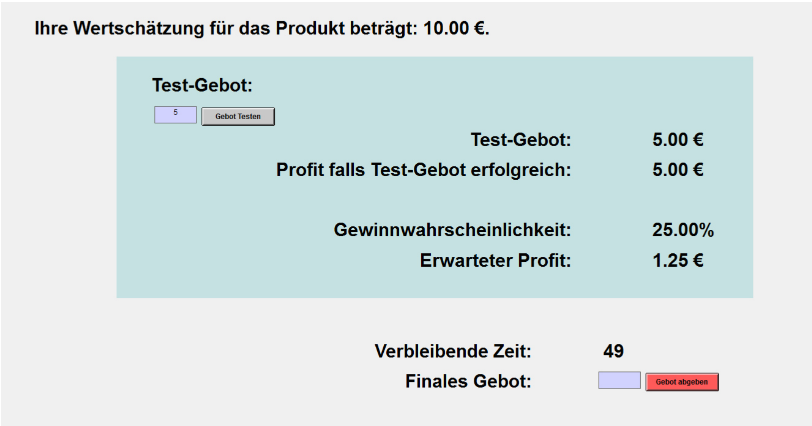
Note

One round always lasts 220 seconds, independently of which price you accept. After you or the other bidder accepted a price, the auction ends but the round will only end after the 220 seconds have elapsed.

Result

After each round, you will see the result of that round. Here you learn the price, whether or not you received the product, and how large your profit is.

4.6.4 SCREENS IN THE LAB EXPERIMENT



Notes: Depicted is the computer interface used in the first-price sealed-bid auction. The individual valuation is depicted at the very top. Participants have a test button *Test-Gebot* (*Test bid*) that allows to enter a bid. Depending on the decision support, the following information is calculated from the test bid: *Profit falls Test-Gebot erfolgreich* (*Profit if bid was successful*) (No, Medium, and Full DSS), *Gewinnwahrscheinlichkeit* (*Winning probability*) (Medium and Full DSS), and *Erwarteter Profit* (*Expected profit*) (Full DSS). A timer displays the remaining time to submit a real bid that can be entered in the text field in the lower right corner and submitted by pressing the button *Gebot abgeben* (*Submit bid*).

Figure 4.3: Computer Interface: FPSBA.

Notes: Depicted is the computer interface used in the Dutch auction. The individual valuation is depicted at the very top. The screen shows the current price, the time until the next price, and the next price. Depending on the decision support, the following information is calculated automatically: *Gewinn bei gegebenem Preis* (*Profit at given price*) (No, Medium, and Full DSS), *Wahrscheinlichkeit, Preis angeboten zu bekommen* (*Probability to be offered the given price*) (Medium and Full DSS), and *Erwarteter Gewinn* (*Expected profit*) (Full DSS). The current price can be accepted by pressing the button *Preis annehmen* (*Accept price*).

Figure 4.4: Computer Interface: DA.

CHAPTER 5

EXPLOITING UNCERTAINTY ABOUT THE NUMBER OF COMPETITORS IN PROCUREMENT AUCTIONS

Abstract

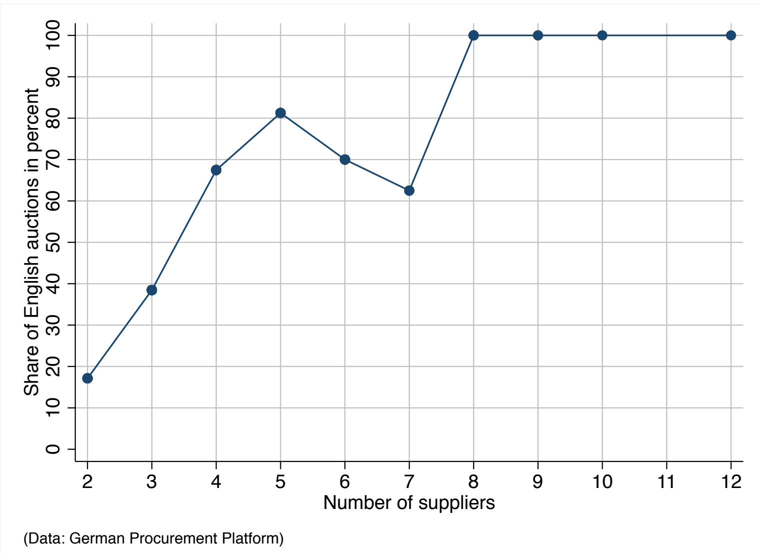
In procurement practice first-price auctions are used if the number of potential suppliers is small and second-price auctions if it is large. This observation cannot easily be explained by standard economic theory as suppliers should anticipate little competition whenever they participate in a first-price auction. We test this setup experimentally and find that buyers employ this strategy. Suppliers *on average* interpret the buyer's selection of a first-price auction as a signal of low competition. However, most suppliers still overestimate the degree of competition in first-price auctions. As a consequence, they bid too aggressive in first-price auctions, which rationalizes buyer's format choice.

5.1 INTRODUCTION

The number of suppliers in procurement seems to have a strong influence on the design of procurement mechanisms. In his book on procurement auctions and negotiations Subramanian (2010, pp. 60–61) recommends: "a sealed-bid auction makes sense when the number of potential bidders is fewer than five or six. The non-transparency of the process invites the possibility that bidders will bid against themselves." And "[...] an open-outcry auction makes sense when you expect several potential bidders to show up." We collected some empirical evidence which hints in the direction that this advice is followed in practice. Our data from an e-auction company, depicted in Figure 5.1, shows that the clients of this company tend to use a Dutch or first-price sealed-bid auction if the number of qualified suppliers is small, whereas an English auction is used if the number is large.

Buyers have information about the number of suppliers, because they make request-for-quotes (RFQ) before they design the auction. Such an RFQ, in which buyers ask potential suppliers to express their interest in the tender, are part of nearly all structured procurement projects and give buyers an overview of qualified suppliers. Motivated by this fact we analyze theoretically and experimentally under which conditions a buyer can exploit her private information about the number of suppliers in a procurement auction.

Figure 5.1: Share of English auctions in the field.



Notes: Displayed is the share of English and second-price auctions on a German procurement platform as compared to first-price formats depending on the number of suppliers.

A naive reasoning behind Subramanian's advice would go as follows: the price in an English procurement auction is a result of the competition between the two strongest suppliers. When the number of suppliers is small, there is a high risk that the second strongest supplier is relatively weak. Then the price in the English procurement auction would be high. The opposite holds true if the number of participants is large. Then the strongest suppliers compete fiercely and drive down the price in the English auction.

In contrast to that, suppliers in a first-price auction are uncertain about the strength of their competitors and cannot react to competitors' behavior. The uncertainty is even more pronounced if they do not observe how many suppliers are participating in the auction. As a consequence, bidding in first-price formats is mainly driven by suppliers' beliefs about competitors and it does not depend on the actual number of competitors. Thus, a first price auction might be optimal if the actual number of bidders is smaller than suppliers expect. However, this line of reasoning does not take into account that suppliers should (in equilibrium) update their beliefs about the actual number of bidders whenever they observe a first-price auction.

Our experimental observations show that using a FPA (SPA) whenever the number of suppliers is small (large) is profitable for buyers in the laboratory. We find that the vast majority of suppliers update their beliefs about the level of competition insufficiently after observing the buyer's format choice. In line with their biased beliefs they bid overly aggressive in FPAs. Hence, buyers can exploit suppliers' uncertainty about the number of competitors.

Theoretical reasoning based on rational behavior cannot easily account for this. Choosing a particular auction format provides information to suppliers, i.e. they should anticipate that the number of competitors is small if they participate in a first-price auction (FPA). As a consequence, the use of a FPA in order to trick suppliers into believing that they have many competitors does not work. We show below that with rational risk-neutral suppliers, there will be complete unraveling in the sense that a FPA will only be used – if at all – for the lowest possible number of competitors and suppliers are aware of this. In all other cases, the buyer will use a second-price auction (SPA).

We identify two possible explanations that rationalize the advice to use FPAs if the number of suppliers is small and SPAs if the number of suppliers is large. The first explanation is based on underbidding in FPAs. Underbidding is a robust finding of the extensive experimental literature on FPAs involving independent private values. It describes the observation that subjects in a FPA bid significantly more aggressive than in the risk-neutral Nash-equilibrium (RNNE). As a consequence, FPAs result in lower prices than SPAs and revenue equivalence between the auction formats no longer holds if the number of suppliers is common knowledge. If the number of competitors is unknown to suppliers, the buyer might in equilibrium use a threshold strategy, such that a FPA is employed whenever the actual number of suppliers is smaller or equal to a certain threshold and a SPA if the actual number is larger. If the actual number of suppliers is equal to the threshold, the buyer faces a trade-off. Choosing a FPA signals a low level of competition which implies that suppliers underestimate the actual number of suppliers and hence place larger bids. However, underbidding makes the FPA attractive and might overcompensate the first effect. Note that in this case suppliers' beliefs are not distorted.

The second explanation is based on cursed equilibrium reasoning (Eyster and Rabin, 2005). The basic assumption is that subjects have correct expectations about their opponents' actions but underestimate the correlation between their opponents' private information and their actions. As a consequence, suppliers have systematically biased beliefs about the number of competitors. In a fully cursed equilibrium subjects completely neglect the correlation between opponents' private information and their actions. In a χ-cursed equilibrium subjects belief that with probability χ there is no correlation between opponents' private information and anticipate the correct correlation with probability $1-\chi$. Applied to our procurement setting a $\chi \in (0,1)$ implies that suppliers do not interpret buyer's format choice correctly. These suppliers expect less than average competition in FPAs, but still overestimate the actual level of competition.

We can use our treatment variation, in that the auction format is randomly determined, rather than making it a choice of the buyer, to test for underbidding separately. We find some support for underbidding in FPAs. However, it cannot explain suppliers' bidding behavior on its own. Thus, cursed equilibrium reasoning is the better explanation for our observations.

5.2 LITERATURE REVIEW

Auction research that considers uncertainty about the number of suppliers concentrates on FPAs and investigates the question whether or not the buyer should reveal information about the number of competitors to suppliers. The literature distinguishes between a setting in which the buyer decides to reveal or conceal information before observing the actual number of suppliers, i.e. unconditionally, and a setting in which she can decide to reveal information after observing the actual number of suppliers, i.e. conditionally on the actual number of suppliers.

In the first setting the buyer is indifferent between revealing and concealing information if suppliers are risk neutral. However, if suppliers are risk or ambiguity averse it is profitable for the buyer to conceal her information. This result is derived theoretically by McAfee and McMillan (1987); Matthews (1987); Harstad et al. (1990); Levin and Ozdenoren (2004). Furthermore, Dyer et al. (1989) provide experimental evidence.

The second setting in which the buyer makes her decision after observing the actual number of competitors to suppliers is analyzed by Bag (2003). He finds that it is profitable for the buyer to fully reveal all the information about the number of suppliers irrespective of their risk attitudes. I contrast to that literature, we concentrate on the choice of auction format rather than the choice of whether to disclose information or not.

Kagel and Levin (1993) experimentally compare FPAs and SPAs and vary the number of suppliers in a setting in which suppliers observe the number of competitors. They find that with a small number of suppliers FPAs generate significantly more revenue than second-price auctions, which is in line with underbidding. However, for a large number of suppliers this difference becomes insignificant. In contrast to this, we analyze the case in which the actual number of bidders is unknown to the suppliers.

5.3 MODEL

We consider a game with $\overline{n}+1$ players, one buyer and $\overline{n} \geq 1$ suppliers. The buyer needs one unit of an indivisible good. The number of qualified suppliers n is known to be randomly drawn from a finite set $N = \{\underline{n}, \cdots, \overline{n}\}$. Let $p_m \in [0,1)$ be the commonly known probability of m qualified suppliers with $\sum_{m=\underline{n}}^{\overline{n}} p_m = 1$. It is common knowledge that suppliers' costs are identically and independently distributed according to a distribution function $F : [\underline{c}, \overline{c}] \rightarrow [0,1]$. The individual cost realizations c_i are suppliers' private information and the actual number of qualified suppliers n is buyer's private information. Being qualified reveals no information about the number of qualified suppliers.

The buyer observes the number of qualified suppliers and then decides whether she wants to procure the good via a first-price (FPA) or second-price auction (SPA). Her strategy is a mapping from the number of suppliers to the auction format, i.e. $\sigma_B : \{\underline{n}, \cdots, \overline{n}\} \rightarrow \{\text{FPA}, \text{SPA}\}$. Suppliers observe their own cost realization and buyer's format choice and then place a bid. Hence a supplier's strategy determines which bid to place depending on cost and the auction format, i.e. $\sigma_S : [\underline{c}, \overline{c}] \times \{\text{FPA}, \text{SPA}\} \rightarrow \mathbb{R}^+$.

Suppliers' ex-ante beliefs μ_m correspond to the commonly known ex-ante probabilities p_m and are updated according to the buyer's strategy using Bayes' rule if possible. Let $\mu_m(FPA)$ and $\mu_m(SPA)$ denote updated beliefs in a FPA and SPA respectively.

5.3.1 ANALYSIS

Suppose that subjects are fully rational and risk neutral. If the buyer can condition her format choice on the number of suppliers, she will never conduct a FPA if the actual number of suppliers is larger than the lowest possible number of suppliers and suppliers anticipate this.

Proposition 9. *In any perfect Bayesian equilibrium the buyer uses a SPA whenever the number of qualified suppliers is larger than* $\underline{n}$*. If the number of qualified suppliers is* $\underline{n}$ *the buyer is indifferent between a FPA and a*

SPA. Suppliers expect to face the minimum number of competitors if they participate in a FPA.

Proof. Suppose that there is a perfect Bayesian equilibrium in which the buyer uses a FPA if the number of qualified suppliers is smaller or equal to some $\hat{n}_{\mathrm{ST}} > \underline{n}$ and a SPA if there are more than $\hat{n}_{\mathrm{ST}}$ suppliers. Given this strategy, suppliers know that they face at most $\hat{n}_{\mathrm{ST}} - 1$ competitors in a FPA.

McAfee and McMillan (1987) show that in this case an equilibrium bidding strategy in the FPA exists and that the expected price for the buyer in the FPA is given by

$$\frac{1}{\sum_{j=\underline{n}}^{\hat{n}_{\mathrm{ST}}} p_j} \cdot \sum_{j=\underline{n}}^{\hat{n}_{\mathrm{ST}}} p_j \cdot E\left[c_2^{(j)}\right]. \tag{5.3.1}$$

Here $c_2^{(j)}$ is the second lowest of j cost realizations and equals $\bar{c}$ if $j = 1$. The expected price in the FPA is equal to the expected price in a SPA with the same stochastic number of bidders.

Now consider the case with exactly $n = \hat{n}_{\mathrm{ST}}$ suppliers. In this case, the expected price in a SPA is given by

$$E\left[c_2^{(\hat{n}_{\mathrm{ST}})}\right], \tag{5.3.2}$$

which is strictly larger than (5.3.1) for $\hat{n}_{\mathrm{ST}} > \underline{n}$ and equal to it if $\hat{n}_{\mathrm{ST}} = \underline{n}$. This implies that the buyer strictly prefers the SPA whenever $n > \underline{n}$ and is indifferent for $n = \underline{n}$ if suppliers expect a threshold strategy. Therefore, any strategy that uses a FPA for some $n > \underline{n}$, is not credible and cannot constitute an equilibrium strategy. The reasoning is similar to the analysis by Bag (2003) who examines the buyer's incentive to reveal the number of suppliers in a FPA.

It remains to be shown that a perfect Bayesian equilibrium exists in which the buyer employs a SPA whenever $n > \underline{n}$ and suppliers are sure to face minimum competition if they participate in a FPA. We have already shown that suppliers cannot expect more than minimum competition in the FPA. Hence, the buyer is indifferent between a FPA and a SPA if $n = \underline{n}$ and strictly prefers the SPA if $n > \underline{n}$. □

Corollary 2. *If the lowest possible number of suppliers $\underline{n}$ is equal to one, it is optimal for suppliers to bid the reserve price in a FPA independent of their costs.*

If the buyer was not informed about the actual number of competitors the revenue equivalence theorem would hold and the buyer would be indifferent between the two auction formats.

Proposition 10. *If the buyer does not know the actual number of suppliers she is indifferent between a FPA and a SPA (McAfee and McMillan, 1987; Matthews, 1987; Harstad et al., 1990).*

Harstad et al. (1990) shows that in this case the optimal bidding strategy β^u of an uncertain supplier in the FPA is given by

$$\beta^u(c) = \sum_{m=\underline{n}}^{\overline{n}} \frac{p_m \cdot G_m(c)}{G(c)} \cdot \beta_m(c). \tag{5.3.3}$$

Here $G_m(c)$ denotes the probability that the supplier's cost c are lower than the costs of the $m-1$ competitors and $G(c)$ the probability that the supplier's cost c are lower than the costs of the competitors not conditioned on their actual number. Furthermore, $\beta_m(c)$ denotes the equilibrium bidding strategy for the case that the actual number of suppliers is known to be m.

Combining Propositions 9 and 10 implies that the buyer cannot exploit her private information about the actual number of suppliers and cannot trick suppliers into overestimating the number of competitors in a FPA. This means the practitioners' advice cannot be explained in our simple procurement setting with independent private cost if subjects are risk neutral and fully rational.

5.4 EXPERIMENTAL DESIGN

We analyze a situation in which one buyer procures one unit of an indivisible good. Her valuation for the good is $v = 130$ ECU. She faces either one or four qualified suppliers. The probability of facing only one supplier is $4/5$ and the probability of facing four suppliers is $1/5$. After observing the number of suppliers, she can decide whether she wants to use a FPA or a SPA to procure the good. The FPA is conducted in form of a first-price sealed-bid auction. The SPA in form of an English-ticker auction. In case of one supplier the SPA immediately stops at the starting price of 100 ECU. For this reason, selecting a SPA if $n = 1$ is a weakly dominated strategy for the buyer.

Suppliers' costs are independently and identically distributed between 0 and 100 ECU, each integer is equally likely. They do not observe the number of competitors but know that the probability of facing competition is one half from suppliers' perspective. After observing the buyer's format choice and before bidding, a supplier is asked to estimate the probability of facing competition in this auction. At the end of each auction participants see the profit they earned in that auction. The buyer's profit is given by the difference between her valuation and the price. The selected supplier earns the difference between the price and his cost. A losing supplier earns zero.

In addition to the just described *buyer's choice* treatment, we also have the *random choice* treatment as a control. The random choice treatment differs from the buyer's choice treatment in two aspects. First, the auction format is randomly determined. Independent of the number of suppliers, both auction formats are conducted with a probability of one half each. Second, suppliers are not asked to estimate the probability of facing competition after observing the auction format.[1]

In the experiments we have a total of 156 participants and use a between-subjects design. We have six independent cohorts for each treatment. Each cohort includes 13 participants, five buyers and eight suppliers. These roles stay fixed during the experiment. In each experimental session two cohorts, one of each treatment, are in the lab at the same time to avoid selection effects.[2] Each subject participates only one time and earning cash is the only incentive offered. All experimental sessions are conducted in the Cologne

[1] Suppliers know that the probability of facing competition is one half independent of the auction format.

[2] Participants are randomly assigned to one of the two treatments. To make this possible we always conduct two treatments at the same time in two neighboring rooms.

Laboratory for Economic Research at the University of Cologne. We recruit participants using the on-line recruitment system ORSEE (Greiner, 2015).

Upon arrival at the laboratory, the participants are seated at computer terminals. We hand out written instructions to them and they read the instructions on their own. When all participants finished reading, they all have to answer control questions at their computer, in order to ensure understanding of the rules of the game. After all subjects have answered all questions correctly, we start the actual game. In each session, each participant takes part in a sequence of 25 procurement interactions. We use random matching and the participants have no possibility to identify each other. At the beginning of each round, the 13 participants in a cohort are divided into five groups. Four of these groups consist of one buyer and one supplier. The fifth group consists of one buyer and four suppliers. Hence, the probability of a buyer to face four suppliers is one fifth and the probability of a supplier to face competition is one half. We program the experimental interface using the zTree system (Fischbacher, 2007a). We compute cash earnings for each participant by multiplying the total earnings from all rounds by a predetermined exchange rate of 75 ECU per Euro and adding it to a show-up fee of 4.00 Euro. Participants are paid their earnings in private and cash at the end of the session. One session lasts about 60 minutes.

5.5 EXPERIMENTAL RESULTS

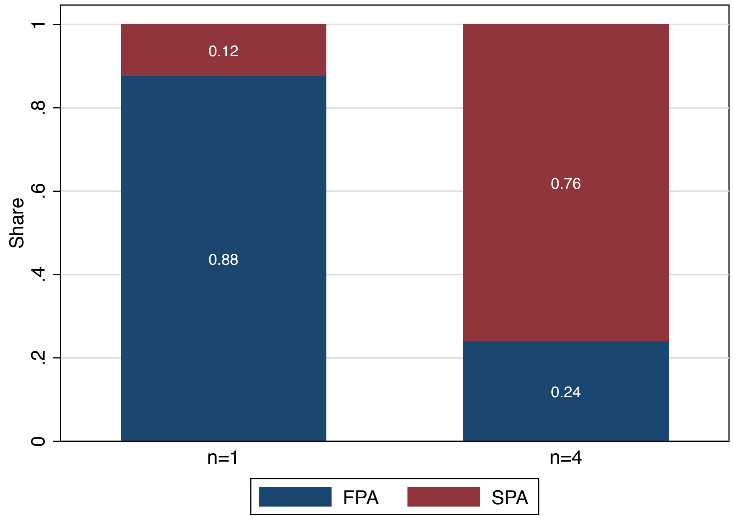
In this section we report our experimental results. We start our analysis by examining buyer's format choice and prices. Then we turn to the supplier side and analyze their beliefs and their bidding behavior. We consider each cohort as one independent observation. We test for differences of distributions with non-parametric Wilcoxon signed-rank (SR) and non-parametric Mann-Whitney-Wilcoxon (MWW) tests. We complement these tests with

Hence, participants are invited for the same session and a random draw upon arrival determines in which treatment a subject takes part.

regressions, because underlying costs and other characteristics are similar but not identical.

5.5.1 FORMAT CHOICE

Figure 5.2: Buyer's format choice.



Notes: Displayed is the format choice in the buyer's choice treatment depending on the number of suppliers. Reported shares correspond to the mean of the average shares of each cohort.

Result 13. *Buyers conduct FPAs more frequently than SPAs if* $n = 1$ *and SPAs more frequently than FPAs if* $n = 4$.

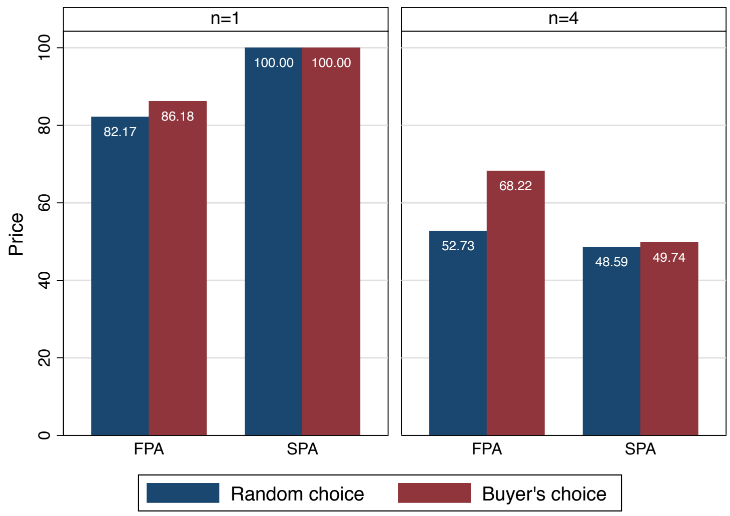
In absence of competition the share of FPAs is 88 percent whereas in presence of competition the share of SPAs is 76 percent as depicted in Figure 5.2. Looking at the session level we find that in each session the FPA is employed more frequently than the SPA if $n = 1$, with frequencies ranging from 71 to 97 percent. For $n = 4$ we observe some variation. In five out of six sessions buyers conduct the SPA more frequently than the SPA, with frequencies ranging from 68 to 96 percent. In one session buyers conduct a

FPA with a probability of 52 percent in case of competition. As a consequence of buyers' format choice suppliers' probability of facing competition in a FPA is on average 20 percent in the buyer's choice treatment. This probability varies between 4 and 41 percent in the different sessions.

Comparing our experimental observations to our field data we observe a similar pattern. If the number of suppliers is small, buyers tend to conduct a FPA and if they face many suppliers they prefer a SPA. This trend is also in line with our theory, which predicts that the buyer should use a SPA if $n = 4$. However, the observed frequency is substantially lower than predicted.

5.5.2 PRICES

Figure 5.3: Prices.



Notes: Displayed are average prices depending on the number of suppliers, the treatment, and the procurement mechanism. Reported prices correspond to the mean of the average prices in each cohort.

Figure 5.3 illustrates prices depending on the number of suppliers, the auction mechanism and the treatment. We first examine the buyer's choice treatment and then turn to the random choice treatment.

Result 14. *The FPA generates prices that are on average 13.8 ECU lower than in the SPA if $n = 1$ in the buyer's choice treatment (SR test: $p = 0.0277$).*

Result 15. *The SPA generates prices that are on average 18.5 ECU lower than in the FPA if $n = 4$ in the buyer's choice treatment (SR test, $p = 0.0464$, Table 5.3: $p = 0.037$).*

In contrast to theory, which predicts that suppliers in the buyer's choice treatment always place the highest possible bid of 100 ECU in a FPA, suppliers in our experiment submit substantially smaller bids. This observation directly implies that suppliers expect, again in contrast to theory, competition in a FPA with strictly positive probability. At this point, however, it is not clear whether suppliers anticipate that buyers do not always conduct SPAs if $n = 4$ and react optimally to this deviation or if suppliers do not consider the correlation between the buyer's private information about the number of suppliers and her format choice.

Result 16. *In the random choice treatment the FPA generates prices that are on average 13.8 ECU lower than in the SPA (SR test: $p = 0.0277$, Table 5.4: $p < 0.001$).*

Result 17. *If $n = 4$ prices in the SPA are on average 4.1 ECU smaller than in the FPA in the random choice treatment. However, the price difference is not significant (SR test: $p = 0.6002$, Table 5.5: $p = 0.413$).*

While the revenue equivalence principle states that in the random choice treatment the average price in a FPA does not differ from the average price in a SPA, our experimental findings show that prices in a FPA are substantially smaller than in a SPA. This observation provides evidence for underbidding. Notably, underbidding is so pronounced that even if $n = 4$ a SPA does not yield prices that are significantly smaller than prices in a

FPA, in which suppliers expect competition only with a probability of one half.

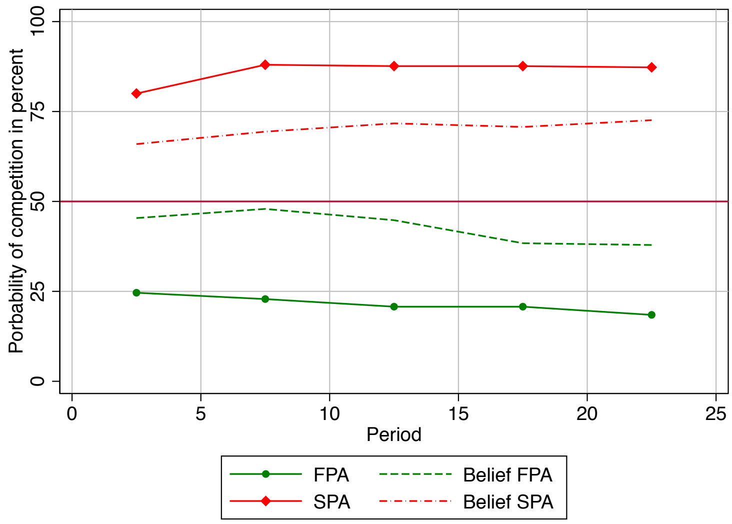
Result 18. *Prices in the buyer's choice treatment are on average 2.5 ECU higher than in the random choice treatment (MWW test: $p = 0.2623$, Table 5.6: $p = 0.006$).*

Result 19. *Prices in FPAs in the random choice treatment are 4.6 ECU lower than the average price in the buyer's choice treatment (MWW test: $p = 0.1093$, Table 5.7: $p = 0.062$).*

If suppliers are fully rational and risk neutral, the expected price in the buyer's choice treatment is the same as in the random choice treatment. In contrast to that we find that prices in the buyer's choice treatment are smaller than in the random choice treatment, which implies that the buyer benefits from her ability to determine the auction format. However, we also observe that a buyer who is uninformed about the actual number of suppliers and always conducts a FPA yields lower prices than buyers in the buyer's choice treatment.

These observations might indicate two things. First, buyers in the buyer's choice treatment can trick suppliers to some extend such that they are overestimating competition in a FPA, which implies that average prices in the buyer's choice treatment are smaller than in the random choice treatment. Second, suppliers are aware that the chance of facing competition in a FPA is substantially higher in the random choice treatment, which in combination with (strong) underbidding makes it attractive for buyers to conduct FPAs unconditional of the number of suppliers. However, a buyer in the buyer's choice treatment cannot do so due to a commitment problem. This would imply that a buyer can trick suppliers but cannot exploit her private information about the number of suppliers in our setting.

Figure 5.4: Suppliers' beliefs.



Notes: Displayed is the probability of facing three competitors depending on the auction format over time and suppliers' belief about facing competition depending on the auction format in the buyer's choice treatment. Reported are average probabilities and beliefs for periods 1 to 5, 6 to 10, 11 to 15, 16 to 20, and 21 to 25.

5.5.3 SUPPLIERS' BELIEFS ABOUT THE NUMBER OF COMPETITORS

We start our analysis of suppliers' behavior by examining their beliefs about the number of competitors after observing the buyer's format choice. Suppliers in our experiment estimate the probability of facing three competitors after observing the buyer's format choice in each period. Eliciting suppliers' beliefs in each period has two consequences. First, we can check for learning. Second, Hoffmann (2015) finds evidence that the elicitation of beliefs makes subjects think (more) carefully about the presented situation, which implies that biased beliefs should be less likely. Furthermore, the fact that choosing a SPA if $n = 1$ is a weakly dominated strategy for buyers should facilitate correct belief updating for suppliers.

Result 20. *On average suppliers interpret the buyer's format choice into the right direction, i.e. they expect less competition in the FPA than in the SPA (SR test, $p = 0.0277$). They overestimate the level of competition in FPAs (SR test, $p = 0.0277$) and underestimate it in SPAs (SR test, $p = 0.0277$).*

Figure 5.4 illustrates suppliers' beliefs about the probability of facing competition and the actual probability of facing competition depending on the auction format over time. Regressions analyzing suppliers' beliefs are presented in Table 5.8. They show that the selection of a SPA lets suppliers anticipate more competition than in a FPA. The differences between the expectations becomes larger over time, which indicates learning. However, even in the last periods there is a substantial difference between the actual level of competition and the anticipated level of competition in both auction formats.

Looking at the individual average beliefs, we find that 46 percent of the suppliers estimate the probability of facing competition in a FPA to be smaller than 50 percent, 29 percent estimate it to be exactly 50 percent, and another 25 percent estimate it to be larger than 50 percent. The average estimate of the probability of facing competition in the FPA is 42.2 percent, whereas the actual probability of facing competition in the FPA in the buyer's choice treatment is only 19.9 percent. This indicates that suppliers on average have biased beliefs.

In order to identify different types of suppliers, we classify suppliers according to their beliefs about facing competition in a FPA. In a first step we perform SR tests to determine if a supplier's individual belief about facing competition in a FPA differs significantly from the ex-ante probability of 50 percent. We say that a supplier expects less than average competition, i.e. updates his beliefs into the right direction, if the SR test results in a z value below -1.645. Those suppliers with a z value above 1.645 are considered to expect more than average competition in the FPA and those with a z value between -1.645 and 1.645 are said to stick to their initial belief about competition.

Result 21. *According to our classification 35 percent of the suppliers expect less than average competition in the FPA, 50 percent do not update their beliefs, and another 15 percent expect more than average competition in the FPA.*

In a second step we determine if their beliefs about facing competition in a FPA differs from the actual level of competition they face in a FPA in their session. We use the same method as before and compare their estimate in a period to the average level of competition in FPAs in their session.

Result 22. *According to our classification 75 percent of the suppliers overestimate the probability of facing competition in a FPA. 23 percent of the suppliers have correct estimates and 2 percent underestimate the probability of facing competition in a FPA.*

This implies that a large fraction of suppliers has difficulties in interpreting the buyer's format choice correctly. Suppliers' beliefs are biased towards the ex-ante probabilities. Hence, buyers can trick suppliers into overestimating the level of competition in FPAs.

5.5.4 BIDDING BEHAVIOR

While a supplier's optimal bidding strategy in a SPA is not affected by his beliefs about the number of competitors, his optimal bidding strategy depends on his beliefs about the number of competitors in a FPA. From (5.3.3) it follows that with fully rational and risk neutral subjects the equilibrium bidding strategy in our experimental setting is given by

$$\beta(c) = \frac{100 \cdot p_1}{p_1 + p_4(1 - c/100)^3} + \frac{[25 + 3c/4] \cdot p_4(1 - c/100)^3}{p_1 + p_4(1 - c/100)^3}. \qquad (5.5.1)$$

The smaller the probability of facing competition in a FPA the higher the optimal bid. This implies that bids in the buyer's choice treatment should be higher than bids in the random choice treatment, because suppliers interpret the buyer's selection of a FPA as a signal of low competition.

Table 5.1: Tobit panel regression of suppliers' bids in FPAs.

	Bid		
	(1)	(2)	(3)
Cost	0.489***	0.490***	0.503***
	(0.0200)	(0.0199)	(0.0192)
Buyer's choice	9.601*	7.871*	8.293*
	(3.929)	(3.714)	(3.764)
Belief		-0.272***	-0.221***
		(0.0489)	(0.0477)
Period			0.649***
			(0.0738)
Constant	61.07***	74.55***	62.98***
	(2.924)	(3.678)	(3.859)
σ_u Constant	18.33***	17.18***	17.50***
	(1.573)	(1.489)	(1.501)
σ_e Constant	17.22***	17.07***	16.33***
	(0.450)	(0.446)	(0.426)
Observations	1253	1253	1253
Censored observations	417	417	417
Suppliers	96	96	96

Standard errors in parentheses

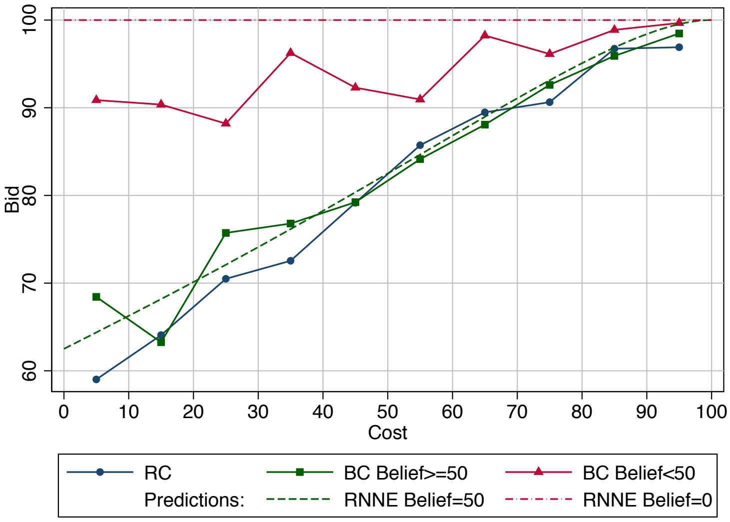
* $p < .05$, ** $p < .01$, *** $p < .001$

Notes: Reported are Tobit panel regression of suppliers' bids in FPAs. Buyer's choice is a dummy variable that is equal to one in the buyer's choice treatment and zero in the random choice treatment. Belief is a variable between 0 and 100 that represents the supplier's estimate about facing competition in the FPA. Since suppliers in the random choice treatment know that the probability of facing competition is 50 percent, the variable Belief is 50 for all suppliers in the random choice treatment. 417 observations equal the highest possible bid of 100.

Result 23. *The average bid in the buyer's choice treatment is 5.8 ECU higher than in the random choice treatment (MWW test: $p = 0.0547$, Table 5.1: $p = 0.015$).*

In both treatments suppliers' bids do not differ significantly from the risk-neutral Nash-equilibrium predictions given their beliefs (SR tests, $p = 0.1159$). However, we find that winning bids in the FPA in the ran-

Figure 5.5: Bidding in FPAs.

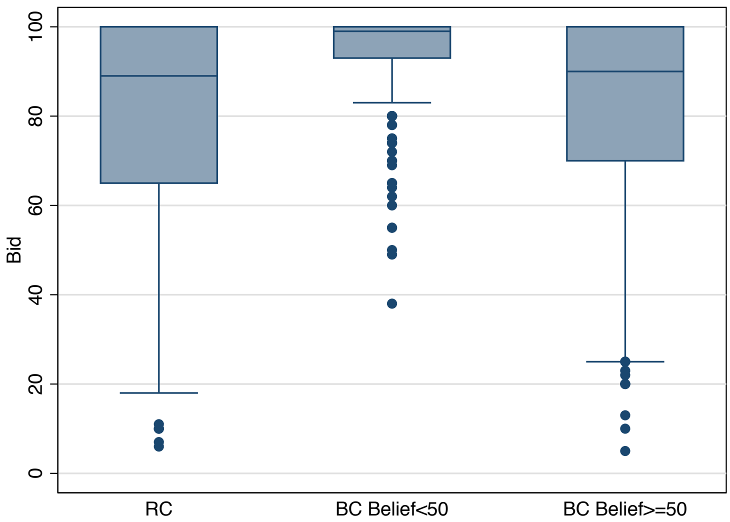


Notes: Displayed is suppliers' bidding behavior in FPAs. We illustrate the equilibrium bidding strategies for the case that the probability of facing three competitors is zero and 50 percent respectively as dashed lines. The blue line represents bidding behavior in the random choice treatment (RC). The green line depicts the bidding behavior of those suppliers in the buyer's choice treatment, who do not update their belief correctly according to our classification (BC Belief>=50). The red line illustrates bidding behavior of those suppliers, who update their belief correctly (BC Belief<50). Markers represent the average bids for costs between 0 and 10, 11 and 20, 21 and 30, etc.

dom choice treatment are significantly smaller than the risk-neutral Nash-equilibrium prediction (SR test, $p = 0.0277$). This shows that also in the random choice treatment, in which suppliers beliefs about competition cannot differ, individual bidding is quite heterogeneous. Furthermore, it indicates that the small price differences between the FPA and the SPA in the random choice treatment with four suppliers must also be due to higher than predicted prices in the SPA.

Table 5.1 presents the result of Tobit panel regressions examining the driving forces behind bidding behavior in FPAs. It shows that suppliers place higher bids in the buyer's choice treatment and increase their bids

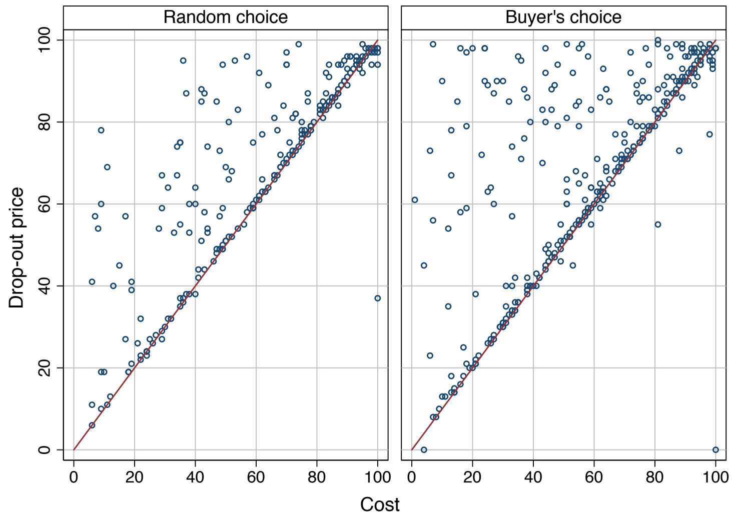
Figure 5.6: Distribution of bids in the FPA.



Notes: Displayed are suppliers bids in the random choice and in the buyer's choice treatment. In both treatments about one third of the bids in the FPA are equal to the maximum bid of 100 ECU. In the random choice treatment the median bid is 89 (average 80.7) ECU. Similarly, those suppliers that do not update their beliefs correctly in the buyer's choice treatment place a median bid of 90 (average 82) ECU. In contrast to that suppliers who update their beliefs correctly in the buyer's choice treatment place median bids of 99 (average 94) ECU.

over time. Looking at suppliers' beliefs about competition, we find that those suppliers who expect more competition place significantly smaller bids in order to increase their winning probability. The strong influence of a supplier's belief on his bidding behavior suggests that those bidders who update their beliefs after observing the buyer's format choice place substantially larger bids than those suppliers that do not update their beliefs, which is depicted in Figure 5.5. As indicated by the regressions we find substantial heterogeneity in bidding behavior that is due to heterogeneity in beliefs.

Figure 5.7: Bidding behavior in the SPA.



Notes: Displayed is suppliers' bidding behavior in the SPA for both treatments. Most of the losers' drop-out prices are close to costs, but many are substantially larger.

Result 24. *Bids of suppliers who do not update their beliefs correctly in the buyer's choice treatment do not differ from the bids of suppliers in the random choice treatment (MWW test:* $p = 0.6310$*, Table 5.9:* $p = 0.639$*).*

Result 25. *Bids of suppliers who update their beliefs correctly and bids of suppliers in the random choice treatment differ significantly (MWW test:* $p = 0.0062$*, Table 5.9:* $p < 0.001$*).*

The same is true for the comparison of bids of suppliers who correctly update their beliefs with bids of suppliers who do not update their beliefs correctly in the buyer's choice treatment (MWW test: $p = 0.0431$, Table 5.9: $p < 0.001$).

The distribution of bids in the FPA is displayed in Figure 5.6. The variance of bids in the FPA has interesting consequences for the optimal bidding behavior. Examining the empirical bid distribution of the random choice treatment reveals that the optimal bid of a supplier with cost of zero

Table 5.2: Random-effects panel regression of bidding behavior in SPAs.

	Drop-out price			
	(1)	(2)	(3)	(4)
Cost	0.690***	0.690***	0.690***	0.690***
	(0.0427)	(0.0421)	(0.0419)	(0.0420)
Period		-0.385***	-0.385***	-0.341**
		(0.0827)	(0.0828)	(0.105)
Buyer's choice			0.0339	1.070
			(1.987)	(3.063)
Buyer's choice×Period				-0.0771
				(0.161)
Constant	26.92***	32.12***	32.10***	31.47***
	(3.407)	(3.671)	(3.447)	(3.718)
Observations	571	571	571	571
Suppliers	96	96	96	96
R^2 (overall)	0.5492	0.5605	0.5605	0.5607

Robust standard errors in parentheses

* $p < .05$, ** $p < .01$, *** $p < .001$

Notes: Displayed are random-effect panel regressions of suppliers' drop-out prices. Buyer's choice is a dummy variable that is equal to one in the buyer's choice treatment and zero in the random choice treatment.

ECU is 98 ECU, which is substantially higher than RNNE prediction of 62.5 ECU. The fact that some suppliers place low bids in the FPA implies that it is profitable for other bidders to concentrate on the case in which there is no competition and place a high bid. Trying to compete is not profitable, because the necessary bids are too low to compensate the higher winning probability. We observe a similar picture in the buyer's choice treatment. However, due to the smaller probability of competition the optimal bids are slightly higher. While smart buyers profit from other buyers that do not select the optimal auction format and thereby distort the signal, smart suppliers suffer from competitors that do not interpret the buyer's format choice correctly if the buyer selects the wrong format.

In the SPA it is optimal to stay in the auction until the displayed price equals cost. We find that in both treatments suppliers drop out early. This makes the SPA less attractive for buyers. In the random choice treatment suppliers leave the auction when the price is 8.3 ECU above their costs (median difference 1 ECU) and suppliers in the buyer's choice treatment on average leave the auction when the displayed price is 10 ECU above their costs (median difference 1 ECU).

Result 26. *In both treatments the bidding behavior differs significantly from the optimal bidding behavior (SR tests, $p = 0.0277$), but in line with theory we find no significant difference between the bidding behavior in the two treatments (MWW test, $p = 0.2971$).*

Applying the same classification method as before, we observe that 52 percent of the suppliers tend to place too high bids, 46 percent bid optimal, and another 2 percent place too small bids. The distribution of types does not differ between treatments (Fisher's exact test, $p = 0.228$) and is not correlated with belief types in the buyer's choice treatment (Fisher's exact test, $p = 0.363$). Bidding behavior in the SPA is depicted in Figure 5.7. The regressions in Table 5.2 show that markups decrease over time, i.e. the difference between observed and optimal bidding behavior becomes smaller over time.

The fact that suppliers often drop out before the price reaches their costs makes SPA less attractive for buyers. This implies that our observation that an uninformed buyer that always conducts a FPA is better of than an informed buyer is only partly driven by suppliers underbidding in FPAs.

5.6 EXPLANATIONS

Looking at our experimental results we find similarities to our field data. Buyers prefer a FPA if the actual number of suppliers is small and a SPA if the actual number is large. We now provide two explanations, underbidding and cursed beliefs, that can rationalize buyers' behavior and test if their predictions for suppliers' behavior are in line with our experimental findings.

5.6.1 UNDERBIDDING

Underbidding relative to the risk-neutral Nash-equilibrium (RNNE) in a reverse FPA is a robust (experimental) finding. It implies that whenever a supplier's bid influences his winning probability, the FPA yields lower expected prices than the SPA. There are several competing explanations for underbidding in reverse auctions in the literature. For example, risk aversion (e.g. Cox et al., 1982b), non-linear probability weighting (e.g. Goeree et al., 2002), and regret (e.g. Engelbrecht-Wiggans and Katok, 2008).

We use risk aversion to model underbidding and focus on the implications of underbidding rather than its reasons. When evaluating his bidding strategy a supplier in a FPA faces a trade-off between increasing his winning probability and decreasing his profit in case of winning by placing a lower bid. In comparison to a risk-neutral supplier a risk-averse supplier puts more weight on the increased winning probability than on the profit in case of winning. This implies that he places lower bids than a risk-neutral supplier if the outcome is risky and is hence underbidding. Risk aversion has no influence on bidding behavior in the SPA. In a SPA it is always optimal to stay in the auction until the price equals cost.

In contrast to the case of risk-neutral suppliers, underbidding can explain the existence of equilibria in which the buyer conducts a FPA even if the actual number of suppliers is larger than the lowest possible number of suppliers. In such an equilibrium the buyer employs a threshold strategy and conducts a FPA if the actual number of suppliers is smaller or equal some $\hat{n}$ and a SPA if it is larger. Suppose the buyer follows such a threshold strategy. If the actual number of suppliers is $\hat{n}$ she faces a trade-off. On the one hand, suppliers will underestimate the number of competitors if she employs the FPA, because they expect at most $\hat{n} - 1$ competitors. This makes the FPA less attractive. On the other hand, sufficient underbidding in the FPA can overcompensate this effect. Note that for a given degree of underbidding there need not exist a unique equilibrium threshold $\hat{n}$.

Applied to our random choice treatment underbidding directly implies that prices in the FPA are smaller than in the SPA. This prediction is in line with our experimental observations.

If suppliers are underbidding two types of equilibria are possible in our buyer's choice treatment. Equilibria of the first type are equivalent to the equilibria in the setting with risk neutral suppliers. These equilibria share the feature that the FPA is at most employed if $n = 1$. As a consequence, suppliers are sure to face no competition in a FPA. Hence, it is optimal for them to place the maximum bid of 100 ECU independent of their risk aversion. The existence of these equilibria does not depend on the extend of suppliers' underbidding and if suppliers' overbidding is at most moderate no other types of equilibria exist. Since we frequently observe prices substantially below 100 ECU in FPAs in our experiment, moderate underbidding cannot explain suppliers' behavior.

Our result that the FPA and the SPA yield similar prices if $n = 4$ in the random choice treatment indicates strong underbidding. In case of strong underbidding a second type of equilibria exists. In such an equilibrium the buyer always employs the FPA independent of the actual number of suppliers. Hence, suppliers in a FPA in the buyer's choice treatment place the same bids as in the random choice treatment. However, in the buyer's choice treatment we find that in case of competition the SPA yields lower prices than the FPA and that buyers frequently conduct SPAs in the buyer's choice treatment. Both observations contradict our equilibrium predictions.

We conclude that underbidding can explain our observations in the random choice treatment but it cannot explain our experimental findings in the buyer's choice treatment on its own.

5.6.2 CURSED EQUILIBRIUM

The former sections have in common that they consider perfectly rational subjects. Now we turn to an explanation based on boundedly rational subjects. In a cursed equilibrium subjects have correct expectations about their opponents' *average* actions but do not fully grasp the correlation between opponents' actions and their private information.

Applying this concept to our experimental setting does not change predictions for our random choice treatment. Cursed beliefs also have no consequences for buyers in our buyer's choice treatment in the sense that they prefer to conduct a FPA if they face one supplier and a SPA if they face four suppliers. However, cursed equilibrium reasoning affects suppliers' beliefs and thereby their bidding behavior in the buyer's choice treatment.

In a fully cursed equilibrium suppliers completely neglect the correlation between the buyer's information about the number of suppliers and her format choice. Hence, such suppliers belief that the probability of facing competition in a FPA is equal to the ex-ante probability of competition of one half. A look at our experimental results reveals that about 50 percent of our suppliers state such beliefs. Theory further predicts that these suppliers employ the same bidding strategy as suppliers in the random choice treatment which is also in line with our observations. This makes it attractive for buyers to conduct a FPA if the number of suppliers is small.

The basic result still holds true if we relax our assumption about the cursedness of suppliers' beliefs. In a χ-cursed equilibrium suppliers assume that with probability χ the buyer's format choice is uncorrelated with her information about the number of suppliers. Hence, suppliers expect competition in a FPA with probability $\chi \cdot 1/2 + (1-\chi) \cdot 0 = \chi/2$ and in a SPA with probability $\chi \cdot 1/2 + (1-\chi) \cdot 1 = 1 - \chi/2$. This means suppliers beliefs are biased towards the ex-ante probabilities, which implies that they overestimate competition in the FPA and underestimate it in the SPA for all $\chi \in (0,1]$. In our experiment we observe that about 75 percent of the suppliers overestimate the level of competition in the FPA. Even a small bias implies that a FPA yields lower prices than a SPA if the number of suppliers is small and can explain our experimental result that bids in the FPA are smaller than 100 ECU.

Summing up, we find that cursed equilibrium reasoning can explain that buyers in the field employ FPAs if the number of suppliers is small and SPAs if it is large. Furthermore, its predictions are in line with suppliers' beliefs and their bidding behavior in our experiment.

5.7 CONCLUSION

Our study is set up to better understand the phenomenon that in procurement practice first-price auctions are used when the number of suppliers is small and second-price auctions if this number is large. An observation that cannot be explained if subjects are rational and risk neutral. We conduct a laboratory experiment and observe that, similar to the field, buyers employ a first-price auction if they face few suppliers and a second-price auction if they face many.

We present two possible explanations (i) underbidding and (ii) cursed equilibrium reasoning that can rationalize buyer's behavior in the field and examine if their predictions are in line with our experimental data. We find strong evidence for cursed beliefs. Cursed beliefs describe that suppliers underestimate the correlation between the buyer's format choice and her information about the number of suppliers. This means suppliers cannot interpret the buyer's format choice correctly, which implies that suppliers' beliefs are biased towards the ex-ante probabilities. We observe that suppliers differ substantially with regard to their ability to interpret buyer's format choice correctly. Our data also provides some support for underbidding. However, underbidding on its own cannot explain our observations.

Observing strong belief distortions is interesting because our experiment is designed to facilitate belief formation. We explicitly ask suppliers for their expectations about the probability of facing competition after observing the buyer's format choice in each period, which should make them think (more) carefully about the informational content of the buyer's format choice. Furthermore, conducting a second-price auction in absence of competition is a weakly dominated strategy for the buyer, which should further facilitate correct belief updating for suppliers. Nonetheless, we observe that most suppliers substantially overestimate the probability of facing competition in first-price auctions and underestimate it in second-price auctions.

Since suppliers' beliefs are biased buyers can exploit their private information about the number of suppliers and benefit from suppliers' uncertainty about the number of competitors. However, we find that a buyer who can commit to conduct a FPA independent of the actual number of suppliers yields even lower prices on average.

5.8 APPENDICES

5.8.1 REGRESSIONS

Table 5.3: Random-effects panel regressions of the influence of the auction format on prices in the buyer's choice treatment in case of competition.

	Price		
	(1)	(2)	(3)
SPA	-16.39**	-13.86**	-11.66*
	(4.994)	(5.054)	(5.581)
Lowest cost		0.680***	0.308**
		(0.106)	(0.0979)
2nd lowest cost			0.470***
			(0.113)
Constant	65.58***	47.88***	35.21***
	(4.582)	(6.731)	(8.136)
Observations	150	150	150
Sessions	6	6	6
R^2	0.0915	0.3648	0.4433

Robust standard errors in parentheses

* $p < .05$, ** $p < .01$, *** $p < .001$

Notes: Reported are random-effects panel regressions clustered on session level. SPA is a dummy variable that is equal to 0 in the FPA and equal to 1 in the SPA.

Table 5.4: Tobit regressions clustered on session level of the influence of the format choice on prices in the random choice treatment.

	Price			
	(1)	(2)	(3)	(4)
SPA	42.66***	40.79***	40.16***	39.50***
	(4.093)	(3.445)	(3.188)	(3.363)
Competition		-64.34***	-51.16***	-57.03***
		(4.649)	(5.033)	(6.395)
Lowest cost			0.416***	0.380***
			(0.0340)	(0.0436)
Competition×Lowest cost				0.256
				(0.137)
Constant	83.69***	94.72***	73.14***	74.72***
	(4.660)	(4.445)	(4.971)	(5.488)
σ Constant	42.11***	27.73***	24.61***	24.36***
	(3.010)	(0.846)	(0.981)	(0.927)
Observations	750	750	750	750
Censored observations	409	409	409	409
Sessions	6	6	6	6

Standard errors in parentheses

* $p < .05$, ** $p < .01$, *** $p < .001$

Notes: Reported are Tobit regressions with an upper limit of 100 clustered on session level. SPA is a dummy variable that is 0 in the FPA and 1 in the SPA. Competition is a dummy variable that is equal to 0 if $n = 1$ and equal to 1 if $n = 4$. Lowest cost corresponds to the costs of the most efficient supplier in the auction.

Table 5.5: OLS regressions clustered on session level of the influence of the format choice on prices in the random choice treatment in case of competition.

	Price		
	(1)	(2)	(3)
SPA	-4.294	-4.718	-4.991
	(5.787)	(5.549)	(5.594)
Lowest cost		0.662***	0.337*
		(0.0376)	(0.0914)
2nd lowest cost			0.405**
			(0.0775)
Constant	53.16***	39.50***	29.85***
	(3.539)	(3.348)	(4.319)
Observations	150	150	150
R^2	0.011	0.316	0.412

Standard errors in parentheses

* $p < .05$, ** $p < .01$, *** $p < .001$

Notes: Reported are Tobit regressions with an upper limit of 100 clustered on session level. SPA is a dummy variable that is 0 in the FPA and 1 in the SPA. Competition is a dummy variable that is equal to 0 if $n = 1$ and equal to 1 if $n = 4$. Lowest cost corresponds to the costs of the most efficient supplier in the auction.

Table 5.6: Tobit regression of the influence of the treatment on prices clustered on session level.

	Price			
	(1)	(2)	(3)	(4)
Buyer's choice	-10.22**	-9.210**	-8.707**	-8.785**
	(3.605)	(3.274)	(3.170)	(3.163)
Lowest cost		0.618***	0.368***	0.326***
		(0.0345)	(0.0393)	(0.0402)
Competition			-40.55***	-49.59***
			(4.415)	(4.532)
Competition×Lowest cost				0.375***
				(0.0586)
Constant	99.63***	71.74***	88.87***	90.59***
	(2.967)	(2.130)	(3.892)	(3.926)
σ Constant	37.60***	31.95***	26.31***	25.93***
	(2.650)	(2.380)	(1.495)	(1.511)
Observations	1500	1500	1500	1500
Censored observations	653	653	653	653
Sessions	12	12	12	12

Standard errors in parentheses

* $p < .05$, ** $p < .01$, *** $p < .001$

Notes: Reported are Tobit regressions with an upper limit of 100 clustered on session level. Buyer's choice is a dummy variable that is equal to 0 in the random choice treatment and equal to 1 in the buyer's choice treatment. Competition is a dummy variable that is equal to 0 if $n = 1$ and equal to 1 if $n = 4$. Lowest cost corresponds to the costs of the most efficient supplier in the auction.

Table 5.7: Tobit panel regressions comparing prices of FPAs in the random choice treatment with prices in the buyer's choice treatment.

	Price			
	(1)	(2)	(3)	(4)
Buyer's choice	6.372	7.535*	6.980	6.772
	(4.295)	(3.677)	(3.609)	(3.629)
Lowest cost		0.598***	0.437***	0.412***
		(0.0380)	(0.0462)	(0.0489)
Competition			-27.94***	-33.67***
			(4.050)	(4.999)
Competition× Lowest cost				0.232**
				(0.0776)
Constant	81.41***	54.14***	66.68***	67.90***
	(3.519)	(3.147)	(4.310)	(4.448)
σ Constant	31.85***	26.01***	23.18***	23.02***
	(1.965)	(1.926)	(1.367)	(1.358)
Observations	1111	1111	1111	1111
Censored observations	340	340	340	340
Sessions	12	12	12	12

Standard errors in parentheses

* $p < .05$, ** $p < .01$, *** $p < .001$

Notes: Reported are random-effects panel regressions clustered on session level. Buyer's choice is a dummy variable that is equal to 0 in the random choice treatment and equal to 1 in the buyer's choice treatment. Competition is a dummy variable that is equal to zero if $n = 1$ and equal to one if $n = 4$. The significance level of the treatment effect in regression (4) corresponds to a p-value of 0.062.

Table 5.8: Fixed-effects panel regression of suppliers' beliefs about the probability of facing competition in the buyer's choice treatment.

	Belief		
	(1)	(2)	(3)
SPA	27.14***	27.17***	17.30**
	(5.501)	(5.489)	(5.034)
Period		-0.163	-0.495**
		(0.0990)	(0.148)
SPA×Period			0.750**
			(0.250)
Constant	42.93***	45.03***	49.34***
	(2.430)	(2.389)	(2.163)
Observations	1200	1200	1200
Suppliers	48	48	48
R^2	0.2175	0.2191	0.2285

Standard errors in parentheses

* $p < .05$, ** $p < .01$, *** $p < .001$

Notes: Reported are fixed-effects panel regressions of suppliers' beliefs about the probability of facing competition. SPA is a dummy variable that is zero if the supplier participates in a FPA and one if he participates in a SPA.

Table 5.9: Tobit panel regression of bidding behavior in FPAs of suppliers in the random choice treatment and those suppliers in the buyer's choice treatment that do not update their beliefs correctly.

	Bid					
	(1)	(2)	(3)	(4)	(5)	(6)
Buyer' choice	1.771	1.932	24.58***	24.55***	-	-
	(4.065)	(4.113)	(5.113)	(5.122)		
Updating supplier	-	-	-	-	22.26***	21.83***
					(5.444)	(5.430)
Cost	0.539***	0.556***	0.482***	0.498***	0.417***	0.418***
	(0.0221)	(0.0214)	(0.0248)	(0.0242)	(0.0271)	(0.0254)
Period		0.675***		0.641***		0.776***
		(0.0812)		(0.0950)		(0.0946)
Constant	58.67***	49.15***	61.37***	52.30***	65.94***	55.95***
	(2.759)	(2.994)	(2.786)	(3.079)	(3.376)	(3.553)
σ_u Constant	16.79***	17.07***	16.60***	16.68***	16.72***	16.76***
	(1.547)	(1.556)	(1.814)	(1.803)	(2.089)	(2.065)
σ_e Constant	17.38***	16.58***	17.33***	16.69***	16.53***	15.42***
	(0.494)	(0.471)	(0.579)	(0.556)	(0.584)	(0.545)
Observations	1020	1020	816	816	670	670
Censored observations	308	308	302	302	224	224
Suppliers	79	79	65	65	48	48

Standard errors in parentheses

* $p < .05$, ** $p < .01$, *** $p < .001$

Notes: Reported are Tobit panel regressions with an upper limit of 100. In regressions (1) and (2) we excluded those suppliers in the buyer's choice treatment that update their beliefs about facing competition in the FPA correctly according to our classification introduced in section 5.5. In regressions (3) and (4) we excluded those suppliers in the buyer's choice treatment that did not update their beliefs about facing competition in the FPA correctly. In regressions (5) and (6) we compare those suppliers in the buyer's choice treatment that update their beliefs to those who do not. Buyer's choice is a dummy variable that is equal to one in the buyer's choice treatment and zero in the random choice treatment. Updating supplier is a dummy variable that is equal to one if the supplier updates his beliefs correctly in the buyer's choice treatment according to our classification and is zero for those suppliers in the buyer's choice treatment, that do not update their beliefs correctly.

5.8.2 INSTRUCTIONS

This section provides the instructions in German (original) and English (translated).

ANLEITUNG ZUM EXPERIMENT

Herzlich willkommen und vielen Dank für Ihre Teilnahme am Experiment. Bitte sprechen Sie ab sofort und bis zum Ende des Experiments nicht mehr mit anderen Teilnehmern. Wir bitten Sie, die Instruktionen sorgfältig zu lesen. Sollten Sie nach dem Lesen Fragen haben, heben Sie bitte Ihre Hand. Einer der Experimentatoren wird dann zu Ihnen kommen und Ihre Frage beantworten.

Dieses Experiment besteht aus 25 Runden, die jeweils die gleiche Abfolge an Entscheidungen haben. Die Abfolge der Entscheidungen wird unten ausführlich erklärt. Es gibt in diesem Experiment zwei Rollen: Käufer und Zulieferer. Zu Beginn des Experiments bekommen Sie eine dieser Rollen zufällig zugelost und behalten diese Rolle für das gesamte Experiment.

Ablauf einer Runde

Zu Beginn jeder Runde werden zufällig neue Gruppen gebildet. In jeder Gruppe befinden sich ein Käufer und entweder ein oder vier Zulieferer. Aus Sicht der Zulieferer sind Gruppen mit einem oder vier Zulieferern gleich wahrscheinlich. Das bedeutet für einen Zulieferer liegt die Wahrscheinlichkeit, keinen bzw. drei Konkurrenten zu haben bei jeweils 50 Prozent.

Der Käufer beobachtet die Anzahl der Zulieferer in seiner Gruppe. [Treatment 1: „Anschließend wählt er das Auktionsformat.“]

[Treatment 2: „Anschließend gibt er an, welches Auktionsformat er wählen würde. Das Auktionsformat wird jedoch zufällig vom Computer bestimmt, beide Formate sind dabei gleich wahrscheinlich.“]

Die beiden möglichen Auktionsformate werden weiter unten ausführlich erklärt.

Nachdem das Auktionsformat bestimmt wurde, beobachten die Zulieferer, an welchem Format sie teilnehmen. Die Zulieferer beobachten die Anzahl der übrigen Zulieferer in ihrer Gruppe nicht.

[Treatment 1: „Bevor die Auktion beginnt, schätzt jeder Zulieferer die Wahrscheinlichkeit ein, in dieser Auktion mit insgesamt drei weiteren Zulieferern zu konkurrieren.“]

Schließlich nehmen die Zulieferer an der ausgewählten Auktion teil. Dabei geben sie Preisangebote ab, zu denen sie bereit sind das Produkt zu verkaufen.

Zulieferer

Die Bereitstellung des Produktes ist für Zulieferer mit Kosten verbunden. Die Kosten, die den Zulieferern entstehen, wenn sie das Produkt verkaufen, werden in jeder Runde zufällig und unabhängig für jeden Zulieferer ermittelt. Alle ganzzahligen Kosten zwischen 0 und 100 ECU sind dabei gleich wahrscheinlich. Der Gewinn des ausgewählten Zulieferers ist

Gewinn = Preis – Kosten.

Nicht ausgewählte Zulieferer machen einen Gewinn von 0 ECU.

Käufer
Die Wertschätzung des Käufers für das Produkt ist 130 ECU. Sein Gewinn ist gegeben als

Gewinn = 130 – Preis.

Ablauf einer Erstpreisauktion
In einer Erstpreisauktion gibt jeder Zulieferer ein verdecktes Gebot ab. Jede ganze Zahl zwischen 0 und 100 ECU kann als Gebot gewählt werden. Der Zulieferer, der das niedrigste Gebot abgibt, gewinnt die Auktion und wird ausgewählt. Sollten mehrere Zulieferer das niedrigste Gebot abgegeben, wird zufällig einer dieser Zulieferer ausgewählt. Der Preis ist gleich dem niedrigsten Gebot. Sollte nur ein Zulieferer an der Erstpreisauktion teilnehmen, gewinnt dieser unabhängig von seinem Gebot und der Preis entspricht diesem Gebot.

Ablauf einer Tickerauktion
In einer Tickerauktion startet die Angebotsanzeige bei 100 ECU. In jeder Sekunde fällt die Anzeige um 1 ECU. Zulieferer können durch klicken die Auktion verlassen. Die Tickerauktion endet, sobald nur noch ein Zulieferer die Auktion nicht verlassen hat. Es gewinnt der Zulieferer, der die Auktion nicht verlassen hat. Der Preis ist gleich dem Wert, den die Angebotsanzeige hatte, als die Auktion endete. Sollte nur ein Zulieferer an der Tickerauktion teilnehmen, endet diese automatisch zu einem Preis von 100 ECU.

Auszahlung
Am Ende des Experiments wird der Computer Ihre Auszahlung angeben und in Euro umrechnen. Dabei entsprechen 75 ECU einem Euro. Zusätzlich erhalten Sie für Ihr Erscheinen 4 Euro. Bitte warten Sie auch nach Ablauf des Experiments ruhig an Ihrem Platz, bis Sie der Experimentator für die Auszahlung aufruft.

Hinweis

Bitte beachten Sie, dass Sie Verluste riskieren, falls Sie sich dazu entscheiden, Gebote unterhalb Ihrer Kosten abzugeben bzw. die Tickerauktion noch nicht verlassen haben, wenn der angezeigte Preis unterhalb Ihrer Kosten liegt.

Instructions

Welcome and thank you for your participation. Please do not talk to other participants during the experiment. Please read the instructions carefully. If you have any question please raise your hand. You of the experimenters will come to you and answer your question.

This experiment consists of 25 rounds. You are in the same situation in each of these rounds. The situation will be explained in detail. There are two roles in this experiment: Buyer and Supplier. At the beginning of the experiment one of these roles is randomly assigned to you and you keep the role during the experiment.

Timing within a round

At the beginning of each round new groups are randomly determined. In each group is one buyer and either one or four suppliers. From a supplier's point of view it is equally likely to be in a group with one or four suppliers. This means for a supplier the chances of meeting no or three competitors are 50%.
The buyer observes the number of suppliers in his group.
[Treatment 1: „Then he determines the auction format."]
[Treatment 2: „The he expresses which auction format he would determine. The auction format is randomly determined by the computer, each format is equally likely. "]
Both auction formats will be explained in detail.

After the auction format is determined, suppliers observe in which auction format they participate. Suppliers do not observe the number of competitors in their group.
[Treatment 1: „Before the auction starts, each supplier estimate the probability of facing three competitors in this auction. "]

Finally, suppliers participate in the auction. They place bids at which they are willing to sell the good.

Suppliers

Providing the good is costly for suppliers. These costs, which only occur if they sell the good are randomly and independently drawn for each supplier in each round. Each integer between 0 and 100 ECU is equally likely. The profit of the selected supplier is given by

Profit= Price – Cost.

Non-selected suppliers make a profit of 0 ECU.

Buyer

The buyer's valuation for the good is 130 ECU. His profit is given by

Profit = 130 – Price.

Timing of a first-price auction
In a first-price auction each supplier places a sealed-bid. Each integer between 0 and 100 ECU can be placed as a bid. The supplier who places the lowest bid wins the auction and is selected. If several suppliers place the same lowest bid, one of them is randomly selected. The price equals the lowest bid. If only one supplier participates in a first-price auction, he wins independent of his bid and the price is equal to his bid.

Timing of a ticker auction
In a ticker auction the price clock starts at 100 ECU. Each second the price is reduced by 1 ECU. Suppliers can click to drop out of the auction. The ticker auction ends as soon as only one supplier has not dropped out. The supplier who did not drop out wins the auction. The price is equal to the price that was displayed when the auction ended. If only one supplier participates in a ticker auction, this auction automatically ends at a price of 100 ECU.

Payment
At the end of the experiment the experiment the computer will display your profit. 75 ECU are equal to 1 Euro. Additionally you receive 4 Euro for your participation. Please wait quietly at your seat until you are called for your payment.

Remark

Please have in mind that you risk losses if you decide to place bids below your costs or stay in the ticker auction when the displayed price is below your costs.

CHAPTER 6

BONUSES AND HANDICAPS IN PROCUREMENT AUCTIONS

Abstract

Quality scores make price offers of different suppliers comparable and play an important role in almost every procurement auction. In this paper, we examine how the framing of these scores as bonuses or handicaps influences suppliers' beliefs about the strength of their competitors and thereby affects their bidding behavior in first-price reverse auctions. Our main finding is that suppliers who receive a bonus (handicap) underestimate (overestimate) the strength of their competitors. As a consequence, procurement auctions with non-price differences framed as handicaps result in lower prices than auctions in which scores are expressed as bonuses.

6.1 INTRODUCTION

In contrast to selling auctions in which revenue maximization is equivalent to maximizing the expected price, the considerations of a buyer in a procurement auction are more complex. Most of the times suppliers do not offer homogeneous goods or services. This implies that a purely price-based auction that does not take into account supplier specific differences yields inefficient outcomes, i.e. a selection purely based on prices may lead to the wrong supplier being selected. Furthermore, purely price-based auctions are suboptimal for the buyer as they do not maximize her expected revenue (e.g. Naegelen, 2002).

Consider, for example, a car manufacturer that needs to procure seats for a new series of models. This manufacturer is not only interested in the price it has to pay per seat but also in non-price attributes. Such attributes can be characteristics of the product like the availability of options like seat heating or the touch and feel of the product but also characteristics of the contract offered like time of delivery, warranty, or the option to adjust the quantity. Obviously, all these attributes can be important for the manufacturer and hence need to be considered when selecting an offer.

One commonly used procurement mechanism that takes into account non-price attributes is a scoring auction. In a scoring auction the buyer[1] determines a scoring rule which assigns monetary values to non-price attributes before the auction starts. This score in combination with a supplier's bid provides a one-dimensional measure the quality-adjusted bid. Thereby, it allows the buyer to set up a binding procurement auction in which suppliers compete on quality-adjusted bids. The bidder who places the lowest quality-adjusted bid wins the auction. One commonly used way to setup a scoring auction is to express a supplier's score as a bonus or as a handicap.

In this paper, we investigate whether it makes a difference if suppliers' quality scores in a first-price procurement auction are framed as bonuses or handicaps. In order to do so we set up an experiment which captures two key aspects of procurement practice. First, the buyer can express her preferences either as bonuses or handicaps. Second, suppliers only learn their own score but not their opponents' scores. Our results show that suppliers place lower bids in case the scores are framed as handicaps compared to the case in which they are framed as bonuses. Furthermore, we find that they overestimate the quality score of their competitors if they receive a handicap and underestimate it if they receive a bonus.

The literature has so far concentrated on the optimal scoring rule, as we discuss below. However, the optimal scoring rule is not uniquely determined – in particular suppliers' scores can be expressed as bonuses or handicaps, or a combination of both. Consider the following example in which a buyer faces two potential suppliers A and B. She wants to buy the good of

[1] In practice, the actual buyer is often only a representative of the procuring company who aggregates the preferences of the company's different departments. Throughout the paper the term buyer's preferences denotes the aggregated preferences of the different departments of the procuring company.

supplier A if this is less than 5.000 Dollar more expensive than the good of supplier B and vice versa the good of supplier B if it is more than 5.000 Dollar cheaper than the good of supplier A. The buyer can express her preferences in many ways. She can assign bonuses to both suppliers, e.g. a bonus of 8.000 Dollar to supplier A and a bonus of 3.000 Dollar to supplier B. She can assign handicaps to both suppliers, e.g. a handicap of 2.000 Dollar to supplier A and a handicap of 7.000 Dollar to supplier B. And she can also assign a bonus to supplier A and a handicap to supplier B, e.g. a bonus of 1.000 Dollar to supplier A and a handicap of 4.000 Dollar to supplier B. All three – and many more – pairs of scores induce the same procurement decision if bids stay unchanged. This implies that only the difference between a supplier's own score and his competitors' scores, i.e. a relative measure, is important but not its absolute value.

Even though it is the relative score which is crucial for a supplier to interpret his own position and to place his bid, suppliers are often only informed about their own score in practice. In this case, the quality-adjustment is still likely to improve allocative efficiency, but it also induces uncertainty about the supplier's own position relative to his competitor. As a consequence, bidding behavior depends crucially on the interpretation of the own quality adjustment or score.

In the next section we review the literature. Section 6.3 presents our experimental design and our hypotheses. In section 6.4 we report our results. Finally, section 6.5 concludes.

6.2 LITERATURE

An optimal scoring auction balances the consideration of price and non-price attributes. On the one hand, non-price attributes have to be considered in order to increase efficiency. On the other hand, the consideration of non-price attributes can induce an asymmetry between suppliers, which reduces price competition, and might therefore have a negative influence on buyer's profit.

Economic literature about scoring auctions distinguishes between situations in which suppliers' non-price attributes are fixed and those in which suppliers can adjust them. Naegelen (2002) analyzes the design of optimal scoring rules in a setting in which suppliers non-price attributes are fixed. She shows that a buyer who can commit herself to a scoring rule before the auction starts maximizes her expected profit by under-rewarding non-price attributes in her scoring rule. This way she reduces the asymmetry between suppliers and thereby intensifies price-competition. One drawback is that such a scoring auction is not efficient. Furthermore, the buyer might be forced to select an offer that is not ex-post optimal for her, which is why she needs commitment power when designing the auction.

Che (1993) shows that a scoring auction which under-rewards non-price attributes is also optimal in a setting in which suppliers can adjust their non-price attributes prior to the auction. Putting less weight on non-price attributes reduces suppliers' incentives to provide high quality. Consequently, it decreases the information rent the buyer has to pay suppliers due to their private information about their quality improvement costs, but also leads to inefficiently low quality provision. Asker and Cantillon (2008) analyze a procurement situation with multiple non-price attributes. They first prove that these attributes can be represented by a single score and then they show that scoring auctions dominate alternatives like buyer-determined auctions and menu auctions, in which suppliers place various offers. Branco (1997) generalizes the model of Che (1993) by allowing for correlated costs. He shows that in this case the optimal procurement mechanism can be implemented as a two-stage mechanism in which suppliers first take part in a scoring auction and the winner then negotiates with the buyer about the adjustment of non-price attributes based on all the bids, i.e. the information elicited in the scoring auction.

In practice buyer's exact preferences are (ex-ante) not public information and suppliers are often able to adjust the characteristics of the good to be provided. This is taken up by Dini et al. (2006) who provide an overview of important aspects of scoring rules from a practitioner's perspective. They focus on situations in which suppliers can adjust their non-price attributes to the scoring rule and recommend simple and predictable scoring rules, which set the right incentives for suppliers to make efficient offers. Here efficiency means that suppliers invest in non-price attributes as long as the marginal costs are smaller than buyer's marginal valuation for the quality improvement. In this context Strecker (2010) argues that the buyer faces a trade-off with regard to the revelation of her preferences towards suppliers. On the one hand suppliers need information about buyer's preferences to make efficient offers, but on the other hand they might exploit this additional information later on. In contrast to that, we focus on a procurement situation in which suppliers' qualities are already determined and the scores can only affect suppliers' bidding behavior but not their quality choice.

Another way to take non-price attributes into account is to conduct a buyer-determined procurement auction in which the buyer assesses the different attributes after suppliers made their offers. In buyer-determined procurement auctions, which are also known as beauty contests, suppliers make offers specifying price and non-price attributes. When all offers are placed the buyer selects the offer that maximizes her utility, which need not be the lowest bid. This way she has the last say in a buyer-determined procurement auction. One advantage of a buyer-determined auction is that it is easy to conduct. The buyer needs not screen all suppliers and does not have to specify her exact preferences beforehand, which might be very complex. However, Fugger et al. (2016) show that buyer-determined procurement auctions are prone to collusion, i.e. are likely to result in high prices. The reasoning is as follows: If suppliers are not aware of the buyer's exact preferences, i.e. her decision rule, they all face a positive winning probability if their bids are similar. As a consequence, they can share profits in expectation and might have no incentive to compete. Engelbrecht-Wiggans et al. (2007) compare BDRAs with price-based reverse auctions and purely price-based mechanisms and find that BDRAs are more profitable for the buyer only if the number of suppliers is large. Similar to Fugger et al. (2016) they observe that price competition is less pronounced in BDRAS. These results suggest that scoring auctions outperform BDRAs if non-price attributes can easily be evaluated before the procurement starts.

6.3 EXPERIMENTAL DESIGN AND HYPOTHESES

We analyze a procurement setting in which one buyer faces two potential suppliers that compete in a first-price sealed-bid scoring auction. One of the two suppliers provides better quality. In the following we denote the preferred supplier as supplier A and the other supplier as supplier B. However, a supplier does neither know if he is the preferred supplier nor the quality difference. In our experiment the buyer's valuation for the good provided by B is $v_B = 100$, whereas she assigns a value of $v_A = 104$ to the good provided by A. In order to take this into account the buyer employs a naive scoring rule that reflects her preferences. She assigns scores $(s_A, s_B) = (s + 4, s)$ which can either be framed as bonuses or handicaps. Scores are called bonuses if $s > 0$ and handicaps if $s < -4$.

In each auction the buyer can choose between two pairs of scores that express her preferences. One of the pairs consists of positive scores (bonuses) and the other pair consists of negative scores (handicaps). Bonuses are integers between 2 and 16 and handicaps integers between -2 and -16. There is a total of 12 bonus and handicap pairs that are all equally likely to be presented to the buyer. The two pairs of scores that the buyer can choose from before the auction starts are symmetric in the sense that if the buyer can assign the k-th highest bonus she can also choose to assign the k-th highest handicap. For example, the buyer might choose between the bonus pair $(2, 6)$ and the handicap pair $(-16, -12)$. Here 2 is the smallest possible bonus and -16 the smallest possible handicap.

Suppliers know that their ex-ante probability of being the preferred supplier is one half. After the buyer decided whether she wants to use bonuses or handicaps, suppliers observe their own costs and their own score. Suppliers' costs are independently and identically distributed between 0 and 100 and each integer is equally likely. They know that their competitor also received a bonus (handicap) in case they received a bonus (handicap). After both suppliers placed their bids the supplier who offered the lower score-adjusted bid wins the auction and earns the difference between his bid and his costs. In case of a tie the supplier with the higher quality is selected. This means for a given bid the own score affects the winning probability but not the profit in case of winning. Suppliers only observe whether they won the auction or not but receive no further information about their competitor's bid or score.

As it is common in procurement practice suppliers have limited information about their competitor's score in our experiment. They only know that their competitor also receives a bonus (handicap) if they receive a bonus (handicap). Consequently, the framing of the score is only slightly informative and should hence not affect bidding behavior.[2] However, for a supplier a focal anchoring point for estimating his competitor's score might be a score of zero. If the estimate of the competitor's score is biased towards this anchoring point, suppliers will on the one hand interpret a positive score, i.e. a bonus, as good news and will on the other hand perceive a negative score, i.e. a handicap, as bad news.

Hypothesis 4. *[Perception bias]*
Suppliers expect to be preferred if they receive a positive score (bonus) and to have a disadvantage if they receive a negative score (handicap).

Based on the assumption that estimates of the competitors' scores are biased towards zero, suppliers who receive a bonus (handicap) believe to be in a stronger (weaker) position than their competitor. We denote a supplier as stronger (weaker) if his score-adjusted costs are drawn from a more (less) favorable distribution than his competitor's score-adjusted costs. A well known result in auction theory is that such weakness (strength) leads to more (less) aggressive bidding behavior, i.e. a bidder that is weaker (stronger) than his competitor places a lower (higher) bid given the same cost realization (Krishna, 2010). Given that Hypothesis 4 holds it follows that suppliers bid more aggressive if they receive a handicap than when they receive a bonus.

[2]Since bonuses (handicaps) are always positive (negative) a bonus (handicap) close to zero implies that it is likely to be in the weaker (stronger) position compared to the competitor. This suggests that bonus bids should be higher than handicap bids. However, we observe that suppliers with lower scores place lower bids as depicted in Figure 6.4.

Hypothesis 5. *[Asymmetry effect]*
Suppliers who receive a bonus bid less aggressive, i.e. place higher bids, than suppliers who receive a handicap.

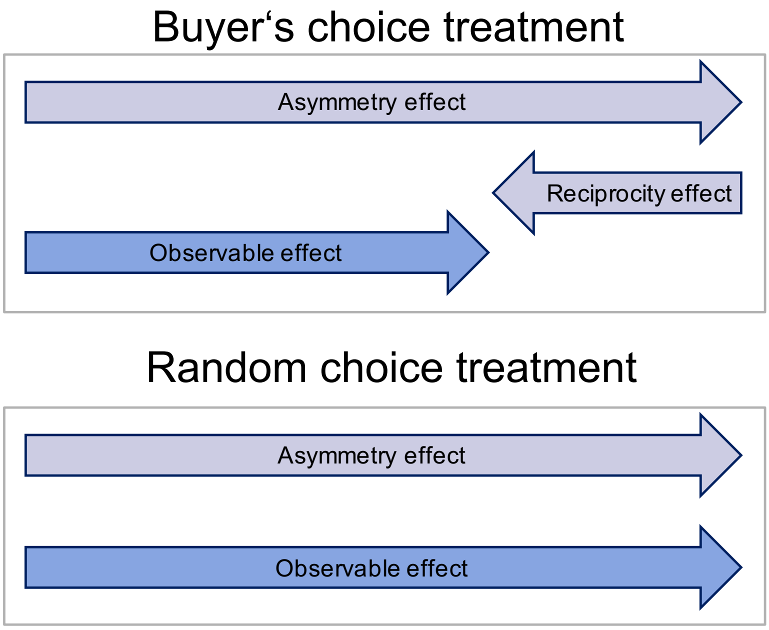
6.3.1 ORGANIZATION

We conducted the experiment in the Cologne Laboratory for Economic Research (CLER). We invited a random sample of the CLER subject pool using the recruitment software ORSEE (Greiner, 2015). Each subject participated only one time and earning cash was the only incentive offered. We programmed the experimental interface using zTree (Fischbacher, 2007a). In the experiment we had 120 subjects divided into four cohorts of 30 subjects. In each cohort 10 subjects were in the role of buyers and 20 in the role of suppliers. Roles were fixed during the experiment. Each subject participated in a total of 50 reverse auctions. Ten standard reverse auctions and 40 scoring auctions. In each auction one buyer faced two suppliers.

To make sure that participants fully understood the instructions they had to answer control questions privately on their computers. The experiment only proceeded when all subjects answered all questions correctly. Before the main part of the experiment started subjects participated in a sequence of ten reverse auctions without a scoring rule. This way suppliers got used to the auction environment. In the main part of the experiment participant first took part in a sequence of 20 scoring auctions in which the buyer chose between bonuses and handicaps followed by a sequence of 20 scoring auctions in which the buyer was passive and the framing of the scores was randomly determined by the computer. To control for order effects we employed a counter balanced design and the order was reversed in half of our sessions. Our control treatment in which the framing is randomly determined allows us to examine if suppliers try to reciprocate the buyer's framing decision as depicted in Figure 6.1.

At the end of the experiment all suppliers estimate their opponent's expected score for the case that the own bonus is 9 ECU and for the case that the own handicap is -9 ECU. Both estimates were incentivized and half of the suppliers were asked in reverse order to control for order effects. A participant who correctly estimated the competitor's expected score earned 4 EUR and for each integer the estimate differed from the correct value 30 Cent were deducted. We argue that this incentivized belief elicitation at the very end of the experiment provides a conservative estimate of suppliers' perception bias, because suppliers had the opportunity to learn during the experiment.

Figure 6.1: Observability of the asymmetry and the reciprocity effect in our treatments.



Notes: Displayed is the observability of the asymmetry and a reciprocity effect. In the random choice treatment we rule out a reciprocity effect by randomizing the framing. Hence, we can directly measure the asymmetry effect. In the buyer's choice treatment the observed effect is an aggregate of the asymmetry and a reciprocity effect.

6.4 EXPERIMENTAL RESULTS

6.4.1 BELIEFS

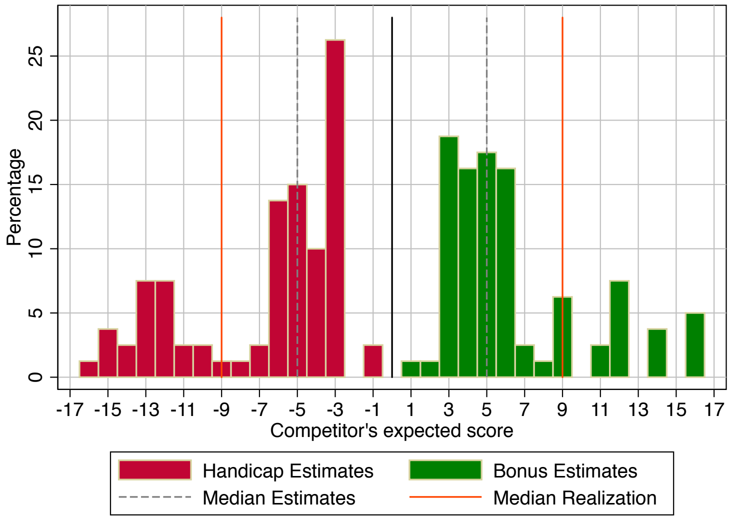
The interpretation of a bonus as an advantage and of a handicap as a disadvantage relies strongly on the beliefs about the competitor's score. For that reason we will first analyze if the experimental findings support Hypothesis 4, which states that beliefs are biased towards zero. In order to examine if a supplier has biased beliefs we compare each supplier's estimate of his competitor's score to his own median score during the experiment. We do this separately for bonuses and handicaps.

Our results show systematic differences between beliefs about the competitor's bonus score and the own median bonus score, as well as between between beliefs about the competitor's handicap score and the own median handicap score. On the one hand, 76 percent of the suppliers underestimate their competitor's expected bonus, i.e. believe that they have an advantage when they receive a bonus. On the other hand, 70 percent overestimate their competitor's expected handicap, i.e. believe that they are disadvantaged when they receive a handicap. This indicates that most suppliers interpret the assignment of a bonus as good news and vice versa the assignment of a handicap as bad news. Furthermore, we find that for most subjects the perception bias is symmetric in the sense that the sum of the individual bonus and the individual handicap estimates is zero. This is illustrated in Figure 6.5.

Figure 6.2 illustrates suppliers' beliefs about their competitors' score and the median of the actual scores. The red bars on the left represent a supplier's belief about the competitor's score given that he himself received a handicap of -9 ECU and the green bars for the case that the own bonus was 9 ECU. The median of actual bonuses is 9 (average 8.6) ECU and the median of the actual handicaps is -9 ECU (average 9.5 ECU). In contrast to that the median estimate of the competitor's score in case of a bonus is 5 (average 6.4) ECU and -5 (average -6.9) ECU in case of a handicap.

Result 27. *Suppliers underestimate their competitors' bonuses (Wilcoxon signed rank test and* t*-test,* $p < 0.001$*) and overestimate their competitors' handicaps (Wilcoxon signed rank test and* t*-test,* $p < 0.001$*).*

Figure 6.2: Distribution of suppliers' estimates about competitors' quality scores.

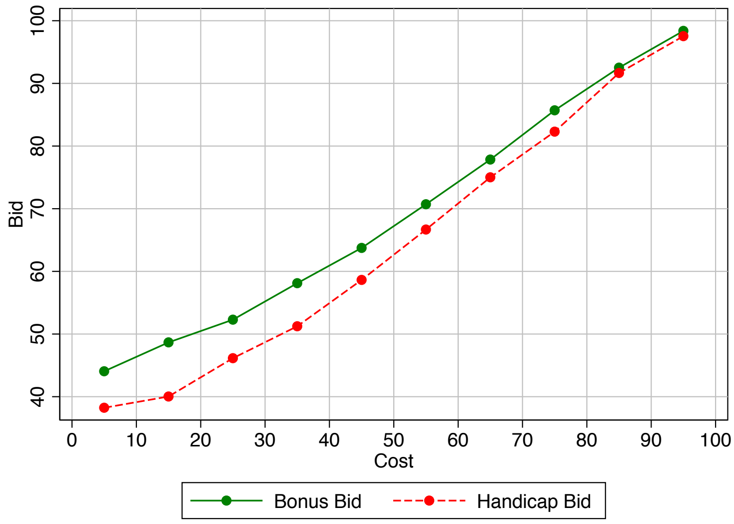


Notes: Displayed are the distributions of suppliers' estimates about their competitors' (expected) scores in case that the own bonus is 9 ECU (green bars) and in case that the own handicap is -9 ECU (red bars). The orange lines illustrate that the median actual scores of competitors' are -9 ECU in case of a handicap and 9 ECU in case of a bonus.

6.4.2 BIDDING

In this section we analyze suppliers' bidding behavior. In particular, we investigate if the framing of the score as a bonus or handicap influences bidding. We find that suppliers place substantially lower bids when they receive a handicap compared to the case in which they receive a bonus. Controlling for suppliers' costs the average bid in case of a handicap is 4.5 ECU smaller than the average bid in case of a bonus. Taking into account that the average bid is 67.7 ECU the influence of the framing is substantial. Figure 6.3 illustrates the bidding behavior.

Figure 6.3: Bonus and handicap bidding.



Notes: Displayed are bonus and handicap bidding functions. Markers illustrate the average bonus and handicap bids given that the costs are between 0 and 10, 11 and 20, 21 and 30, etc.

Running individual regressions for each supplier we find that 90 percent of the suppliers place lower bids when they are assigned a handicap compared to the case in which they are assigned a bonus. For 75 percent of the suppliers this difference is significant on a ten percent level. For the majority of suppliers average bonus bids are between 3.4 and 7.3 ECU higher than handicap bids. The distribution of individual bid difference is depicted in Figure 6.6.

Table 6.1 presents a random-effects panel regression of suppliers' bidding behavior.[3] Here Handicap represents a dummy variable that is one if the score is framed as a handicap and zero in case of a bonus.[4] The variable Buyer is a treatment dummy that is one if the buyer chooses between

[3]Running fixed-effects regressions leads to the same results as shown in Table 6.3.

[4]Regressions with the score as explaining variable are reported in Table 6.4.

bonuses and handicaps and is zero if the score is randomly assigned by the computer. One feature of our within-subject design is that it inherently provides a between-subject design which we use to check for consistency. The results of the between-subjects analysis, which only considers bids in the first sequence of scoring auctions, are presented in the first two columns and those of the within-subjects analysis, which takes into account all bids placed in stage two and three, in the last two columns.

The regressions reported in Table 6.1 confirm the substantial influence of the framing decision. We further observe that bids become more aggressive over time and find no indication for a reciprocity effect. Even though the assignment of handicaps is more profitable for the buyers than the assignment of bonuses they use bonuses roughly as often as handicaps (48.6% vs. 51.4%) and do not change their behavior over time. For an illustration see Figure 6.7.

Result 28. *Suppliers bid more aggressive when they have a handicap than when they have a bonus (Table 6.1, $p < 0.001$).*

An important question especially for practitioners is whether the effect that handicaps make suppliers bid more aggressive wears off over time. While Table 6.1 shows that bidding becomes more aggressive over time, we analyze if the time trend is different for bonuses and handicaps in Table 6.2. When taking into account all 80 rounds of scoring auctions we find a weakly significant time trend towards lower bids when scores are framed as bonuses ($p = 0.0954$) and a highly significant time trend towards lower bids when scores are framed as handicaps ($p = 0.002$). However, we find no indication that the time trends differ. This implies that the effect of the framing is stable over time.

Table 6.1: Random-effects panel regressions of bidding behavior.

	Bid			
	Between-subjects design (Stage 2)		Within-subjects design (Stage 2+3)	
	(1)	(2)	(3)	(4)
Costs	0.653***	0.653***	0.662***	0.662***
	(0.0176)	(0.0177)	(0.0172)	(0.0172)
Handicap	-4.543***	-4.192***	-4.767***	-4.516***
	(0.450)	(0.654)	(0.392)	(0.496)
Period	-0.119*	-0.119**	-0.0498**	-0.0501**
	(0.0463)	(0.0463)	(0.0163)	(0.0162)
Buyer		0.0462		-0.242
		(1.133)		(0.396)
Buyer × Handicap		-0.706		-0.509
		(0.920)		(0.572)
Constant	39.25***	39.26***	37.50***	37.63***
	(1.845)	(2.009)	(1.448)	(1.448)
Observations	1600	1600	3200	3200
Participants	80	80	80	80
R^2	0.7995	0.7996	0.8075	0.8076

Robust standard errors in parentheses

* $p < .05$, ** $p < .01$, *** $p < .001$

Notes: Reported are random-effects panel regressions. Handicap is a dummy variable that is equal to zero in case of a positive score and equal to one in case of a negative score. Buyer is a dummy variable that is equal to one if the buyer determines the framing of the scores and equal to zero if it is randomly determined.

Table 6.2: Random-effects panel regressions of bidding behavior over time.

	Bid	
	Between-subjects design (Stage 2) (1)	Within-subjects design (Stage 2+3) (2)
Costs	0.653***	0.662***
	(0.0176)	(0.0172)
Handicap	-3.403***	-4.151***
	(0.941)	(0.635)
Period	-0.0658	-0.0348
	(0.0600)	(0.0209)
Handicap × Period	-0.109	-0.0300
	(0.0797)	(0.0262)
Constant	37.50***	36.69***
	(1.620)	(1.393)
Observations	1600	3200
Participants	80	80
R^2	0.7999	0.8075

Robust standard errors in parentheses

*** $p < 0.001$

Notes: Reported are random-effects panel regressions. Handicap is a dummy variable that is equal to zero in case of a positive score and equal to one in case of a negative score.

6.5 CONCLUSION

Quality scores are an essential part of most procurement auctions. These quality scores, which assign monetary values to non-price attributes, are necessary to set up binding procurement auctions and influence suppliers' bids. Even though suppliers' bidding behavior should only depend on the relation between the own score and the competitor's score, suppliers typically only learn their own score, i.e. their own bonus or handicap, in practice.

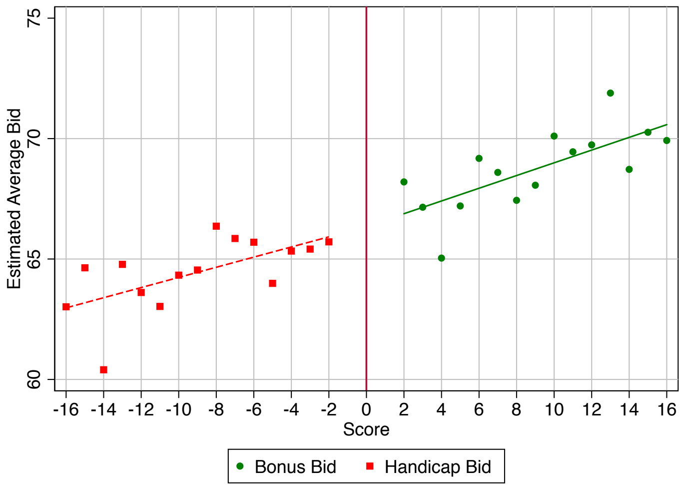
Since procurement managers every day face the question whether they should frame their quality scores as bonuses or handicaps when communicating them to suppliers, we analyze this question experimentally. We find that the framing of the scores influences suppliers' beliefs about their relative position. A supplier who receives a handicap (bonus) expects to be in a weaker (stronger) position than his competitor, i.e. he believes that his competitor has a score closer to zero. As a consequence, suppliers who receive a handicap bid more aggressive than suppliers who receive a bonus in order to compensate their disadvantage. We find strong support that framing the quality score as a handicap increases the profits of the firm buying the tendered good.

We find no evidence that the profitability of handicaps wears off over time nor that suppliers receiving a handicap feel treated unfairly and hence increase their bids. However, one has to take into account that in our setting participation in the auction is costless for suppliers. Supplier who receive a handicap expect lower profit from the participation in the auction, because they expect to be in a weak position and bid more aggressive. This implies that for a supplier it is less likely to participate in the auction if he receives a handicap and the participation is costly. Hence, there might be a trade-off between attracting more bidders and making them bid more aggressive in some situations.

6.6 APPENDICES

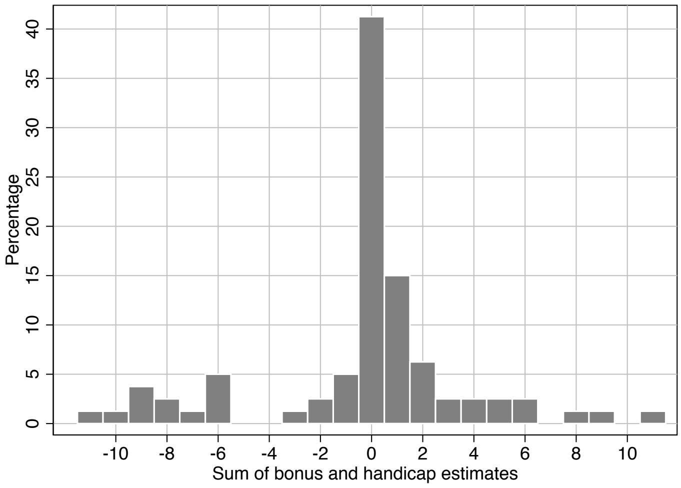
6.6.1 GRAPHS

Figure 6.4: The influence of quality scores on bids.



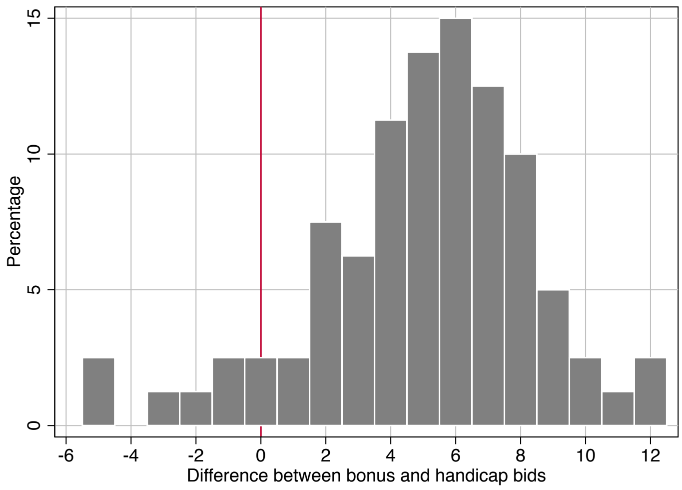
Notes: Displayed are estimates of the average bids given a quality score. Scores smaller zero are called bonuses and scores larger zero are called handicaps. The lines represent a linear fits of the influence of the quality scores on bidding in case of bonuses and in case of handicaps. Estimates for the average bid given a certain quality score are obtained by running separate regressions for each score assuming that a supplier with costs of 100 ECU offers a price of 100 ECU.

Figure 6.5: Distribution of the sum of individual bonus and handicap estimates.



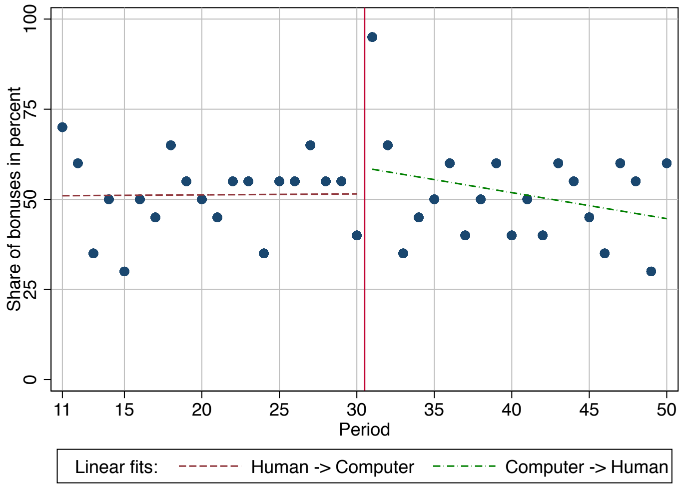
Notes: Displayed is the distribution of the sum of suppliers' individual beliefs about their competitor's score for the case in which the own bonus is 9 ECU and for the case in which the own handicap is -9 ECU.

Figure 6.6: Distribution of individual differences between bonus and handicap bids.



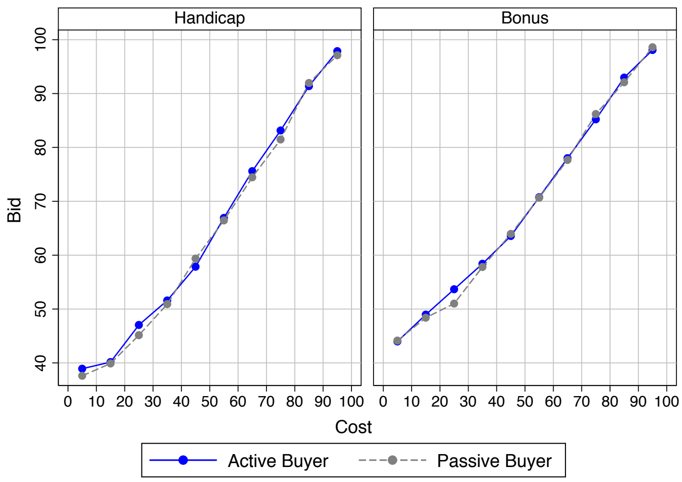
Notes: Displayed is the distribution of the difference between individual bonus and handicap bids. We obtain these differences by running individual regressions for each supplier. In these regressions the observed bid is explained by the supplier's cost and a dummy variable that is one in case of a bonus and zero in case of a handicap. The coefficient of this dummy variable is an estimate for the difference between bonus and handicap bids which takes into account that underlying costs may differ. The distribution of these coefficients is displayed, the bin size is one.

Figure 6.7: Buyers' framing decisions over time.



Notes: Displayed are buyers' decisions about using bonuses or handicaps over time. In the left half of the graph we see the behavior of those buyers who started in the active position. In the right half of the graph we observe the behavior of those buyers who started in the passive role and could only determine the framing in period 31 to 50. In both treatments the average share of bonuses is close to 51 percent.

Figure 6.8: The influence of the role of the buyer on bonus and handicap bidding.



Notes: The left graph illustrates suppliers' bidding behavior in case of a handicap and the right graoh their bidding behavior in case of a bonus. The solid blue lines show suppliers' bidding behavior for the case that the buyer determined the framing of the scores and the dashed gray lines represent the case in which the framing was randomly assigned. Dots illustrate the average bids given that the costs are between 0 and 10, 10 and 20, and so on.

6.6.2 TABLES

Table 6.3: Fixed-effects panel-regression of bidding.

	Bid			
	Between-subjects design (Stage 2)		Within-subjects design (Stage 2+3)	
	(1)	(2)	(3)	(4)
Costs	0.653***	0.653***	0.662***	0.662***
	(0.0176)	(0.0177)	(0.0172)	(0.0172)
Handicap	-4.552***	-4.181***	-4.791***	-4.536***
	(0.457)	(0.656)	(0.393)	(0.495)
Period	-0.119*	-0.120*	-0.0497**	-0.0501**
	(0.0463)	(0.0463)	(0.0163)	(0.0162)
Buyer × Handicap		-0.751		-0.516
		(0.930)		(0.570)
Constant	39.26***	39.29***	37.51***	37.64***
	(1.505)	(1.509)	(1.024)	(1.021)
Observations	1600	1600	3200	3200
Participants	80	80	80	80
R^2	0.847	0.847	0.858	0.858

Robust standard errors in parentheses

* $p < .05$, ** $p < .01$, *** $p < .001$

Table 6.4: Random-effects panel-regression of bidding.

	Between-subjects design (Stage 2)		Within-subjects design (Stage 2+3)	
	Bid	Bid	Bid	Bid
Costs	0.652***	0.652***	0.662***	0.661***
	(0.0176)	(0.0177)	(0.0173)	(0.0173)
Score	0.257***	0.237***	0.257***	0.242***
	(0.0247)	(0.0341)	(0.0220)	(0.0279)
Period	-0.0934*	-0.0940*	-0.0450**	-0.0453**
	(0.0458)	(0.0459)	(0.0162)	(0.0162)
Buyer		-0.374		-0.538
		(1.137)		(0.285)
Buyer × Score		0.0381		0.0305
		(0.0509)		(0.0318)
Constant	36.43***	36.64***	34.94***	35.22***
	(1.813)	(2.030)	(1.423)	(1.436)
Observations	1600	1600	3200	3200
Participants	80	80	80	80
R^2	0.8024	0.8025	0.8096	0.8098

Robust standard errors in parentheses

* $p < .05$, ** $p < .01$, *** $p < .001$

6.6.3 INSTRUCTIONS

ANLEITUNG ZUM 1. TEIL

Herzlichen Dank für Ihre Teilnahme am Experiment. Bitte sprechen Sie bis zum Ende des Experiments nicht mehr mit anderen Teilnehmern. Dieses Experiment besteht aus mehreren Teilen, wobei Ihre Entscheidungen in den einzelnen Teilen **keinen** Einfluss auf die anderen Teile haben.

Dieser Teil des Experiments besteht aus **10 Runden,** die jeweils die gleiche Abfolge an Entscheidungen haben. Die Abfolge der Entscheidungen wird unten ausführlich erklärt. Es gibt in diesem Experiment 2 Rollen: **Käufer** und **Zulieferer**. Zu Beginn des Experiments bekommen Sie eine dieser Rollen zufällig zugelost und behalten diese Rolle für das gesamte Experiment. Auf dem ersten Bildschirm sehen Sie, welche Rolle Sie haben.

Überblick über die Entscheidungen in einer Runde

Zu Beginn jeder Runde werden **zufällig neue** Gruppen bestehend aus einem Käufer und zwei Zulieferern gebildet. Im Folgenden findet dann eine Auktion statt, in der die beiden Zulieferer ihr Gut anbieten. In der Auktion geben die Zulieferer ein Preisangebot ab, zu dem sie bereit sind, das Gut zu verkaufen. Die Bereitstellung des Gutes ist mit Kosten verbunden. Die Kosten, die den Zulieferern nur entstehen, wenn sie das Gut verkaufen, werden in jeder Runde zufällig und unabhängig für jeden Zulieferer ermittelt. Alle ganzzahligen Kosten zwischen **0** und **100** sind dabei gleich wahrscheinlich.

Ablauf der Auktion

Zunächst geben beide Zulieferer ein Preisangebot ab. Anschließend wird der Zulieferer ausgewählt, der das niedrigere Gebot gemacht hat.

Die Gewinne der Zulieferer

Der Gewinn des ausgewählten Zulieferers ist gegeben durch die Differenz zwischen seinem Preisangebot und seinen Kosten. Der nicht ausgewählte Zulieferer macht einen Gewinn von 0.

Der Gewinn des Käufers

Der Gewinn des Käufers ist gegeben durch die Differenz zwischen seiner Wertschätzung für das Gut und dem Preis, den er dafür zahlen muss.

Die Auszahlung

Wenn alle Teile des Experiments abgeschlossen sind, wird die Summe aus Ihren Gewinnen in den einzelnen Teilen gebildet. Anschließend wird dieser Gewinn in Euro umgerechnet, dabei entsprechen 100 ECU einem Euro. Zusätzlich erhalten Sie ein Show Up Fee in Höhe von 2,50€.

ANLEITUNG ZUM 2. TEIL

Dieser Teil des Experiments besteht aus **20 Runden,** die jeweils die gleiche Abfolge an Entscheidungen haben.

Überblick über die Entscheidungen in einer Runde

Weiterhin werden zu Beginn jeder Runde **zufällig neue** Gruppen bestehend aus einem Käufer und zwei Zulieferern gebildet. Im Folgenden findet dann eine Auktion statt, in der die beiden Zulieferer ihr Gut anbieten. In der Auktion geben die Zulieferer ein Preisangebot ab, zu dem sie bereit sind, das Gut zu verkaufen. Die Bereitstellung des Gutes ist mit Kosten verbunden. Die Kosten, die den Zulieferern nur entstehen, wenn sie das Gut verkaufen, werden in jeder Runde zufällig und unabhängig für jeden Zulieferer ermittelt. Alle ganzzahligen Kosten zwischen **0** und **100** sind dabei gleich wahrscheinlich.

Ablauf der Auktion

Die Auktion besteht nun aus zwei Stufen.

Stufe 1:

In jeder Runde bevorzugt der Käufer das Gut eines der beiden Zulieferer. D.h. der Wert dieses Gutes ist für den Käufer größer als der Wert des Gutes des anderen Zulieferers. Somit besitzt der Käufer eine höhere Wertschätzung für das bevorzugte Gut und eine niedrigere Wertschätzung für das nicht bevorzugte Gut.

Um dies zu berücksichtigen, vergibt der [Treatment 1: „Käufer“] [Treatment 2: „Computer“] entweder einen **Bonus** oder einen **Malus**.

- Bonus: Der [Treatment 1: „Käufer“] [Treatment 2: „Computer“] vergibt an die Zulieferer unterschiedlich hohe **Boni**
- Malus: Der [Treatment 1: „Käufer“] [Treatment 2: „Computer“] vergibt an die Zulieferer unterschiedlich hohe **Mali**

Sowohl die Boni als auch die Mali spiegeln die Präferenzen des Käufers wider. Ein Bonus sorgt dafür, dass das Preisangebot des Zulieferers attraktiver ist. Ein Malus bewirkt das Gegenteil und verringert die Attraktivität des Preisangebots des Zulieferers (Details siehe später).

Falls der [Treatment 1: „Käufer“] [Treatment 2: „Computer“] Boni vergibt, erhalten beide Zulieferer einen Bonus, wobei der Zulieferer des bevorzugten Gutes einen höheren Bonus als der andere Zulieferer erhält. Bsp: Der bevorzugte Zulieferer erhält einen Bonus von 6, der sein angepasstes Preisangebot um 6 Einheiten senkt, also attraktiver macht, während der andere Zulieferer einen Bonus von 2 erhält.

Falls der [Treatment 1: „Käufer“] [Treatment 2: „Computer“] Mali vergibt, erhalten beide Zulieferer einen Malus, wobei der Zulieferer des bevorzugten Gutes einen niedrigeren Malus als der andere Zulieferer erhält.

Bsp.: Der bevorzugte Zulieferer erhält einen Malus von 2, der sein angepasstes Preisangebot um 2 Einheiten erhöht, also verschlechtert, während der andere Zulieferer einen Malus von 6 erhält.

Die Wahrscheinlichkeit der bevorzugte Zulieferer zu sein, ist für beide Zulieferer gleich hoch.

Stufe 2:

In der zweiten Stufe der Auktion erfährt jeder Zulieferer seine eigenen Kosten sowie den Bonus oder Malus, der ihm zugewiesen wurde. Im Anschluss gibt jeder Zulieferer sein Preisangebot ab, zu dem er bereit ist, das Gut zur Verfügung zu stellen. Anschließend wird der Auktionsgewinner bestimmt.

Entscheidungsregel

Welcher Zulieferer die Auktion gewinnt, hängt von den **angepassten Preisangeboten** ab. D.h. nicht nur von den Preisangeboten selbst, sondern auch von den zugeteilten Boni/Mali.

Die Auktion gewinnt der Zulieferer, der das **niedrigste angepasste Preisangebot** hat. Sollten beide Zulieferer gleiche **angepasste Preisangebot** gemacht haben, so wird der bevorzugte Bieter den Zuschlag erhalten.

$$\text{angepasstes Preisangebot} = \text{Preisangebot} \begin{cases} -\ \text{Bonus, im Falle eines Bonus} \\ +\ \text{Malus, im Falle eines Malus} \end{cases}$$

Die Gewinne der Zulieferer

Der Gewinn des ausgewählten Zulieferers ist gegeben durch die Differenz zwischen seinem Preisangebot **(nicht angepasstes Preisangebot)** und seinen Kosten. Der nicht ausgewählte Zulieferer macht einen Gewinn von 0.

Der Gewinn des Käufers

Der Gewinn des Käufers ist gegeben durch die Differenz zwischen seiner Wertschätzung für das Gut und dem Preis, den er dafür zahlen muss. Die Wertschätzung des Käufers hängt davon ab, ob er das erworbene Gut von seinem bevorzugten oder von seinem nicht bevorzugten Lieferanten erhält. Wird der Käufer von seinem bevorzugten (nicht bevorzugten) Zulieferer beliefert, so ist seine Wertschätzung größer (kleiner) als seine durchschnittliche Wertschätzung.

Übersicht über die Entscheidungen

Stufe 1: [Treatment 1: „Käufer“] [Treatment 2: „Computer“] entscheidet zwischen Bonus und Malus

Stufe 2: Zulieferer geben Gebote ab

ANLEITUNG ZUM 3. TEIL

Dieser Teil des Experiments besteht aus **20 Runden,** die jeweils die gleiche Abfolge an Entscheidungen haben.

Überblick über die Entscheidungen in einer Runde

Dieser Teil des Experiments gleicht dem 2. Teil des Experiments bis auf die Tatsache, dass nun der [Treatment 1: „Computer“] [Treatment 2: „Käufer“] zwischen der Verwendung von Boni oder Mali entscheidet.

Instructions part 1

Thank you for participating in this experiment. Please do not talk to other participants during the experiment. This experiment consists of several parts. Your decisions in one part of the experiment do **not** have any influence on other parts of the experiment.

This part of the experiment consists of **10 rounds**. You are in the same situation in each of these rounds. A detailed description of the situation follows. There are two roles in this experiment: **Buyer** and **Supplier**. At the beginning of the experiment one of these roles is randomly assigned to you and you keep this role for the entire experiment. The first screen shows your role.

Overview of the decisions in one round
At the beginning of each round **new** groups consisting of one buyer and two suppliers are **randomly** determined. Then an auction is conducted in which both suppliers offer a good. In the auction both suppliers place a bid at which they are willing to sell their good. The provision of the good is costly. These costs that only occur if suppliers sell their good are independently and randomly determined for each supplier in each round. Each integer between **0** and **100** is equally likely.

Timing of an auction
First, both suppliers place a bid. Then the supplier who placed the lower bid is selected.

Suppliers' profits
The selected supplier's profit is given as the difference between the supplier's bid and the supplier's cost. The non-selected supplier earns 0.

Buyer's profit
The buyer's profit is given as the difference between the buyer's valuation for the good and the price.

Payment
At the end of the entire experiment we sum up your profits in the different parts of the experiment. This profit is converted to Euro, 100 ECU are equivalent to 1 Euro. Additionally, you receive a show up fee of 2.50 Euro.

Instructions part 2

This part of the experiment consists of **20 rounds**. You are in the same situation in each of these rounds.

Overview of the decisions in one round
Equivalent to the first part of the experiment **new** groups consisting of one buyer and two suppliers are **randomly** determined at the beginning of each round. Then an auction is conducted in which both suppliers offer their good. In the auction both suppliers place a bid at which they are willing to sell their good. The provision of the good is costly. These costs that only occur if suppliers sell their good are independently and randomly determined for each supplier in each round. Each integer between **0** and **100** is equally likely.

Timing of an auction
The auction now consists of two stages.

Stage 1
In each round the buyer prefers the good of one of the two suppliers. This means the buyer's valuation for this good is larger than the buyer's valuation for the good of the other supplier. Hence the buyer has a higher valuation for the preferred good and a lower valuation for the non-preferred good.
In order to take this into account the [Treatment 1: „buyer“] [Treatment 2: „computer“] assign a **bonus** or **handicap**.

- Bonus: The [Treatment 1: „buyer“] [Treatment 2: „computer“] assigns **bonuses** of different size to both suppliers.
- Handicap: The [Treatment 1: „buyer“] [Treatment 2: „computer“] assigns **handicaps** of different size to both suppliers.

Both bonuses and handicaps reflect the buyer's preferences. A bonus makes a supplier's bid more attractive. A handicap reduces the attractiveness of a supplier's bid. (details follow).

If the [Treatment 1: „buyer“] [Treatment 2: „computer“] assigns bonuses, both suppliers receive a bonus. The bonus of the preferred supplier is larger than the bonus of the other supplier. Example: The preferred supplier receives a bonus of 6 that reduces the supplier's score-adjusted bid by 6 units, i.e. it becomes more attractive, whereas the other supplier receives a bonus of 2.

If the [Treatment 1: „buyer“] [Treatment 2: „computer“] assigns handicaps, both suppliers receive a handicap. The handicap of the preferred supplier is smaller than the handicap of the other supplier. Example: The preferred supplier receives a handicap of 2 that increases the supplier's score-adjusted bid by 2 units, i.e. it becomes less attractive, whereas the other supplier receives a handicap of 6.

The probability of being the preferred supplier is the same for both suppliers.

Stage 2
In the second stage of the auction each supplier observes his cost and the bonus or handicap that is assigned to him. Then each supplier places a bid at which he is willing to provide the good. Finally, the winner is determined.

Award criterion
Score-adjusted bids determine which supplier wins the auction. This means the award decision does not only depend on suppliers' bids but also their bonuses or handicaps.

The supplier who placed the lower **score-adjusted bid** wins the auction. If both suppliers place the same **score-adjusted bid** the preferred supplier is selected.

$$\text{score-adjusted bid} = \text{bid} \begin{cases} -\text{bonus, in case of bonuses} \\ +\text{handicap, in case of handicaps} \end{cases}$$

Suppliers' profits
The profit of the selected supplier is given as the difference between his bid (**not score-adjusted bid**) and his cost. The non-selected supplier earns 0.

Buyer's profit
The buyer's profit is given as the difference between his valuation for the good and the price he has to pay. The valuation of the good depends on whether the good is provided by his preferred supplier or his non-preferred supplier. If the good is provided by the preferred (non-preferred) supplier, his valuation is larger (smaller) than his average valuation.

Overview

Stage 1: The [Treatment 1: „buyer“] [Treatment 2: „computer“] chooses between bonuses and handicaps.

Stage 2: Suppliers place bids.

Instructions part 3

This part of the experiment consists of **20 rounds**. You are in the same situation in each of these rounds.

Overview of the decisions in one round

This part of the experiment is equivalent to the second part of the experiment with the only exception that now the [Treatment 1: „computer“] [Treatment 2: „buyer“] chooses between bonuses and handicaps.

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