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Bidding behavior in multi-item auctions - an experimental study

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Abstract

For many years auctions are used as a process of buying and selling goods or services. Often not only a single item but several ones are auctioned, which increases, among others, the complexity in terms of computation and communication, since more (combinations of) items have to be evaluated and submitted. Our contribution is two fold.
First, sealed-bid procurement auctions with two different ***items*** from the same product are tested. Since homogeneous goods are auctioned, the items are called ***lots***. Second, we analyze sealed-bid and dynamic combinatorial auctions that are frequently used in practice for the sales of spectrum licenses. The bidders' complexity increases, since they have to evaluate a large number of different combinations of items, so called ***bundles***. In our environment up to 2,400 different bundles are possible.

In the procurement context, two sealed-bid single-item multiple lot split-award auctions are considered, namely the parallel and the Yankee auction. These mechanisms are multi-object extensions of the first-price sealed-bid (reverse) auction and can be found regularly in procurement practice. The split decision for these auctions is made ex-ante. Different ***risk-neutral Bayes Nash equilibrium*** (***RNBNE***) strategies are developed for the Yankee and the parallel auction. Surprisingly, both mechanisms result in the same expected costs for a procurement manager. We will analyze, if human bidders are able to follow the RNBNE strategy - a question that is recently discussed in many papers.
The strategic considerations in these auction formats are more difficult than in single-lot first-price sealed-bid auctions. Hence, it is questionable, whether expected utility maximization can explain human bidding behavior in such multi-object auctions. The assumption that human bidders would be able to mimic Bayes Nash equilibrium strategies has been challenged, and it is still an open issue, if they explain human bidding behavior even in easy settings,

like single-item auctions.
One main contribution is, that the predictive accuracy of equilibrium strategies in the lab is examined. We find underbidding for low cost draws in single-lot and split-award reverse auctions. Conversely, overbidding for high cost draws can be observed. Similar results can be found in experimental research on "forward" first-price sealed-bid auctions. To increase the prediction accuracy of the RNBNE strategies, we used the strategy method, i.e., we elicited bidders' bidfunctions, which we reused in a large number of computerized auctions. By this configuration risk aversion is eliminated, since speculation might make no sense. In addition, human bidders competed against computerized agents to reduce other effects like spite or uncertainty about other bidders' behavior.
In computerized experiments, where bid functions are reused in 100 auctions, there was actually no significant difference to the RNBNE bid function. This was not to be expected, since previous experiments showed a consistent pattern of overbidding in first-price sealed-bid auctions. As a consequence, our result rules out strategic complexity as a reason for deviations from equilibrium bidding. We attribute the results to our experimental design.
Hence, we can conclude that the cognitive complexity of deriving a RNBNE strategy is not the right explanation for underbidding. Also when human agents competed against other humans, the RNBNE strategies can be used as a baseline model for bidding behavior in split-award auctions. Overall, the experiments suggest that risk-neutral Bayes-Nash equilibrium strategies serve as a surprisingly accurate model for human bidding behavior in split-award auctions. Strategic complexity is an unlikely explanation for deviations from the equilibrium strategy.

Our second contribution models the sales of spectrum licenses as it is done in many countries worldwide, where decision makers have the choice between a large number of bundles. In contrast to the experimental environment in the procurement context, we do not have a theoretical baseline as point of reference. By experimental research we give practical implications to governmental institutions how to sell magnetic radio spectrum by auctions.
Since 1994, when the ***personal communication services*** (***PCS***) auction was conducted by the ***Federal Communications Commission*** (***FCC***) of the US, spectrum auctions have raised hundreds of billion dollars worldwide. Hence, auctions have become a role model for market-based approaches in the public and private sector.
The PCS spectrum was sold via a ***simultaneous multi-round auction***

(***SMRA***), a format that has been used for more than a decade in the US and elsewhere. In the SMRA, bidders compete for licenses individually even though they typically value certain combinations of licenses. Therefore, since bundle bids are not possible, it might happen, that bidders do not win their preferred combination but only a subset of it. Contrarily, in ***combinatorial auctions*** (***CA***), where several items are sold simultaneously, bidders can submit indivisible bundle bids on groups of items. This might improve the performance in comparison to SMRA, since synergies between items, i.e., considering economies of scale and scope, can be expressed by bids. Even because of this advantage, the first combinatorial spectrum auction only took place in 2008.
Since that time, many countries used the ***combinatorial clock auction*** (***CCA***) to sell their magnetic radio spectrum in order to increase the performance, like the social welfare and the revenue. However, the complexity of the auction became bigger, since many licenses have been sold simultaneously which leads to an exponential growth of the number of possible packages. To address this problem, we analyze in the laboratory main auction design choices, that governments face, i.e., the selection of the auction format, bid language and payment rule.
We focus on bid languages with different expressiveness, where the following trade-off has to be mastered. The more complex the bid language, the better efficiency can be reached in theory. However, the more complex the bid language, the more combinations of items have to be considered by humans. Contrarily, a simple bid language may not be very efficient from a theoretical point of view, since bidders might not express their valuation detailed. A complex language in turn is good in theory, but practically bad, what has negative effects on the efficiency. We analyze the impact of a simple "compact" versus complex "fully expressive" bid language. Additionally, we test simple "pay-as-bid" pricing rules, which can be understood easily by bidders, and complex "bidder-optimal core-selecting" pricing rules, which generate good results in theory.
To widen the scope, we look at ascending, and sealed-bid, i.e., one round formats. We find that simplicity of the bid language has a substantial positive impact on the auction's efficiency. Also an easy pricing rule has positive effects on the revenue that is generated by the auction. Finally, it can be concluded that the CCA with a complex bid language and pricing rule ends in the worst results. This outcome has directly impact on decision makers, since the CCA was applied in previous auctions and is supposed to be used in many countries.

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All errors, idiocies and inconsistencies remain my own.

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Chapter 1

Introduction

Auctions are used in many economic environments and can be found in procurement, energy markets, transportation and the sales of spectrum licenses.
Especially when several items are sold, bids on combinations of items, called ***packages*** or ***bundles***, might increase economic efficiency, since there are often super-additivities as well as economies of scale (and scope) between items. Bundle bids are possible in ***combinatorial auctions*** (***CAs***), which are often implemented with multiple rounds. In these dynamic auctions the auctioneer computes allocations and ask prices after each round. This would not be possible without IT-based auction platforms which solve complex computational problems in each auction round. This is a main reason why CAs have been a topic in much recent Information Systems (IS) research. Examples can be found in Guo et al. (2007), Bichler et al. (2009), and Bichler et al. (2013b). The IS literature also proposed a lot for bidder decision support, designs for new application domains, and the analysis of bidder behavior in CAs (see also Adomavicius and Gupta (2005), Ausubel and Milgrom (2006), Bapna et al. (2000)). An overview of current research in IS can be found in Bichler et al. (2010a).

In this thesis we study experimentally, how humans behave in multi-item auctions. First, we study a quite simple setting, namely two sealed-bid split-award auctions with ex-ante split decisions as they can be regularly found in procurement practice. These auction formats are multi-object extensions of the first-price sealed-bid auction. We analyze the predictive accuracy of ***risk-neutral Bayes Nash equilibrium*** (***RNBNE***) strategies by means of laboratory experiments. We conclude with suggestions for dynamic, i.e., multi-round, extensions of these sealed-bid formats.

Second, we analyze multi-item auctions in an environment with several items, which can be found in the sales of spectrum licenses, and achieve a better understanding of the design of CAs. Mainly, we accomplish the work of Bichler et al. (2013a) in addressing some current issues, like bidders' (communicational) complexity, which is determined by the degree of competition, number of items, bidders and possible bundles. We try to solve the problem, that bidders might not be able to submit bids on all possible combinations which have a positive valuation as recommended in theory. On the one hand, people do not identify the "right bundle" they should bid for; on the other hand, there are too many alternatives. Current research has shown, that even with decision support, people cannot deal with a large amount of information. This phenomenon is known as information overload in the literature and discussed in many papers for different applications (see e.g. Maes et al. (1994)).
A growing number of papers in recent years have focused on the design of auctions for multiple non-identical objects. Examples can be found in the sales of spectrum licenses and industrial procurement or logistics where multiple heterogeneous goods or services need to be purchased (Cramton et al. (2006a)).

1.1 Split-award auctions

In the first part, we analyze two forms of sealed-bid auctions that can regularly be found in procurement practice for dual sourcing. Two lots of a product with different sizes are sold in one round. The lots in such auctions could be the 30% and the 70% share of the demand for a particular raw material. The buyer chooses the split decision ex-ante. The suppliers are restricted to submitting either one single bid in the so called ***Yankee auction*** or two bids on the two lots in the ***parallel auction***.

In the Yankee auction each bidder submits only one bid as the unit price for both lots. Then, the bidder with the lowest bid wins the large lot and the bidder with the second lowest bid wins the small lot.
Conversely, in the parallel auction each bidder submits one bid as the unit price of the product for each lot. The bidder with the lowest bid on each

lot wins that lot, whereas each bidder can win at most one lot to ensure the split outcome. If one bidder is the best bidder for both lots, he will be awarded the large one. Such auction formats with an ex-ante split are easy to implement for procurement managers, and it is interesting to understand bidding strategies.

Ceylan and Guler (2005) introduce variable awards. In their model the sourcing decision, sole source, i.e., that the best bidder wins the whole amount, or split-awards, as well as the definition of the split parameter depend on the submitted bids. Also ex-post split decisions might be interesting to analyze but will not be the focus of this work.
Corey (1978), Woodside and Vyas (1987), and Seshadri et al. (1991) discuss cases of split-award contracts with predefined splits in different industries. Game theoretical analysis or experimental work is not done in these papers. Recently, Gong et al. (2012) assume a single bid second-price split-award auction with an ex-ante split similar to the Yankee auction in our paper. However, their focus is different, since they analyze suppliers' incentives to invest and not a RNBNE strategy.

In this thesis, the theoretical analysis and the Bayes Nash characterization of the parallel and the Yankee auction is used from Kemal Guler of our joint work in Bichler et al. (2014a). It is analyzed to which extent such models and the corresponding RNBNE strategy have explanatory power in lab experiments. To our knowledge, none of the split-award auctions discussed in the literature have been analyzed in the lab in spite of their practical relevance. Our models are in the first-price sealed-bid auction framework, which is straightforward to implement and reflects the real-world practice. Previous studies in ascending auctions (Palfrey (1983)) or auctions with complete information (Tranæs and Krishna (2002)) are not particularly realistic and hardly used in procurement.

Bayesian Nash equilibrium analysis is the standard approach to model sealed-bid auctions and much recent research has tried to extend this type of analysis to multi-object auctions (Krishna (2009)). The RNBNE analysis of multi-object auctions is technically much more challenging than that of single-object auctions. Hence, there are only a small number of papers deriving RNBNE strategies for specific combinatorial or non-combinatorial multi-object auction formats (Goeree and Lien (2010b), Ausubel and Baranov (2010), Sano (2011), Sano (2012)). Given the strategic complexity of these

multi-object auctions, it is all but clear that RNBNE predictions explain human behavior well.
Similar analysis are done with uniform-price auctions by Engelbrecht-Wiggans and Kahn (1998) and for multi-unit auctions with common values by Back (1993).
For first-price sealed-bid auctions of a single-object the bidder's decision is one dimensional. Only the level of bid shading, i.e., the difference between the bid price and the costs, has to be considered. In multi-object first-price sealed-bid auctions bidders also need to decide which objects they want to bid on and additionally, how much they want to shade their bids.
For example, in the parallel split-award auctions not only the number of bidders and the prior distribution, but also the split parameter determines the level of bid shading. In the Yankee auction the bidders also need to take into account the risk of winning the small lot rather than the large lot with a certain bid price.

Interestingly, the predictive accuracy of RNBNE predictions for multi-object auctions in the lab is largely unexplored. However, there is a growing literature on first-price sealed-bid auctions of single-objects which shows that bidding behavior in the lab deviates substantially from the RNBNE prediction and overbidding is a common phenomenon. Engelbrecht-Wiggans and Katok (2009) explain overbidding by risk aversion, spite, and regret. A number of authors have challenged the overall approach of models based on rational choice and expected utility maximization (Bourdieu (2005), Nell et al. (2007)).
Ockenfels and Selten (2005) and Neugebauer and Selten (2006) use dynamic concepts, such as learning, instead of the equilibrium concept as an explanation. Experimental results on first-price sealed-bid auctions of a single-object seem to confirm this criticism.
Even if bidders were able to mimic their RNBNE strategy in a single-lot auction, it is far from obvious that RNBNE models would still be a good predictor for multi-object auctions. In single-lot auctions, bidders might just estimate the right level of bid shading. As described above, split-award auctions are strategically more complex, and it is interesting to understand, if bidders are able to mimic their RNBNE strategy.
If the RNBNE strategy does not explain bidding behavior in split-award auctions, there is little hope that it would explain bidding behavior in more complex multi-object auctions such as combinatorial auctions. In summary, we try to understand if, in spite of the increased strategic complexity of

split-award auctions, RNBNE bid functions can serve as a baseline model for human bidding behavior.
In the procurement context, we start with the introduction of closed form increasing Bayesian Nash bidding strategies for the Yankee and the parallel auction. Then, welfare assumptions concerning the total procurement costs are made. This Bayes Nash characterization has been missing in the growing literature of multi-object auctions and is particularly relevant for procurement. A main finding is that, although the parallel and the Yankee auction mechanisms yield the same expected costs to the buyer, other aspects of the two models, including the equilibrium bidding strategies as well as winning bidders ex-post profits differ significantly.

Most previous studies in this area, like Armstrong (2000) and Anton and Yao (1992), focus on the comparison of auction mechanisms in terms of the expected revenue. We also compare the different mechanisms in terms of other measurements like the equilibrium bidding strategies as well as winning bidders ex-post profits, which are important considerations in real-world procurement practice.
Chaturvedi et al. (2011) also define a optimal long-term split-award auction that minimizes the procurement costs for a while. The difference to us is, that the procurement costs are increased by qualification costs, i.e., the buyer has to pay for qualifying suppliers and maintain a supply pool to avoid qualifying new suppliers for each auction. To keep bidders motivated multi-sourcing is necessary, since if more bidders are winning, more will be interested in future business. Finally, they conclude that the supply base size decreases with an increase in the cost to qualify suppliers.

One of our main contributions is that we are the first to report on lab experiments with split-award procurement auctions. We designed lab experiments with different levels of control where human bidders competed either against other human bidders or computerized bidders. The latter are designed to mitigate the impact of behavioral biases such as risk aversion, regret, and spite.
We found that human subjects in experiments against computerized bidders were actually able to mimic the RNBNE strategy surprisingly well without knowing the strategy of the computer agents. We added experiments where we provided the RNBNE strategy of computer agents explicitly. The differences in bidding behavior between these two treatments were small.
Experiments with human subjects in repeated auctions are modeled after procurement auctions as they are found in the field. We could observe

learning in the initial rounds, but observed underbidding compared to the RNBNE prediction for low cost draws. Although the impact of risk aversion should be reduced with many repeated auctions, residual risk aversion, wrong expectations about other bidders or regret can all serve as explanations for this underbidding. The level of underbidding was comparable to the result in single-lot reverse auctions, which we conducted as a point of reference.

In summary, the deviations from the RNBNE strategy are small in the human subjects experiments after a few rounds. The computerized experiments show that bidders can handle the strategic complexity well and their bid functions are surprisingly close to the RNBNE prediction compared to earlier literature on first-price sealed-bid auctions on a single-object. We attribute this to our experimental design and the large number of repetitions, in which a single bid function is used. This also shows that strategic complexity provides little explanation for the deviations from the RNBNE in experiments with human subjects, even though the strategic complexity is considerably higher than in single-object auctions.

1.2 Combinatorial auctions

Nowadays, the sale of spectrum licenses is often done by complex multi-item auctions. The amount of items is much higher than in split-award auctions described in the last section. It is interesting, how bidding behavior changes, when humans have to deal with more information.

Spectrum licenses are in high demand due to the variety of different applications in industry. Especially, providers in the telecommunications sector demand more licenses than are available in order to offer certain services. This effect is even strengthened by the increasing demand for mobile data, since users want to run applications with a sufficient data supply. Several other methods different from auctions have been used to assign licenses to companies.
Spectrum auctions with thirty or more items have been conducted or are planned in Austria, Australia, Canada, Switzerland, the Netherlands, Ireland, and the UK. For example, in the 2012 auction in the Netherlands, 41 spectrum licenses in the 800 MHz, 900 MHz and 1800 MHz bands

were sold. Switzerland auctioned 61 licenses distributed over 11 bands in 2012.

Instead of using an auction, companies could apply for their requested license by comparative hearings or beauty contests (see Hoffman (2011)). However, even the preparation for such a process and the evaluation of the selection of the right partners takes a long time. The outcome is often unclear and not transparent, since the reasons why some companies get the license but others do not are hardly understandable for the losers.
Another procedure consists of lotteries where all interested people would have to apply for a ticket. Then the licenses are allocated to the applicants at random. This might create the problem that the people/companies who really want to use the licenses do not win - but other firms that participated only because of fun or speculation do. Hoffman (2011) found out that many applicants only take part into a lottery in the US to speculate without any interest in using the licenses. Milgrom (2004) concluded that these speculations led to bad results in actual allocation processes in North America. The government earned less money and licenses were not allocated to the right provider that could offer services to citizens in some areas. Even the introduction of a nationwide mobile telephone service in the US was delayed.

Because of the downside of other allocation methods, auctions became more and more popular. Already Coase (1959) suggested that market-based mechanisms, like auctions improve the allocation of spectrum resources. But his early advice was not taken for decades. Only since the early 90's spectrum auctions have been a common topic in research, after the regulatory authority in the USA, the ***Federal Communication Commission*** (***FCC***), expressed their willingness to sell spectrum licenses nationwide via auctions. The 1994 sale of radio spectrum for ***personal communication services*** (***PCS***) changed the policy of the FCC, since they finally started to run the first auction for selling spectrum license. For the design of its PCS auction, the FCC took the advice of several economists and game theorists. Finally, the FCC followed the proposal of the Stanford professors Milgrom and Wilson to run the ***simultaneous multi-round auction*** (***SMRA***). The success of the PCS auction, which raised over six hundred million dollars for the US Treasury, vindicated Coase's vision.

The SMRA is a straightforward multi-item extension of the single item English auction. It is frequently used in art sales, and the simplicity of its rules has contributed to its popularity. Therefore, more than 70 spectrum

auctions were run using the SMRA since the early 90's with a generated for revenue of 200 billion US dollars (Cramton et al. (2006a)).
Despite the simplicity of its rules, the strategic complexity is quite high in the SMRA when there are synergies between licenses that cover adjacent geographic regions or between licenses in different frequency bands. Bidders who compete aggressively for a certain combination of licenses risk winning an inferior subset at high prices, since they cannot place bids for indivisible bundles. When bidders anticipate this exposure problem, competition will decrease the auction's performance. The exposure problem has led auction designers to consider CAs which enable bidders to express their preferences for an entire set of licenses directly. Baranov (2010) has shown, that in environments with complementarities, non-package auction designs can easily fail to achieve efficient allocations. Hence, lower revenue for the seller is generated because bidders cannot express their synergies across items.
Chernomaz and Levin (2008) conclude that package bidding improves (hurts) efficiency at high (low) levels of synergies. Bundle bids introduce free-riding incentives for local bidders, i.e., small bidders force other small bidders to overbid the large bidders. This asymmetric bidding behavior reduces efficiency when synergies are low but increases it when those are high. Small bidders, who either win all together or lose all together, try to motivate each other for free-riding. As a result they win and pay less than the other (small) bidders. This free-riding incentive lowers the incentive for bidding for both local and global bidders. Consequently, revenue is reduced at all levels of synergies.
The effect of package bidding on revenues is negative when global bidders are not allowed to bid on single items (a feature of the equilibrium) and positive when this restriction is relaxed and synergies are high. In accordance with some other results, Brunner et al. (2010) summarize that SMRA is actually superior in value models with quite low synergies.

To avoid the problems of the SMRA CAs might be proper, since bidders can express their valuations better. The design of CA, however, led to a number of fundamental design problems, and many contributions during the past few years have been made (see for example Ausubel et al. (1997), Plott (1997), Banks et al. (2003), Plott and Salmon (2004), Cramton et al. (2006b), Cramton et al. (2006a) and chapter (4.1)). Figure (1.1) summarizes developments in the field of spectrum auction design concerning their application in different countries. It can be seen, that licenses of different bands, like at 700/800/900 MHz, 1800 MHz, 2600 MHz are often sold simultaneous in a single auction.

Country	700/800/900 MHz	1800 MHz	2600 MHz
Australia	CCA (2013)	-	CCA (2013)
Austria	CCA (2013)	-	CCA (2010)
Denmark	-	SMRA (2010)	CCA (2010)
Germany	SMRA (2010)	SMRA (2010)	SMRA (2010)
Finland	-	-	SMRA w. switching (2009)
France	Sealed-bid CA (2011)	-	Sealed-bid CA (2011)
Hong Kong	-	-	SMRA
Netherlands	-	CCA (2012)	CCA (2010)
Italy	SMRA w. ranking (2011)	SMRA w. ranking (2011)	SMRA w. ranking (2011)
Ireland	CCA (2012)	CCA (2012)	CCA (2012)
Norway	-	-	SMRA w. switching (2007)
Spain	SMRA (2011)	Beauty contest	SMRA (2011)
Sweden	SMRA w. switching (2011)	CCA (2011)	SMRA w. switching (2008)
Switzerland	CCA (2012)	CCA (2012)	CCA (2012)
UK	CCA (2012)	-	CCA (2012)

TABLE 1.1: Developments in the field of spectrum auction design.

Cramton (2013) proposed to use a specific CA, namely the ***Combinatorial Clock Auction*** (***CCA***). The CCA, based on Maldoom (2007), consists of two rounds and has been used since 2008 in several countries.
The CCA uses in the first round an ascending auction where individual license prices rise over time (clock phase) in response to excess demand for price discovery. In the second round, the supplementary phase, bidders submit sealed-bids to reach a final allocation with high efficiency. In the clock phase a complex activity rule is used to motivate bidders to submit many bids from the start of the auction on. Besides, they should reveal their preferences truthfully (Bichler et al. (2013a)).

On the one hand, the CCA avoids the exposure problem, since bidders can bid both on bundles and on individual items. On the other hand, the complexity in terms of communication, computation, strategy, and valuation increases significantly, since the number of possible bids grows exponentially with the number of licenses. First, bidders have to evaluate all the possible bundles of items (***valuation complexity***); second, depending on the strategy, the "right" bundles have to be selected (***strategic complexity***) and third, all the chosen bids have to be submitted (***communicational complexity***). Finally, the auctioneer has to determine both the provisional and final allocation, as well as the ask prices at each round and the final pay prices. However, this ***computational complexity*** is not the focus of this study.

The number of possible combinations is bigger than one billion, if we have only 30 different licenses. Nisan (2000) already stated that for fully efficient allocations in a CA the communication requirements grow exponentially. This communication complexity can lead to inefficiencies because the winner-determination algorithm assigns a missing bid for a possible bid the value zero.
Milgrom (2010) proposed to simplify bidders' message spaces such that desirable equilibrium outcomes are not eliminated in order to face this problem. In this manner, efficiency and revenue losses should be avoided.

In spectrum auctions it is often well known before the auction which combinations of licenses generate the most synergies. For example, in most European auctions there are high synergies within bands, especially at the 800 MHz band, but not between. Packages with two licenses often have a much higher value than twice the value of a single license.
Another band, frequencies of the 2.6 GHz band, is available for mobile services in all regions of Europe. The 2.6 GHz spectrum band includes 190 MHz which are divided into blocks of 5 MHz. It can be used to deliver wireless broadband services or mobile TV. In particular, there are two standards which will likely be used in the 2.6 GHz band, LTE and WiMAX. LTE uses paired spectrum (units of 2 blocks), while WiMAX uses unpaired spectrum (units of 1 block). For the new LTE mobile communication standard, telecom companies even aim for four adjacent blocks of spectrum to offer the new standard in a high quality.

Our value models are designed similar to the practice and have been already used by Bichler et al. (2013a) who compared CCA and the SMRA auction in the lab with two value models. In each value model, 4 bidders participated and 24 lots were sold. The small model consisted of two bands with 14 and 10 blocks respectively, the large one of 4 blocks with 6 bands each. In total, in the small value model, the complexity for bidders was substantially lower, because they needed only to calculate approximately 50 possible bundles. Conversely, in the large value model around 2,400 (7^4-1) possible bundles needed to be evaluated. Mainly because of this high degree of complexity, the efficiency of CCA in the lab was considerably lower than that of SMRA in Bichler et al. (2013a).

In Chapter 4, a simple and a compact bid language that covers the main synergies is examined. We see how this configuration affects the performance in multi-band spectrum auctions. Our simple bid language allows bidders to specify ***either-or*** bids on packages within a band (***XOR language***) and ***and-or*** bids between different bands (***OR language***). This way, the number of different bids is reduced substantially from 2,400 to 12 bundles and the recent criticism of Cramton (2013) is addressed, that bidders could not submit enough bids in a value model consisting of 2,400 possible bundles.

Of course, we do not suggest that there is a one-size-fits-all bid language, nor a specific bid language for a particular application. It is actually one of the most important tasks in market design to understand the value model, like the knowledge of super-additivity and the fixed descending complementarity type, in order to find the right mechanism.

Milgrom (2010) concluded that a simplified bid language is superior if it is designed right. This is in accordance with Baranov (2010) who stated that some level of flexibility of package bids can increase the performance.
In this thesis, we want to show by examples the potential benefits of a compact bid language over a fully expressive one.

Another important feature of the CCA is the core-selecting payment rule. This payment rule is quite complex and not easy to understand for bidders (see, e.g., Day and Milgrom (2008)). Even a game-theoretic analysis is so far not possible. The outcomes can appear non-transparent because small changes in the bids can lead to substantial variations in the payments. The bidders do not know the payments before the auction ends. Hence, we also use a simple pay-as-bid payment rule and analyze the changes in bidders' behavior. The simple payment rule is also of current interest, since it is transparent, because bidders pay what they have bid when they win. The pay-as-bid payment rule is easy to understand and has been currently used in the Romanian spectrum auction. The initial design goal of the core-selecting payment rules was to avoid low revenue like it might happen in the second-price or Vickrey Clarke Groves (VCG) auction which is described in detail in chapter (4.1) because of its importance.
The auctioneer's revenue is the key result in any spectrum auction, because efficiency can only be analyzed in the lab but not in the field. Real-world bidders are hardly willing to reveal their true valuation of items. Transparency of the auction process and the law of one price, i.e., one license costs the same for all bidders, are additional goals that might not be obtained with the complex payment rule and are partly in conflict with revenue and efficiency.
The different treatments of our experiment allow us to measure how auction

revenue and efficiency vary when using the pay-as-bid or core-selecting payment rule.
In summary, we consider the treatment variations, simple versus complex bid language and simple versus complex payment rule, for both ascending and sealed-bid formats. Then, we can analyze how bidding behavior in multi-item auction changes with different degrees of complexity.

1.3 Research question

Our research question can be summarized of how humans behave in multi-item auctions with practical relevance. We thereby explore current issues in experimental economics.
In a split-award environment which can be found in a procurement context, we run experiments to get insights if and/or when bidders are able to follow a theoretical prediction.
Within the complex domain of spectrum auctions we show how bidding behavior is changing by different degrees of complexity and other parameters.
The research objectives can be expressed as follows:

- Does the Bayes-Nash equilibrium predict bidding behavior?
- How do the expressivity of the bid language, the payment rule and the auction format influence the auction outcome?

1.4 Outline

This study has the following structure:

- Chapter 2 introduces basic theoretical concepts. Then we describe the findings in the split-award and combinatorial auction context in detail.
- Chapter 3 tests how humans behave in a simple multi-item context. Experiments are performed to analyze if bidders can mimic a theoretical prediction (see Guler et al. (2012) and Bichler et al. (2014a)).

- Chapter 4 deals with complex multi-object applications of auctions, namely the sale of spectrum licenses via combinatorial auctions. We analyze how bidders deal with a large number of items (see Mayer and Shabalin (2013) and Bichler et al. (2014b)).

- Chapter 3 and Chapter 4 are organized in a similar manner. At the beginning, we introduce the theoretical background which is indispensable for further understanding (in section (2.2) general theoretical insights are given; conversely, chapter (4.1) cares about combinatorial auctions.) and explain the different auction formats (sections (3.1) and (4.2)). The experimental setup (sections (3.2), (4.3)) and the results (sections (3.3), (4.4)) are presented, followed by a brief outlook (sections (3.4), (4.5)) is given.

- Chapter 5 concludes by summarizing the results of our research and giving an outlook for future work.

  The experimental instructions we gave to our participants and relevant screenshots are summarized at Appendix A. Additional plots are provided at Appendix B for the sake of completeness.

Chapter 2

An introduction into auction design

In this chapter, we give a brief introduction into auction design. In economics, a market mechanism describes the interaction between buyers and sellers in a monetary exchange. Resources are allocated according to the given demand and supply, whereas the price has to generate the best distribution of goods and/or services. The design of market mechanisms is discussed in economics, mathematics and computer science. Generally, three different types can be distinguished.

In a free market mechanism the private sector, e.g. individuals, companies etc., allocates all available resources. Conversely, in a planned economy, the public sector, e.g. the government or governmental institutions, assigns the resources to companies and/or persons. Both the private and the public sector are responsible for the assignment in a mixed economy.

Auctions are one of several applications that can arrange the distribution of goods and have been used for quite a long time. Herodotus, who lived from 484 to 425 BC and is described as "The Father of History" by Cicero, reported that people held auctions during his lifetime. Since ancient times, many commodities like tobacco, fish and fresh flowers have been sold by auctions. In recent history, land, factories and other assets have been auctioned in order to privatize public holdings. Many examples can be found in the former Soviet Union as well as their satellite states. Nowadays, rights to use the electromagnetic spectrum for communications are auctioned in many countries. For example, in 2010 the German 4G auction took place, where the government earned around €4.4 billion for selling spectrum licenses in the 0.8 GHz, 1.8 GHz, 2.1 GHz, and 2.6 GHz bands. In an earlier auction 2000, the income was much higher, namely around €50 billion.

Besides the practical application, there are many theoretical contributions. The relevant academic fields include game theory and decision theory. Especially, ***combinatorial auctions*** (***CA***s) have attracted the attention of researchers in the fields of mathematics, operations research, economics, information systems, and computer science.

In an auction mechanism, the allocation rule, the value model, the payment rule and the range of possible actions of all participating agents are essentially determined. From now on we shall call the agents ***auctioneer(s)*** and ***bidder(s)*** instead of *seller(s)* and *buyer(s)*. The rest of the thesis focuses on both ***forward*** and ***reverse*** auctions.
In a reverse, ***buy*** or ***procurement auction***, several sellers want to sell one or more products to a single auctioneer, who has the role of a procurement manager. Therefore, such kinds of auctions can often be found in supply chain or procurement departments in the G2B and B2B sector. Conversely, different bidders try to buy good(s) that are offered by an auctioneer in a forward or ***sell*** auction.

Auctions determine the price in a trade dynamically, which is important for perishable goods in volatile markets (fish, flowers), scarce, exceptional goods (arts, rare wine), goods with unknown and unpredictable value (mining licenses) and markets with high competition. However, setting up an auction requires higher transaction costs compared to using a simple list price. Therefore, auctions are attractive only when the expected price is high, or the setup costs are low. Often, auctions are used when the seller is unsure about the value of the relevant item and about the bidders who could be attracted. If the seller knew the values, he could offer the object to the bidder with the highest value at or just below his willingness to pay. Uncertainty regarding values facing both buyers and sellers is an inherent feature of auctions, i.e., the seller does not know the type of potential bidders and bidders know their own type, but not the types of potential competitors. A price list might be an alternative instead of an auction. But, setting the correct price is difficult.

Also, lotteries or beauty contests have their downsides, because low efficiency and/or low revenue is often generated.

A common, widespread auction format is the ***English auction***, where a single item is sold. The auctioneer begins by calling out a low price (***reserve price***), e.g., zero, to several bidders who are invited to submit higher bids. A new bid always has to exceed the current ***standing bid***, i.e., the market price. The auctioneer raises the price in small, often fixed increments until there is only one remaining bidder. This bidder wins the item and pays his (own) final bid.
The counterpart to the English auction is the ***Dutch auction***. Here, the auctioneer begins by calling out a price sufficiently high so that no bidder is willing to purchase the item at that price. The price is reduced by a decrement until some bidder indicates interest in purchasing the item at the given price. The first bidder who submits a bid obtains the item and pays the price at which he decided to enter the auction.
Another single-item auction which is similar to the English auction is the ***button auction***, also known as the ***Japanese auction***. Each bidder presses his auction button as long as he is willing to buy the item at the current price. The termination rule is fulfilled when only one bidder holds the button down. Alternatives to iterative versions are sealed-bid auctions. Here, each bidder places his bid in a single round and the best bidder wins the item.

Besides these single-sided auctions, there are also ***double-sided auctions***, which are not the focus of this work, but have to be mentioned for the sake of completeness. Sealed-bid double-sided auctions are famous as call or stock markets; iterative versions are known as continuous double auctions. In these auctions many sellers and buyers compete against each other. Each participant can act on both sides. Hence, the auctioneer has to be an independent person who is not interested in selling or buying an item.

Another important feature of auction mechanisms is the pricing rule. The most important ones are the first-price and the second-price rule. The pricing rule determines the price that has to be paid by the winning bidder. In many applications either the amount of his own bid (first-price or pay-as-bid) or the bid of the second highest bidder (second-price) (Davis and Holt (1992)) has to be paid by the winner. "The second-price auction is a sealed-bid auction in which the buyer making the highest bid claims the object, but pays only

the amount of the second highest bid. This arrangement does not necessarily entail any loss of revenue for the seller, because the buyers in this auction will generally place higher bids than they would in the first-price auction." Milgrom and Weber (1982b, p. 1090)
Due to its importance, the second-price, also known as the ***Vickrey-Clarke-Groves (VCG)*** auction (see Vickrey (1961)) is described in detail in chapter (4.1). Also other rules, like the third-price payments might be possible, but are not discussed here.

Auction mechanisms should exhibit several properties. The auctioneer tries to maximize the efficiency, i.e., the bidder with the highest valuation respectively lowest production costs in reverse auctions should win the item in order to maximize ***the social welfare***. Additionally, ***strategy proofness*** should be imposed. Auctions that feature this property have a dominant strategy, i.e., bidders do not have to learn or guess other bidders' behavior, since they have the best possible strategy independent from their competitors. Bidders should not achieve any advantage if they misreport their valuation for items. If truth telling by all agents is an equilibrium, then a mechanism is ***incentive compatible***. Also the ***core property*** is essential, which means that bidders cannot form any coalition with the auctioneer where anybody can achieve a better result than in the current solution given the market prices. Finally, bidders should not expect a negative payoff for participating (***individual rationality***).

Not only one item, but several are often auctioned, whereas we describe some terms in the following in the context of CAs. A CA is an auction where bids are allowed on individual items, and indivisible combinations of items, i.e., ***bundles*** or ***packages***. Hence, especially in economies of scale and/or scope, CAs are a good choice, since bidders can express their complementarities and submit bids for bundles. Different bidders can win item(s) in a CA with the restriction that each item can only be assigned to one bidder.

2.1 The economic environment

There are different possible value models that characterize the market. The default case for formulations are forward auctions in order to avoid repetitions.

In the ***independent private values (IPV)*** model "each individual value is independently drawn from a known distribution, and while the distribution is common knowledge, each individual only knows their own particular realization from the distribution" (Lusk and Shogren (2007, p. 20)). Bidders know exactly what values they themselves place on all items, but not the values others place on them. Hence, bidders might evaluate with this information their ***willingness to pay (WTP)*** [1] and/or their ***willingness to accept (WTA)***[2]

Conversely, in the ***common value model*** the valuation for some item(s) is the same for all bidders, but the estimation can be different. "Unlike the private values theory, the common value theory allows for statistical dependence among bidders' value estimates, but offers no role for differences in individual tastes." (Milgrom and Weber (1982b, p. 1095)).
Common value items are dependent on the resale price or (estimated) market value, e.g. mineral rights (McAfee and McMillan (1987)). In case of a first-price auction with many bidders, the equilibrium price assuming common values is a consistent estimator for the true value of the item (Milgrom and Weber (1982b)).

According to McAfee and McMillan (1987), bidders' behavior does not reflect exactly one of the above mentioned value models, but is somewhere between them. He states that bidders' valuations are correlated to other bidders' valuations and the true value of an item. This concept is known as ***affiliated values*** (see Milgrom and Weber (1982b)).
The objective for bidders is to maximize his own payoff, which is the difference between their own valuation and the pay price, and therefore, independent from the valuation concept. In reverse auctions, valuations are often denoted as costs, and the payoff is computed by the subtraction of the costs from the price.
For forward auctions we denote bidder i's valuation v for item A with $v_i(A)$; in reverse auctions bidder i's production costs c for item A without fixed costs K are defined as $c_i(A)$.

[1] The *willingness to pay*" is the amount a person will pay that makes them indifferent to improving the quality of the good or keeping the status duo quality." (Lusk and Shogren (2007, pp. 35 f.))

[2] The *willingness to accept*" is the compensation required to make a person indifferent to the reduction in quality and the status duo." (Lusk and Shogren (2007, pp. 36 f.))

Often, not only a single item, but different ones are sold and bidders' valuations for several items, like for item A, $v(A)$, and item B, $v(B)$, are not additive. If A and B are ***complements***, i.e., $v(AB) > v(A) + v(B)$, the valuations are defined as ***super-additive***. In reverse auctions, we get $c(AB) < c(A) + c(B)$; such a structure can often be found in procurement with economies of scale (and scope). Companies that aim for a horizontal merger might be motivated by these synergies in order to save production costs.
Also in spectrum sales, some services can only be offered when more items are won. Like in the British 4G Auction in 2013, Vodafone and Telefonica won a pair of 5 MHz licenses in the 800 MHz band and not a single block in order to build a nationwide network with maximum reach (See for details [3] or chapter (4.3).)

In case of ***additive*** valuations, i.e., $v(AB) = v(A) + v(B)$, the valuations of different items are independent. If items are (perfect) ***substitutes***, the corresponding valuations are ***sub-additive***, i.e., $v(AB) < v(A) + v(B)$ (respectively $c(AB) > c(A) + c(B)$).

2.2 Theoretical background

We introduce some basic solution concept in game theory, whereas many definitions are based on Shoham and Leyton-Brown (2009).
Preferences are often measured by ***cardinal*** or ***ordinal utility functions***. Interpersonal comparisons are only possible with cardinal functions.
Most of microeconomic results hold for all monotonic transformations of utility. ***Social welfare functions*** map utility functions to allocations or social choices. An utilitarian welfare function sums the utility of each individual in order to obtain society's overall welfare. In this context, we also want to describe the four axioms that describe rational behavior of individuals (see Kuhn et al. (2007) and Holt (1986)):

1. ***Completeness***: For any two alternatives, A and B, an individual either prefers A over B, or prefers B over A, or is indifferent between the two;

[3] http://stakeholders.ofcom.org.uk/spectrum/spectrum-awards/

therefore, one and only one of the following holds: $A < B$, $A > B$ or $A = B$.

2. ***Transitivity***: In case of a third alternative, C, it holds that $A < B$ and $B < C$ imply $A < C$.

3. ***Continuity***: $A < B < C$ implies the existence of an α such that: $A \cdot \alpha + C \cdot (1 - \alpha) = B$.

4. ***Independence***: The preference relation between two alternatives, A and B, holds independently of the possible existence of a third possible ("irrelevant") outcome: If $A < B$, then for any alternative C it holds $p \cdot A + (1 - p) \cdot C < p \cdot B + (1 - p) \cdot C$.

A decision maker whose preferences satisfy the four axioms is said to have a ***von Neumann-Morgenstern utility function*** (see Kuhn et al. (2007)), which is usually used to model rational decision makers.

2.2.1 Relevant game-theoretical solution concepts

Theory is not always the proper approach to answer all questions regarding bidding behavior and different auction formats. However, in this chapter, we present some theoretical foundations of Bikhchandani and Ostroy (2002) and Ausubel and Milgrom (2006) to provide understanding for equilibrium strategies.
In game theory, researchers are mainly interested in the outcome of the game. Participants are predefined with a set of possible strategies they can play.
Conversely, in mechanism design, the rules for a game like the auction format are defined. The result might change due to different rules or restrictions. Shoham and Leyton-Brown (2009) describe ***static games*** as ***normal-form games***, which consists of a tuple I of n players, their ***action profile*** and ***utility functions***. In the action profile all possible actions are summarized. Each player will choose his actions to maximize his own utility, i.e., ***expected payoff***, which is common knowledge. Such games are known as ***complete information*** games, since bidders know all possible actions including the corresponding utility and the number of competitors.

Shoham and Leyton-Brown (2009) define a ***pure strategy*** when a player chooses one single action to play. Conversely, in a ***mixed strategy*** a player

chooses two or more different actions based on certain ***probabilities***. A temporal structure can be modeled as ***extensive-form*** game using a tree, where you can note other bidders' behavior. Hereby, the choice of a bidder is represented by a tree node, the possible action by an edge. In the leaves, the final outcome of a player is noted.
In ***perfect information*** games, nodes which contain bidders' utility can be seen by all players during the game. However, in auctions, bidders' payoffs are private, so auctions can be described as an ***incomplete information*** game. Shoham and Leyton-Brown (2009) show that the uncertainty about the number of competitors and their available auctions can be reduced to the uncertainty about payoff. In a ***Bayesian game players' types***, i.e,. all the private information, and ***the probability distribution*** over the players' types are added compared to a normal form game. Bidders' utility function is dependent on both the action profile and the players' types. In bidders' private information, their own valuations and beliefs about others' valuation profile are summarized.

A solution concept formulates rules and predicts the result of a game (Vazirani et al. (2007)).
The following definitions are based on Ziegler (2012). Bidder i's objective is to maximize his payoff, whereas his behavior is dependent from the current prices and other bidders' strategies. If he knows these, then he can compute his ***best-reply*** to these strategies, i.e., to choose the payoff maximizing decision.
We define in the following important solution concepts and provide examples by theorems, which can be also found in Krishna (2002). Bidder types, i.e., their valuation v, are supposed to be private, independent and identically distributed and bidding strategies denoted by $\beta(v)$.

In a ***Pareto-dominated*** strategy profile, some player can be made better off without making anyone else worse off. Pareto domination gives a partial ordering over strategy profiles. Consequently, a single best outcome cannot be identified. A strategy is ***Pareto-optimal***, or is strictly ***Pareto-efficient***, if there is no strategy that dominates this strategy. Every game has at least one optimum like this.

Definition 1. *If in a strategy profile every player's strategy is a best reply to the strategies of the opponents, then the strategy profile is called* **Bayes-Nash**

equilibrium. *Best responses are evaluated after a player learns his private information, but before he learns the private information of the other players.*

In a Nash equilibrium, it makes no sense for a single bidder to deviate from the strategy if the other bidders follow the Bayes-Nash equilibrium strategy, i.e., behave risk-neutral. If a prediction was not a Nash equilibrium, it would mean that at least one individual will have an incentive to deviate from the prediction and thus increase his utility.
According to Shoham and Leyton-Brown (2009) every game has at least one Nash equilibrium, but it may not be in pure strategies. There is a considerable amount of literature devoted to the conditions under which a pure strategy equilibrium can be guaranteed (see (Maskin and Dasgupta (1986) or Milgrom and Roberts (1990)).

Theorem 1. ***Bayes-Nash equilibrium***. *In the first price sealed bid auction with n bidders, whose values are uniformly distributed on $[0, 1], \beta(v) = \frac{n-1}{n}v$ is a Bayes Nash equilibrium. Hereby, β is a symmetric, strictly increasing and differentiable strategy (see Krishna (2009) and Krishna (2002)).*

A stronger concept is the ***Ex-Post Nash Equilibrium***.

Definition 2. ***Ex-Post Nash Equilibrium.*** *Each player's equilibrium strategy remains an equilibrium even after learning the realization of each player's private information.*

Theorem 2. *In the English auction, $\beta(v) = v$ is an Ex-Post Nash equilibrium (see Krishna (2002)).*

If every opponent behaves truthfully, each bidder will stay in the auction until his value v is reached. It is an Ex-Post Nash equilibrium to increase the bids gradually; however, it is not a dominant strategy. It is not always the optimal strategy to increase the bids truthfully by the minimum amount required unless every opponent follows it. Hence, a gradual bidding strategy is not dominant.

In contrast, in first-price sealed-bid auctions truthful bidding always results in a zero payoff. On the one hand, bidders know that the higher the amount of ***bid shading***, i.e., the difference $v - b(v)$, the higher their payoff can get. On the other hand, the lower the bid shading, the higher the probability of winning. Bidders have to define their optimal level of bid shading, what is only possible, when they know the opponents' strategies and valuations.

The strongest solution concept is a ***dominant strategy equilibrium***, where bidders do not have to speculate about opponents' strategies or types.

Definition 3. ***Dominant Strategy Equilibrium.*** *Each player's strategy is a best response, regardless of the strategies of the other players. It is robust to be uncertain about the strategies adopted by the other players and their private information.*

Obviously a dominant strategy equilibrium is also a Nash equilibrium.

Theorem 3. *In the second-price or VCG sealed-bid auction, $\beta(v) = v$ is a dominant strategy (see Vickrey (1961)).*

Bidders cannot influence the pay price by their own bid, since they always pay the price of the second best bid. If they bid above v, they risk making a loss when the pay price is higher than their own valuation. Conversely, bidding less than v might result in another bid winning.
Under certain assumptions, the first-price and VCG sealed-bid auction end in

the same revenue for the auctioneer (***Revenue Equivalence Theorem***). This is the case when bidders are risk-neutral and symmetric, the number of participants is known, the IPV condition is kept and the payment is a function of bids alone.
However, these assumptions are not always realistic. In lab experiments and in real-world auctions, bidders are often risk-averse. Value models are sometimes better described as affiliated or common values. Furthermore, bidders can often be clustered into recognizably different classes (e.g., high-price and low-price bidders) and are not symmetric. In practice, an explicit or implicit participation fee is a problem, and the number of auctions is unknown, for example in online auctions.

By an auction or other allocation mechanisms, ordinal preferences have to be aggregated. One possibility is voting rules that take as input a vector of votes (submitted by the voters). The output contains either the winning candidate or an aggregate ranking of all candidates. However, according to Arrow (1950), there is no voting rule for the aggregation of preferences that is simultaneously Pareto efficient, non-dictatorial and independent of irrelevant alternatives. An alternative to make social choices is a market mechanism where the price is expressed in terms of money. Here, dominant strategies can be obtained, but preferences have to be restricted.

In mechanism design, we will assume ***quasi-linear bidder utilities***.
We define for that purpose, that a bidder i has a type Θ_i. The outcome $o = (x, p)$ is determined by the auctioneer based on reported preferences, i.e., bids. The auctioneer wants to maximize the social welfare. Hereby, x is the obtained allocation and p the price vector.
Using these definitions we can formulate a quasi-linear function as $u_i(o, \Theta) = u_i(\Theta, x) - f(p_i)$. The function $f(p_i)$ characterizes the risk attitude and the monetary value for bid, and the value of money. Generally, in auction theory agents can transfer utility via money (transferable utility).
If we assume a reverse auction with a combination of items S and a risk-neutral bidder we get as utility $\pi_i(S, \mathcal{P}_{pay}) := p_{pay,i}(S) - x_i(S)$ and $\pi_i(\emptyset, \mathcal{P}_{pay}) := 0$ [4]. This implies that the bidders have no budget constraints and do not care how much others pay.
Objectives in mechanism design are ***efficiency***, ***truthful revelation of***

[4] For sales auction the utility is defined as $\pi_i(S, \mathcal{P}_{pay}) := v_i(S) - p_{pay,i}(S)$ and $\pi_i(\emptyset, \mathcal{P}_{pay}) := 0$ vice versa.

preferences, i.e., there is no motivation to lie about one's own valuation, ***individual rationality*** and ***budget balance***, i.e., the sum of payments is 0. A ***direct-revelation mechanism*** might fulfill that goal since the optimal strategy is to announce his private information. A mechanism is ***incentive compatible*** if truth telling by all agents is in equilibrium.

2.2.2 Bidders' risk attitudes

Before we start with some definitions, we introduce three types of risk attitudes. A similar classification was developed and applied by Bernoulli (1954), Friedman and Savage (1948) and Pratt (1964). Risk attitudes are frequently used as an explanation in literature when bidders deviate from an equilibrium bid prediction.

Let's assume the following example. A person has the choice between getting a certainty equivalent in the value of \$0.5 and participating in a lottery. In the lottery he earns at 50% \$1 and at 50% nothing. The expected payoff is the same in both scenarios, namely \$0.5.
A ***risk-neutral*** person maximizes his expected earnings. Consequently, he is indifferent to getting the certainty equivalent or taking part in the lottery. His decision is not affected by the degree of uncertainty. In auctions, where a risk-neutral Bayesian Nash equilibrium strategy is known, these bidders play exactly this strategy.

If a person accepts a certainty equivalent less than \$0.5 instead of playing the lottery, he behaves ***risk-averse***. In reverse auctions, risk-averse bidders usually apply underbidding as opposed to the equilibrium strategy, i.e., they bid with a smaller margin in order to ensure that they win[5]. A more detailed discussion can be found in chapter (3.2). The difference between the expected value and the certainty equivalent is defined as insurance premium. In first-price or Dutch auctions, risk-averse bidders will get higher expected revenue than in second-price, Japanese or English auctions.

Risk-seeking people even disregard a certainty equivalent higher than \$0.5 and prefer to play the gamble to gain a risk premium. However, we have

[5]Similarly, in forward auctions, overbidding is a widespread phenomenon.

to note that the degree of risk aversion and risk taking strongly depends on bidders' risk profile. Generally, risk-seeking bidders achieve a higher expected revenue second in second-price, Japanese or English auctions than in first-price or Dutch auctions.

2.3 Classification of experimental objectives

The main findings in this thesis are based on experimental work. Roth (1988) describes experiments as tool to study the behavior of subjects in a controlled environment. Experiments can be held as field studies or laboratory experiments to study human behavior in markets.

Field studies are often applied in existing applications like eBay to analyze real-world data. According to Lusk and Shogren (2007) it can be assumed, that the participants are aware of the rules and the environment, whereas no additional introduction into such a framework is needed. Aronson and Carlsmith (1968) identify the problem that external factors cannot be controlled by the experimenter and no given assumptions can be tested explicitly.

2.3.1 Types of experiments

Davis and Holt (1992) classify experiments into the classes ***test of behavioral hypothesis***, ***theory stress tests*** and ***searching for empirical regularities*** from a theoretical perspective.

Often, economic theories, like Bayesian Nash equilibrium strategies discussed in this paper are evaluated in the laboratory (see Chapter 3) by the first category. It will be checked, if certain assumptions of a theoretical model hold up in realistic settings (Davis and Holt (1992)). The experimental environment has to be defined as similar to the assumptions as possible in the model to get conclusive results. Often bidders deviate from the theoretical prediction. A discussion about that topic in the first-price sealed-bid auction context can be found at Chapter 3. By analyzing the structural assumptions and the experimental evidence, experiments can engender new theories, like the effect of risk aversion, which can lead to further theoretical and experimental research.

Davis and Holt (1992) describe the stress test theory, where the sensitivity of hypotheses is tested to measure the robustness of practical implications. In such experiments, several assumptions are marginally changed and the resulting outcome is checked. Often the amount of information is varied to explore how bidding behavior changes with more information. If too much information is provided, bidders might be "overloaded", i.e., bidders cannot deal with a high amount of data.

In third class, experiments are hold to find empirical regularities. Frequently, applications of auctions, like in the spectrum context are too complex for a theoretical analysis. Therefore, experimental studies as in Chapter 4 are made to find regularities between observed economic variables.

In contrast, Kagel and Roth (1995) distinguish different kinds of experiments concerning their purpose and define the classes ***speaking to theorists***, ***searching for facts*** respectively ***searching for meaning*** and ***whispering in the ears of princes***.

In the first class hypotheses are falsified, in the second one sensitivity analyzes of variables are made to widen the theoretical scope. If the experimenter finds some regularities, follow-up experiments might be designed as "searching for meaning experiments". Experiments belonging to the last class try to explore new policies and their impact on the market. Here, the real-world is modeled in the laboratory to give advice to responsible authorities for designing mechanisms in certain markets.

Both Davis and Holt (1992) and Kagel and Roth (1995) define the categories, test of a theory, and searching for empirical regulations/implications. In our thesis, both categories are analyzed at Chapter 3 and Chapter 4.

In lab experiments, if designed well, the experimenter can control any external effect. It is indispensable to define treatment variables, like auction, value models, payment rules, etc. that reflect the decisive parameters (Lusk and

Shogren (2007)). One downside is that the outcome of lab experiments might differ from real-world behavior. Aronson and Carlsmith (1968) state that subjects are likely to deviate from their natural behavior in artificial environments.

2.3.2 Validity of experiments

Aronson and Carlsmith (1968) define ***internal validity*** as the degree of confidence concerning results that are obtained from experimental data. The objective is to minimize systematic errors under the assumption that the controlled independent variable is the only reason for changes in the dependent variable. If significant systematic errors occur, the experimental design might not reflect all impact factors. According to Aronson and Carlsmith (1968, p. 129), the "essence of good experimental design is to control the assignment of participants to treatment groups and the conditions of treatment delivery in such a way as to rule out or minimize threats to the internal validity of the study."

In contrast, by ***external validity*** the generalization of experimental results is checked. "External validity refers to the robustness of a phenomenon - the extent to which a causal relationship, once identified in a particular setting with particular research participants, can safely be generalized to other times, places, and people." Aronson and Carlsmith (1968, p. 130). Lusk and Shogren (2007) conclude the experiments with students are proper to observe general behavioral phenomena.

Validity guarantees that the results of laboratory experiments are trustworthy. A decisive factor is the reward mechanism to control participants' motivation. Fundamental work in this area was done by Smith (1976). To get reliable results, the experimental design should induce new preferences and neutralize humans' individual preferences. All actions done in the experiment should only be determined by the "induced preferences".
The total money holding of a participant can be defined as the sum of earnings based on the experimental outcome and his private initial endowment independent from the experiment. Subjects' unobservable preferences are determined by the money holding and other motives according to Smith (1976).

Assumptions for controlling preferences are ***monotonicity*** or ***nonsatiation***. People should not be satiated by financial reward and their utility should be a monotone increasing function of the payoff they get from the experiment. ***Dominance*** means that changes in subjects' utility are mainly based on the earning in the lab experiment; other motives can be neglected. If monotonicity and dominance are realized, subjects preferences are induced successfully.

Experiments with a long duration and many rounds should be avoided, since these might be recognized as boring. Also public information about individual payoffs can effect motives like envy, fairness and spite. Some experimenters might give subtle hints for what subjects should do, whereas subjects want to help or hinder the experimenter.
To avoid these problems, the performance based payment in the experiment should be large enough and flat payment, like show up fee, quite low. Also a neutral language in the instructions is helpful.
In a follow up paper of Smith (1976), Smith (1982) gives further suggestions in addition to dominance and monotonicity to create a well-defined environment in the laboratory, where the relevant variables can be measured and controlled.

Saliency means that people should understand the reward mechanism. As we did in our instructions, the performance-based financial payment to the subjects has to be explained in addition to the auction formats. Then, the participants develop trust in the auctioneer and understand the impact of their actions on the reward. When both monotonicity and saliency are fulfilled, the participants are motivated by monetary incentives and an experimental microeconomy is created. Within this environment hypotheses can be tested and internal validity is given.

Privacy is realized when the participants in the experiment only know their own valuation and payoff alternatives but not others'. Generally, information about others' payoffs should not become public and the purpose of the experiments can only be explained afterwards.

Parallelism describes the situation when the experimental environment models the real-world well, i.e., propositions about the market mechanism and the behavior of subjects are fulfilled. This condition is important when results that are obtained by experiments are supposed to be transferred to reality (external validity).

There is always a trade-off between internal and external validity. "Where internal validity often requires abstraction and simplification to make the research more tractable, these concessions are made at the cost of decreasing external validity." Schram (2005, p. 130). Good experimental design balances this tension in order to achieve meaningful results that can be applied to real life settings. If the abstraction is high and the complexity of the reality is reduced, e.g., when fewer items are sold, the internal validity increases, since experimental results are more tractable and reproducible. Smith (1985) states, that in some situations experimental results with high external validity can differ fundamentally from the predicted results. Conversely, findings of experiments with high internal validity can be transferred back to complex real-world applications.

The construction of validity refers to both the correct identification of independent and dependent variables and the underlying relationship between them. Another necessary but not sufficient condition for validity is reliability, which describes how repeated measurements of values relate to each another (Lusk and Shogren (2007)).
To sum it up, internal validity is provided if robust and replicable results can be produced. External validity checks if findings from the lab environment can be transferred.

When the focus of experiments is on a practical application, Friedman and Sunder (1994) state that it is natural to reward subjects with money. Read (2005) concludes that humans behave rationally, if they are motivated by monetary rewards. A mixture between fixed and performance-based income might make sense as applied in chapters (3.2) and (4.3.4). On the one hand, people get some show-up fee, so that they are compensated for their effort; on the other hand they are extrinsically motivated to perform at a high level.
For testing a theoretical model, the validity is determined by the reconstruction in the laboratory.

If it is not possible to reflect the reality in the lab, it is rather a problem of the economic model, which should be orientated closer to reality and not of the experimenter (see Guala (2005)). When the complexity of the target environment is too high to model in detail, the experimental environment might be too abstract and hence the results leave some room for interpretation (Friedman and Sunder (1994)). For example, in chapter (4.3.4), a specific market was not modeled, but a general structure which can be found in the sales of spectrum licenses. However, the implementation is in each market different. Hence, we can not give recommendations to decision makers in one specific country, but define guidelines that should be considered when auctions are designed.

Chapter 3

Split-award auctions

In this chapter which is based on joint work of Bichler et al. (2014a), a simple setting in the reverse auction context is introduced. The formulation of the equilibrium strategy was done by Kemal Guler. Conversely, the implementation of the auction platform, the experiments and the data analysis were my key part and are described detailled in this thesis.

Split-award auctions are a simple but wide-spread type of multi-object auction which is often used for multi-sourcing. Companies like Sun and HP procure products valued at several million Dollars using different types of multiple sourcing auctions (Tunca and Wu (2009)). Elmaghraby (2000) gives a literature overview on sourcing strategies and recommendation for the supplier selection process.
According to Major (2005) online procurement auctions can result in an average price reduction from 10 to 30 percent in comparison to traditional pricing methods.

Allowing access to a larger supplier base, reducing the procurement time cycle and achieving competitive market prices are factors that contribute to the rapid spread of reverse auctions. Similar mechanisms can be found in the sales of frequency licenses (Wambach (2002)) and electricity (Luiz et al. (2011)). In real-world business, more and more firms are using auctions with non-identical objects to procure raw materials. These firms usually want to have more than just one supplier for risk considerations, to reduce safety stocks and therefore, the total inventory-system costs. An efficient supply chain is crucial for companies' success. Especially in manufacturing, procurement costs are the main cost driver (see Cavinato (1994)). Good practical reports about current applications of reverse auctions and corresponding (dis-) advantages can be found within Wyld (2012a) and Wyld (2012b).

3.1 Auction formats

We introduce two sealed-bid single-item multiple lot split-award auctions which are multi-object extensions of the first-price sealed-bid auction. In this environment 2 items, from now on called ***lots***, of the same raw material are bought via split-award auctions.
The setting for all auctions we focus on is the same and based on our joint work in Bichler et al. (2014a).

A procurement manager buys a given volume of a product using an auction. The total required amount is ex-ante divided into into two lots with a share of q in ***lot 1*** and $(1-q)$ in ***lot 2***. We further assume that $q > 0.5$, whereas lot 1 is the ***large lot*** and lot 2 the ***small lot***. For our theoretical consideration the whole volume is normalized to one unit. An amount of n risk-neutral bidders competes for the $m = 2$ lots. Bidder i's private constant marginal production costs c_i are identically and independently distributed according to a uniform distribution with $F(c_i) = \frac{c_i - \underline{c}}{\overline{c} - \underline{c}}$ and the density function $f(c_i) = \frac{1}{\overline{c} - \underline{c}}$ with support $[\underline{c}, \overline{c}]$.
Besides the per-unit production costs c_i, each supplier must also incur fixed costs K to complete the production, which are equal and public information for all bidders. Finally, we assume that there is no reservation price.

3.1.1 The single-lot auction

Before we describe the split-award outcome, we consider the single-lot case with $q = 1$, which is a standard sealed-bid first-price auction with n bidders competing for the single-lot. In this ***winner-takes-all format*** one bidder wins the whole amount and a split outcome is excluded. Hence, in theory, the procurement costs for the buyer might be lower in a short-term view, since the bidder with the lowest c_i might win the full amount. The difference between the procurement costs in the single-lot and split-award auction can be interpreted as price for the insurance premium. Especially, risk-averse companies might be willing to pay these higher costs.

The equilibrium strategy can be denoted as the standard Bayesian Nash equilibrium strategy by

$$\beta(c_i) \quad = \quad c_i + K + \int_{c_i}^{\overline{c}} \left(\frac{1 - F(x)}{1 - F(c_i)} \right)^{n-1} \quad dx. \tag{3.1}$$

In this case, the boundary condition has to be kept so that the bid does not exceed the highest costs a bidder can receive $\beta(\overline{c}) = \overline{c} + K$.

3.1.2 The parallel auction

The first split-award auction introduced is the ***parallel auction***. The rules of the ***sealed-bid parallel auction*** are as follows:
After having observed his private per-unit constant marginal production costs c_i each bidder can submit two bids for the different lots.
Hereby, b_i^1 is bidder i's per-unit price for the large lot and b_i^2 for the small lot. The lots are awarded to the lowest bid on each lot and the winning bidder gets the contract at his bid price. If one bidder has the lowest bids on both lots, he will only win the large lot. We will denote the expected payoff of bidder i whose bids are b_i^1 and b_i^2 by $\Pi(b_i^1, b_i^2, c_i)$.
Then

$$\begin{aligned} \pi(b_i^1, b_i^2, c_i) = {} & \Pr(\text{bidder } i \text{ wins both lots}) \cdot \left[\left(b_i^1 - c_i \right) q - K \right] \\ & + \Pr(\text{bidder } i \text{ wins lot 1 and loses lot 2}) \cdot \left[\left(b_i^1 - c_i \right) q - K \right] \\ & + \Pr(\text{bidder } i \text{ loses lot 1 and wins lot 2}) \cdot \left[\left(b_i^2 - c_i \right) (1 - q) - K \right]. \end{aligned} \tag{3.2}$$

The three terms in equation (3.2) reflect the three possible outcomes of the auction game. Losing the game is not considered in the equation, but if a bidder gets no lot, there is no payment for him (individual rationality). The first possibility is that a bidder submits the lowest bid on each lot and hence, he could win both lots. But, if we consider the auction rule, he is only awarded the large lot to ensure the split-award outcome. The second possibility is that he only wins the large lot and the last term describes the situation, where he only wins the small lot. Conditional on other bidders behavior, bidder i chooses the bidding strategy by maximizing the expected payoff.

In Bichler et al. (2014a) Bayesian Nash equilibrium strategies are developed for the Yankee and also the parallel auction. In these strategies bids are supposed to be continuous, strictly increasing and almost everywhere differentiable functions of costs. It is not the focus of this work to derive the strategy. The detailed assumptions and proofs can be found at Bichler et al. (2014a). The equilibrium strategies for the small and the large lot are defined as $\beta_2(c)$ and $\beta_1(c)$. Bidders receive what they bid, since we assume a simple first-price payment rule.

Proposition 1: *In the parallel sealed-bid first-price procurement auction model with two lots and n risk-neutral bidders, the symmetric Bayesian Nash equilibrium bidding strategies for the large $\beta_1(c)$ or small lot $\beta_2(c)$ are given by:*

$$\begin{aligned}\beta_1(c_i) =& c_i + \frac{K}{q} + \frac{1}{q[1-F(c_i)]} \cdot \int_{c_i}^{\overline{c}} \left(\frac{1-F(x)}{1-F(c_i)}\right)^{n-2} \cdot \Bigg[q\,[1-F(x)] \\ &+ (1-q)(n-1)[F(x)-F(c_i)] \Bigg] \quad dx\end{aligned} \tag{3.3}$$

with the boundary condition $\beta_1(\overline{c}) = \overline{c} + \frac{K}{q}$.

$$\beta_2(c_i) \quad = \quad c_i + \frac{K}{1-q} + \int_{c_i}^{\overline{c}} \left(\frac{1-F(x)}{1-F(c_i)}\right)^{n-2} \quad dx \tag{3.4}$$

with the boundary condition $\beta_2(\overline{c}) = \overline{c} + \frac{K}{(1-q)}$.

Besides, $\beta_1(c_i)q > \beta_2(c_i)(1-q)$ and $\beta_2(c_i) > \beta_1(c_i)$ under the condition that K is bigger than a threshold K_0.

$$\begin{aligned}K_0 :=& \frac{(1-q)}{(2q-1)} \cdot \int_{c_i}^{\overline{c}} \left(\frac{1-F(x)}{1-F(c_i)}\right)^{n-2} \\ &\left[\frac{[nq-(n-1)]\,[F(x)-F(c)]}{1-F(c)}\right] dx.\end{aligned} \tag{3.5}$$

In our experiments with the parallel auction, we tested if subjects were able to follow the equilibrium strategy defined in proposition 1. It is not obvious that humans can mimic the ***Risk-Neutral Bayesian Nash Equilibrium Bidding Strategy*** (***RNBNE***) given the distribution of the variable costs, their variable costs, the number of participants and the fixed costs.

However, proposition 1 calls for a few comments. First, as we have seen above, the equilibrium bidding function for the small lot is the same as the bidding strategy in a standard sealed-bid first-price auction with n bidders competing for the small lot (see equation (3.1)). Second, the bidders bid less aggressively than the equilibrium bid they submit in a standard sealed-bid first-price auction with bidders competing for the large lot. This is because the bidders need to take into account the possible loss from losing the large lot and winning the small lot when they submit bids for the large lot. Third, ex-post, the winning bidders make positive profits no matter which lot they get. The detailed proof for the RNBNE can be found at Bichler et al. (2014a) and would be beyond the scope of this thesis.

Proposition 2: *In the parallel sealed-bid first-price procurement auction model with two lots and n risk-neutral bidders,*
(i) As n increases, bidding becomes more aggressive for both lots:
$\frac{\partial \beta_1(c)}{\partial n} < 0$ *and* $\frac{\partial \beta_2(c)}{\partial n} < 0$.
(ii) As q increases, bidding becomes more (less) aggressive for the large lot 1 (the small lot 2):
$\frac{\partial \beta_1(c)}{\partial q} < 0$ *and* $\frac{\partial \beta_2(c)}{\partial q} < 0$.

Proposition 2 is partly proven within this thesis, since we ran experiments both with $q = 0.7$ and $q = 0.9$. In further research, it would be interesting to vary the number of bidders.

3.1.3 The Yankee auction

After having discussed the parallel auction, we focus now on the second format, the ***Yankee auction***.

In contrast to the parallel auction, each bidder i can only submit one bid b_i as the per-unit price for both lots of the product in the ***sealed-bid Yankee auction***. The large lot is awarded to the bidder with the lowest bid and the small lot to the bidder with the second lowest bid. If both bidders submit exactly the same bid, the winner will be determined at random. As for the parallel auction, the first-price payment rule is used. In this auction model, the expected payoff for bidder i is denoted by

$$\begin{aligned}\pi(b_i, c_i) = {} & \Pr(\text{bidder } i \text{ wins lot 1}) \cdot \left[(b_i - c_i)\, q - K\right] \\ & + \Pr(\text{bidder } i \text{ loses lot 1 and wins lot 2}) \cdot \left[(b_i - c_i)\,(1 - q) - K\right].\end{aligned} \tag{3.6}$$

Conditional on other bidders behavior, bidder i chooses the bidding strategies by maximizing the expected payoff (see equation (3.6)). As for the parallel auction, this work is restricted to strictly increasing differentiable symmetric RNBNE strategies.

Proposition 3: *In the Yankee sealed-bid first-price procurement auction model with 2 lots and n risk-neutral bidders, the increasing symmetric Bayesian Nash equilibrium bidding strategy is given by:*

$$\begin{aligned}\beta(c_i) = {} & c_i + \frac{\int_{c_i}^{\overline{c}} \left[1 - F(x)\right]^{n-1} q + (n-1) \cdot F(x) \left[1 - F(x)\right]^{n-2} (1-q) dx}{\left[1 - F(c_i)\right]^{n-1} q + (n-1) \cdot F(c_i) \left[1 - F(c_i)\right]^{n-2} (1-q)} \\ & + K \cdot \frac{1 + (n-2) \cdot F(c_i)}{\left[1 - F(c_i)\right] q + (n-1) \cdot F(c_i)(1-q)}\end{aligned} \tag{3.7}$$

with the boundary condition $\beta(\overline{c}) = \overline{c} + \frac{K}{1-q}$.

Corollary 1: *In the Yankee sealed-bid first-price procurement auction model, ex-post,*
(i) the winner of the large lot always makes a positive profit and
(ii) the profit for the winner of the small lot can be either positive or negative.

Corollary 1 reveals an important difference between the two models. In the parallel auction mechanism, bidders bid in such a way that, ex-post, they always make a positive profit no matter which lot is awarded.

Conversely, in the Yankee mechanism, ex-post, the bidder who wins the small lot will earn either a positive or negative profit depending on his private

production costs. This implies that bidders with high production costs will probably refrain from participating into such auctions since they are not likely to win the large lot. If they win the small lot, the probability of losing money will be high.
An analogy between the Yankee auction and the war of attrition is obvious (see Krishna and Morgan (1997b)).

In the war of attrition or second-price all-pay auction, each participant has to pay his bid except for the winning bidder who pays the second highest bid. Although this concept was originally formulated in the context of animal conflicts (see Smith (1974)), the behavior patterns and the models were adapted to auction theory. Such competitive situations occur when participants efforts are quite costly, and losers are not compensated for these efforts (Gneezy and Smorodinsky (2006)). Such situations can be found in various settings, e.g., in politics, decision making in committees and oligopolies (see for more details Bulow and Klemperer (1999)).

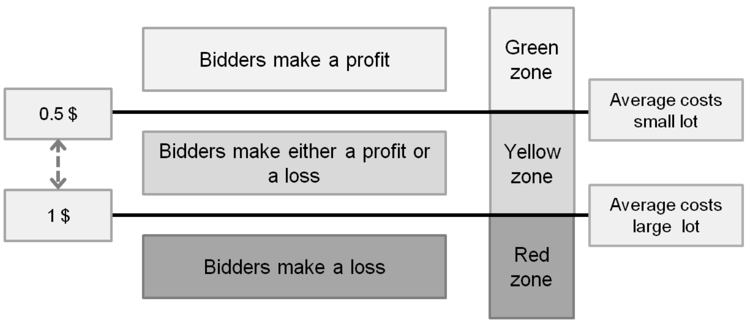


FIGURE 3.1: Similarities of the Yankee and the Dollar auction.

The Dollar auction is a famous example for wars of attrition in auctions (Shubik (1971)). The auctioneer offers \$1 to two bidders with a starting price of zero. Each bidder can decide if he bids more than the current price or drops off the auction by paying the market price. The auction terminates when no bidder is willing to bid more than the previous bidder. Then, the bidder with the highest bid wins the Dollar note for his bid price, but also the second highest (loosing) bidder has to pay. If the price is lower than \$0.5, both players could cooperate and share the profit. By this strategy, both bidders would get a positive payoff.

Similarly in the Yankee auction, when bidders' average costs, i.e., the variable costs and the normalized fixed costs, for the small lot are higher than the bid, then they definitely end up in a profit. But if the bid is between the average costs for the small and the large lot, bidders might either make a loss if they get the small lot or a profit if the large lot is assigned to them. In the $ auction, this situation occurs when the price is between $0.5 and $1.0 because there is no motivation to cooperate any more. Bidders who bid lower than the average costs for the large lot always make a loss. In the $ auction, nobody has a positive earning, when the price gets higher than $1. The analogy is summarized in figure (3.1).

Besides the similarities, there are two main differences between the Dollar and the Yankee auction.
First, subjects in the Dollar auction are completely informed about the value of the auctioned object, namely $1. In our setting, they only know the common fixed costs but not the others' variable costs.
Second, in the Dollar auction, after having agreed to participate in the auction, there is no way to leave the auction out without making a loss (Mayer and Louca (2013)). In the Yankee auction, the winner can avoid making a loss if he never bids below his average variable costs for the small lot.

Krishna and Morgan (1997a) compare equilibrium strategies in all-pay auctions as well as in wars of attrition with affiliated values where losing bidders are also required to pay positive amounts. Thereby, they extend the work of Milgrom and Weber (1982a) for the sealed-bid case. Hoerisch and Kirchkamp (2009) also analyze equilibrium strategies in all-pay auctions and wars of attrition for both sealed-bid and iterative auction mechanisms.

Proposition 4: *In the Yankee sealed-bid first-price procurement auction model with two lots and n risk-neutral bidders,*
(i) As n increases, bidding becomes more (less) aggressive if the fixed cost K is greater than (smaller than) a threshold

K_1: $\frac{\partial\beta(c)}{\partial n} > 0(< 0)$ *if* $K > (<)K_1(n, c, F)$, *where*

$$K_1(n, c, F) = \frac{\int_{c_i}^{\overline{c}} A + B + D \quad dx}{[1 - F(c_i)]^n F(c_i)(2q - 1)}, \text{ and}$$
$$A = [F(c_i) - F(x)][1 - F(x)]^{n-1}[1 - F(c_i)]q^2,$$
$$B = [F(c_i) - F(x)][1 - F(x)]^{n-2}F(x)F(c_i)(1 - q)^2,$$
$$D = [F(c_i) - F(x)][nF(c_i) - 2(n - 1)F(c_i)F(x) + nF(x) - 1]$$
$$[1 - F(x)]^{n-2}q(1 - q).$$

(ii) As q increases, bidding becomes more (less) aggressive if the fixed cost K is greater than (smaller than) a threshold
K_2: $\frac{\partial\beta(c)}{\partial q} > 0(< 0)$ *if* $K > (<)K_2(n, c, F)$, *where*

$$K_2(n, c, F) \quad = \quad \frac{1}{1 + (n - 2)F(c)} \frac{n - 1}{n(F(c) - 1)} \int_{c_i}^{\overline{c}} \left(\frac{1 - F(x)}{1 - F(c)}\right)^{n-2} [F(x) - F(c)]dx.$$

In chapter (3.3) our experiments only partly support proposition 4.

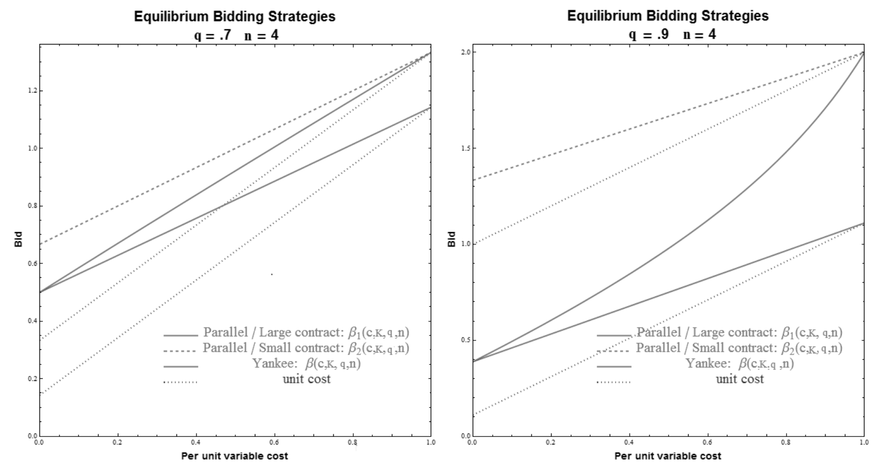


FIGURE 3.2: Bidding functions for the standard uniform distribution in the parallel and in the Yankee auctions in a market with 4 bidders and a split parameter of q=0.7 or 0.9.

The Bayesian Nash equilibrium bidding functions for the parallel and the Yankee auction are visualized in figure (3.2). It shows how the bids are modified depending on different cost draws.

3.1.4 Procurement cost comparisons

Having derived the symmetric equilibrium bidding strategies for both the parallel and the Yankee auctions, the implications of the two mechanisms on expected cost can now be compared. The proof for Proposition 5 can be found at Bichler et al. (2014a) and it also follows from Engelbrecht-Wiggans (1988).

Proposition 5: *Suppose that the private production costs are independently and identically distributed and all bidders are risk-neutral. Then, the sealed-bid first-price parallel procurement auction and the sealed-bid first-price Yankee procurement auction yield the same expected costs to the buyer.*

The equivalence result is a useful piece of information for business decision-makers. They can now look into other dimension of the differences between the two formats and recommend which format to adopt in practice without worrying about the expected costs concerns by using different auctions.

3.2 Experimental design

In our thesis, we tested on the one hand 128 participants in the context of forward auctions, but far more, namely 209, were in sealed-bid procurement auctions. By means of this method, our study's main contribution is to determine whether the Bayesian Nash equilibrium is a good predictor for bidding behavior. Before we describe the experimental environment, we give a brief summary about related research in this area, like at Bichler et al. (2014a).

3.2.1 The underbidding puzzle in sealed-bid auctions

Kagel (1995) tested single-lot first-price sealed-bid auctions in the laboratory. They found out that humans overbid significantly, which means, that their bid was higher than the prediction of the risk-neutral Bayes Nash equilibrium. Most of other research papers also tested forward auctions and got similar results. In our thesis we consider sealed-bid procurement auctions in which underbidding, i.e., bidding less than the equilibrium prediction, is a phenomenon. Interestingly, there is hardly any research in this area.

There are several theories that explain the deviation from the equilibrium strategy. Cox et al. (1982) analyze bidding behavior in both single-object

English and Dutch auctions. For the theoretical research, they assume that bidders have identical risk preferences and state that the risk attitude is the decisive parameter for the actual bid. In the experiments they find out that the risk-neutral Bayesian Nash equilibrium function is not a good predictor for human behavior.
Cox et al. (1988) include in their first-price auction model heterogeneous bidders, i.e., bidders can be characterized by a different risk attitude. In their experiments they show that bidders behave ***risk-averse***.
Cox et al. (1992) also support that risk aversion is the main driver that motivates bidders to apply underbidding.
However, it is very difficult to measure risk aversion in the laboratory. Kagel and Levin (2012) proof experimentally that bidders are risk-averse, especially, if the bidder submodularity condition (see a good definition for example at Bikhchandani and Ostroy (2002) respectively Ausubel and Milgrom (2002)) is observed. In such an environment bidders are more valuable when added to a smaller coalition. Hence, risk aversion might be a better predictor than risk-neutrality for bidding behavior in reality. It is quite realistic that a human might prefer to get 10 million Dollars without any risk than to participate in a lottery which yields 100 million Dollar with a probability 10% and otherwise zero.
Rabin (2000) showed that anything but virtual risk neutrality over modest stakes implies unrealistic risk aversion over large stakes.

An interesting approach is done by Isaac and James (2000). They compare estimates of risk preferences from first-price sealed-bid auctions to the Becker-DeGroot-Marshak (BDM) procedure for different risky choices. Aggregate measures of risk preferences under the two procedures showed that bidders were risk-averse in the first-price auction but risk-neutral, or moderately risk-loving, under the BDM procedure. Overall, risk attitudes not only differed across assessment methods, but also varied within the same method (Payne et al. (1980)). This result is also supported by MacCrimmon and Wehrung (1990).
Krahnen et al. (1997) ran experiments to proof if bidders risk attitude can be elicited by certainty equivalents. They found out that the risk attitude between subjects differs a lot and that this individual behavior might be the reason for over- or underbidding. Also, Schoemaker (1993) finds that by testing certainty and probability equivalents, bidders react differently. Therefore, it is hardly possible to characterize bidders' risk attitude. Paired lottery choices, which have been defined by Holt and Laury (2005) became

more popular recently, but risk aversion is still recognized as a complex and context specific phenomenon (Dohmen et al. (2005)).

Besides risk aversion, ***regret*** is a common reason to explain bidders' underbidding. It has been discussed as an effect in many papers; fundamental research is provided at Bell (1982) and Loomes and Sugden (1982). Engelbrecht-Wiggans (1989) state that bidder regret the auction outcome when they see the results. Therefore, they have an incentive to overbid in first-price sealed-bid forward auctions or underbid in reverse auctions. In another paper, they analyze regret experimentally, since they give the bidders different kinds of feedback after the auction. Engelbrecht-Wiggans and Katok (2009) conclude that the more information the bidders get after an auction, the more they regret the result and therefore, deviate from the RNBNE.
Filiz-Ozbay and Ozbay (2007) also assume that deviations from the RNBNE strategy are due to regret. They differentiate between loser regret, i.e., bidders see after the auction the actual winning bid, and winner regret, where bidders see the best loser bid.
Loser regret is defined as a function of the difference between bidders' valuation and the winning bid if the winning bid is affordable. Conversely, winner regret is a function of the difference between actual payment and the minimum amount that would preserve her winning position after she learned the other bids (see also Bell (1982)). They test three different treatments separately. In the first treatment, bidders see only whether they have won or not, in the second one winner regret and in the third looser regret is tested. Their main result is that especially bidders that lost in a previous auction are motivated to underbid to win in one of the following auction. They even resign themselves to making a modest profit, only to expire the joy of winning.

Also ***wrong expectations about other bidding behavior*** (see Kirchkamp and Reiß (2011)) or problems in computing a best response to other bidding behavior (**strategic complexity**) might serve as explanations for underbidding. As we have seen, the derivation of a RNBNE, especially in the split-award context is very complex. Therefore, it might not be realistic that bidders can select the risk-neutral bidding strategy in a short span of time in the laboratory. In the literature, there are contradictory claims as to whether people reason according to Bayesian inference (Gigerenzer and Hoffrage (1995)). We will refer to the problem of deriving the RNBNE bid function based on given prior distributions about valuations as the strategic complexity of the auction. Morgan et al. (2003) show that bidders bid more aggressively when they have spiteful incentives.

Eyster and Rabin (2005) and Crawford and Iriberri (2007) also realize a gap between the bid prediction and the actual behavior of humans in experiments. They state that bidders' expectations about others' preferences are wrong, but the reply due to an expectation is correct. Conversely, Goeree and Holt (2002) assume that the expectations are correct, but bidders do not reply correctly. One reason could be, that they make quantal-response errors. Kirchkamp and Reiß (2011) also argue in the same way.

For Ockenfels and Selten (2005) and Neugebauer and Selten (2006), the main reasons is the experimental structure. Often, participants play many subsequent auctions, whereas they get different kinds of feedback after the termination. This ex-post learning leads to deviations from the RNBNE equilibrium strategy.

Davis et al. (2011) analyze if alternative models other than the RNBNE explain better experimental data in the context of setting an optimal reserve price. Especially, they test risk aversion, anticipated regret, and probability weighting which describes that the human seller might fail to calculate expected utilities correctly. So the number of bidders is changed between the different treatments. They report that risk aversion explains the underbidding for only a few bidders. However, it does not predict a dependence between the reservation prices and the number of bidders. Regret describes most of the qualitative aspects of their data. This phenomenon even explains that the optimal reserve price increases with the number of bidders. Probability weighting explains the behavior worse than risk aversion or regret, but better than the RNBNE prediction.

The literature on explaining underbidding and on risk aversion is huge and beyond the scope of this section. In general, cognitive bias arises from various processes that are sometimes difficult to distinguish. These include information processing heuristics, limited information processing capacity of humans, emotional and moral motivations, or social influence. In the auction literature, risk aversion, regret, spite, and wrong expectations about the bids of others are the most common hypotheses for underbidding in first-price sealed-bid auctions.

We do not intend to discuss and define all the possible behavioral reasons for underbidding in detail, but propose experimental designs with different levels of control for these hypotheses. In our computerized experiments, expected utility maximization should be the dominant force.

3.2.2 Treatment combinations

In our experiments we tested if bidders were able to mimic the theoretical predictions in the laboratory. In order to get robust results, we tested different designs and varied the level of control. Humans had to play both against other humans and computers. The computerized experiments are conducted to understand whether bidders are able to mimic their RNBNE strategy or whether the strategic complexity is too high and bidders deviate from this model. Conversely, in human subject experiments, we test real-world situations. Since we played 16 auctions in each session, bidders had the chance to learn and adapt their behavior. So we could find out, how well the RNBNE strategy explained bid functions in realistic environments with human bidders.

In our treatments, we did not ask bidders to place bids for individual cost draws, but for several possible costs to elicit their bidding function. This strategy method is similar to Selten (1999), Pezanis-Christou et al. (2003) and Güth et al. (2003). For example, in Kirchkamp and Reiß (2011), bidders had to submit bids for six hypothetical valuations in each of the 12 auctions to elicit their bid functions. In each of the treatments, two participants competed for a single-lot. Other experiments show that bidding behavior that is observed with the strategy method is very similar to the behavior observed with alternative methods (Kirchkamp and Reiss (2006)). They explore the approach of playing multiple auctions with a given bidding function and find that playing multiple auctions induces bidders to behave in a more risk-neutral way. They find that a small number of auctions played already eliminate a substantial part of risk.

In the following, we describe the four different treatments, starting with the one with the most control. In **C100+**, one human bidder played against three computerized agents, which used the RNBNE strategy. We let the participants know the computerized competitors had been programmed to bid in a way that would maximize their expected earnings when they bid against competitors programmed in the same way. Their bidding strategies are only based on their cost draw, the distribution of costs, the fixed costs, and the number of competitors, which are known to all bidders. Before each auction, they draw new variable costs. Additionally, we show the RNBNE bid function to the participants as decision support. We tested computerized experiments to avoid wrong expectations about other bidders' behavior, which in the literature is sometimes told as reason why humans are not able to mimic a RNBNE strategy (Kirchkamp and Reiß (2011)). The bid function was used in 100 auctions, where the single human bidder competed against the three computerized agents in each round. As a matter of course, the strategy of the computerized agents did not change across the different auctions. Bidders earned the average payoff over all auctions. By this configuration we tried to induce risk neutrality. For each new auction, we drew a cost value randomly and determined the bid based on the bid function of a bidder. Effects like joy of winning (see for example Dohmen et al. (2011)) and regret (Loomes and Sugden (1982)) were minimized, since bidders did not learn about the outcome of individual auctions or the actual bids depending on the cost of others.

Bidders only had to mirror the RNBNE of their computerized opponents. Since the bidders are all ex-ante symmetric, the information in C100+ implicitly tells the subjects what their equilibrium bidding function would be. Therefore, the participants' task is only, to copy the computer agents' strategy. We consider deviations from the RNBNE in this case as ground noise or irrationality, which provides a baseline for other experiments. We cannot expect subjects in experiments with less control to be closer to the RNBNE prediction.

C100 is almost identical to C100+, but we do not show the RNBNE strategy in the decision support. However, we tell the participants, that all computerized competitors play the same risk-neutral RNBNE strategy. If bidders behave differently to C100+, we explain it by wrong expectations about others. Additionally, the strategic complexity might be too high to deviate a RNBNE strategy in the laboratory. In C100 it is less obvious that bidders would bid their RNBNE bid function. This treatment is similar to Walker et al. (1987), because they also ran experiments with computerized bidders. However, the participants have not been informed about their opponents' strategy like in C100.

For the first two treatments the same bid function was used for 100 auctions, but for **C1** only in a single auction. A different bidding behavior might be due to risk aversion.

In **H**, humans play against each other, whereas we applied random remachting, which means, that they did not know who the opponent was. Such a situation models quite realistic procurement practices. After having assigned the cost draw to the bidders, they were matched to a group of four opponents. Before each of the 16 auctions, different bidders played against each other. In this way, we could exclude collusion and signaling. After each auction, bidders got to know their own cost draw and all bids of other bidders, but not their costs. Similar applications can be found in public sector auctions to combat collusion or bribery (Thomas (1996)). Participants can learn in the 16 played auctions and risk aversion is a pattern, which can be motivated by real-world tenders. Bidders could adapt their bidding costs after each repetition. Conversely to the computerized experiments, which were designed to understand the potential impact of risk aversion or wrong expectations on underbidding, the results of the treatment combination H should have external validity as they are close to real-world practices.

Our hypotheses sum up the discussion above and are explained in detail to comprehend the experimental contribution of this work:

Hypothesis 1: *Bidders in human subject experiments will underbid below the RNBNE bid function due to reasons such as risk aversion, regret, wrong expectations, or strategic complexity.*

As we indeed found underbidding in line with earlier experiments on single-lot auctions, we introduced additional treatments to control for different conjectures why bidders underbid. A second group of treatment combinations (C1) had human subjects compete against computerized agents, which played their RNBNE strategy. Bidders did not learn about other bids in the auction, just whether they won or lost an auction, which should minimize the impact of regret. Of course, risk aversion and wrong expectations can still be a driver for deviations from the RNBNE.

Hypothesis 2: *Bidding against computerized agents without information about the bids of others after the auction mitigates regret and eliminates underbidding.*

The third group of treatment combinations (C100) is identical to C1, but the bid function of a user is reused in a 100 auctions, which should mitigate risk aversion. For each new auction, we drew a cost value randomly and determined the bid based on the bid function of a bidder to participate in an auction against computerized bidders. The subject was then paid the average of his winnings in the 100 auctions. The impact of regret should also be minimal, because bidders did not learn about the outcome of individual auctions or the bids of others. The difference between C100 and C1 provides an estimate for the impact of risk aversion in these auctions.

Hypothesis 3: *Bidding against computerized agents without information about the bids of others, where bid functions are reused in 100 auctions mitigates regret and risk aversion and eliminates underbidding.*

The fourth group of treatment combinations (C100+) uses the same experimental design as C100, but we also provide explicit information about the RNBNE function of the computerized agents. Since the bidders are all ex-ante symmetric, the information in C100+ tells the subjects implicitly what their equilibrium bidding function would be. Bidders should just replicate the RNBNE strategy of others. Here we control for wrong expectations about the computerized bidders, which might be different from wrong expectations that bidders have in human subject experiments. It is still valuable to understand which impact explicit information about the bidding strategies of others has on bidders compared to a treatment where this information is not available in C100. We consider deviations from the RNBNE in C100+ as ground noise or irrationality, which provides a baseline for other experiments. We cannot expect subjects in experiments with less control to be closer to the RNBNE prediction.

Hypothesis 4: *Bidding against computerized agents without information about the bids of others, where bid functions are reused in 100 auctions, and bidders see the equilibrium bid functions of their computerized opponents mitigates regret, risk aversion, and wrong expectations about the others, and eliminates underbidding.*

Table (3.1) provides an overview of how we control for different hypotheses for deviations from the RNBNE in the four different treatment combinations. A + signs, if this effect might be a reason for deviations in a certain treatment. If a field is marked with a **-**, we indicate that a certain reason might note serve as reason for a deviation from the RNBNE strategy.

	C100+	**C100**	**C1**	**H**
Strategic complexity	+	+	+	+
Wrong expectations	-	+	+	+
Risk aversion	-	-	+	+
Regret	-	-	-	+

TABLE 3.1: The control for reasons of deviations from the RNBNE in different treatment combinations.

Although the strategic complexity in C100+ is limited to imitating the RNBNE of others, this might not be obvious to some, so we marked this cell with a + suggesting that strategic complexity can still be an explanation for deviations from the RNBNE. In C100 bidders only get the prior cost distributions. Here wrong expectations and strategic complexity can both explain deviations. The difference to C1 is only the number of times in which the bid function is reused. Therefore, a difference between C1 and C100 can be explained by risk aversion. Treatment combination H allows for all explanations, although the 16 repetitions should mitigate risk aversion to some extent.

The individual treatment combinations are described in table (3.2). Overall, 209 students in the area of mechanical engineering, computer science and information systems took part in our experiments. 152 participants played treatments with q=0.7. In all treatment combinations variable costs per unit, c_i, were i.i.d. and random variables drawn from a uniform distribution with a support of [0.0,...,10.0]. The fixed cost K was 1 for all bidders in all experiments. The split parameter in the experiments reported in the following with treatment combinations H, C100, and C100+ was q=0.7.

In addition, we performed experiments with single-lot auctions (q=1) to understand how the results compare with traditional reverse auctions. This was necessary, because we are not aware of similar experiments with a reverse first-price sealed-bid auction. Overbidding on high cost draws in sales auctions might just be different from underbidding for low cost draws in

reverse auctions.
In table (3.2) we describe all treatment combinations. The first column **Bid**

Treatment	Bid fct. reused	Opponents	Information	Split	Auction format	No. of Subjects
C100+.S	100	Computer	Prior & RNBNE bid fct.	1.0	single-lot	10
C100+.P	100	Computer	Prior & RNBNE bid fct.	0.7	Parallel	11
C100+.Y	100	Computer	Prior & RNBNE bid fct.	0.7	Yankee	11
C100.S	100	Computer	Prior distribution	1.0	single-lot	11
C100.P	100	Computer	Prior distribution	0.7	Parallel	13
C100.Y	100	Computer	Prior distribution	0.7	Yankee	13
C1.S	1	Computer	Prior distribution	1.0	single-lot	12
C1.P	1	Computer	Prior distribution	0.7	Parallel	12
C1.Y	1	Computer	Prior distribution	0.7	Yankee	11
H.S	1	Human	Prior & bids of past auctions	1.0	single-lot	16
H.P	1	Human	Prior & bids of past auctions	0.7	Parallel	16
H.Y	1	Human	Prior & bids of past auctions	0.7	Yankee	16

TABLE 3.2: Overview of treatment combinations in the experiments.

fct. reused describes if the same bid function, that the participants submitted was used once or 100 times. On the second one you find against which kind of **Opponents**, the humans played; then, the degree of **Information** is noted. Finally, the **Split**, the **Auction format** and the **No. of Subjects**, that participated in experiments for the relevant treatment can be found.

We also ran additional computerized experiments of C100+ and C100 with a split parameter of $q = 0.9$ to make sure that the high predictive accuracy of the RNBNE function that we found for the split of q=0.7 is robust against changes of the split parameter. This could be confirmed.

3.3 Experimental results

We will now describe bidder behavior for the parallel and the Yankee auction in the lab. It is tested how well the RNBNE bid function explains the empirical observations. Before this, we will analyze underbidding in single-object procurement auctions in which the entire quantity goes to one supplier. This will provide us a baseline against which to compare bidding behavior in split-award procurement auctions. It is important, since most of the empirical literature deals with sales auctions. Complementray plots are provided in the Appendix B.

3.3.1 The single-lot auction

Result 1: *The RNBNE strategy explains the empirical data in C100 and C100+ in the single-lot auction well. This suggests that wrong expectations and strategic complexity of the parallel auction have little impact on the bidding behavior. In C1 we found underbidding on low cost draws showing that risk aversion has substantial impact on bidder behavior. There was learning in treatments H, and the level of underbidding decreased after a few rounds. However, the underbidding is still significantly higher compared to C100+. We fail to reject Hypothesis 1, 3 and 4 but can reject Hypothesis 2.*

Support: We analyze the outcome of linear regression models in the different treatments and compare it with the equilibrium bid functions for the small and the large lot [1]. As a matter of course, for the single-lot respectively Yankee auction we compare single bids. We use a fixed effects model with a dummy variable u_i to estimate the unobserved heterogeneity of bidders, namely

$$y_{it} = \alpha + u_i + \beta c_{it} + \gamma r_{it} + \delta w_{i(t-1)} + \epsilon_{it}.$$

The dependent variable y_{it} describes the bids of bidder i. The unit costs c_{it} were used as the main independent variable. Table (3.3) summarizes the intercept α, the regression coefficient β for the unit cost parameter, and the multiple R^2 of the linear regression. The coefficients u_i for the bidder ID of all the bidders describe bidder idiosyncrasies, which are omitted from the table. Variable r describes the number of the auction, which is relevant only in H. Variable $w_{i(t-1)}$ describes whether a bidder won in the previous auction and δ the impact of winning in the last round.

We also compute the mean squared error (MSE) of the RNBNE function to understand how well the model explains the data in the different treatment combinations. This metric is lowest in C100+, indicating that the variance around the RNBNE bid function is low. Additional plots of the empirical bid functions can be found at Appendix B. We compare the MSE of the linear RNBNE function against the MSE of a LOESS estimation of the data (see

[1] Seemingly unrelated regression (SUR) is one possibility to deal with these two sources of data. However, because each equation contains exactly the same set of regressors, the estimators of a SUR are numerically identical to ordinary least squares estimators, which follows from Kruskal's theorem (Davidson and MacKinnon (1993)).

	α	β (unit cost)	Std. error β (p-value)	Mult. R^2	MSE RNBNE	MSE LOESS	# bids/ bidders
RNBNE	**2.53**	**0.748**					
C100+.S	2.08	0.797	0.008 (0.000)	0.991	0.104	0.083	100/10
C100.S	2.53	0.727	0.033 (0.000)	0.922	0.415	0.392	110/11
C1.S	1.92	0.767	0.039 (0.000)	0.862	4.828	4.740	120/12
H.S	2.11	0.821	0.005 (0.000)	0.923	0.854	0.676	2560/16
H.S (# 1)	1.51	0.869	0.028 (0.000)	0.897	2.127	1.936	160/16
H.S (# 7)	1.87	0.793	0.016 (0.000)	0.952	0.587	0.387	160/16
H.S (# 16)	1.70	0.829	0.014 (0.000)	0.966	0.699	0.353	160/16

TABLE 3.3: Regression coefficients for the empirical bid functions (w/o bidder ID) of the single-lot auction.

Cleveland and Devlin (1988)). LOESS is also known as locally weighted polynomial regression, which can be considered a best case model for the empirical data. At each point in the data set, a low-degree polynomial is fitted to a subset of the data. The value of the regression function for the point is obtained by evaluating the local polynomial using the explanatory variable values for that data point.

The line H.S in table (3.3) describes the regression coefficients of all the bid functions with the number of the auction (r) as an additional covariate. This additional covariate had a small significant negative effect on the regression (-0.0377). The subsequent lines describe the results of the regression for the empirical bid functions in individual auctions (number 1, 7, and 16) in H. The low intercept α together with a higher β compared to the RNBNE function indicates that there is underbidding on average on low cost draws in H compared to the RNBNE bid function. In auction 7, for example, there is an underbidding of 18.7% at a unit cost of 1 compared to the RNBNE bid function, while there was underbidding of 2.75% for high-cost draws of 9 Francs.

The value of intercept α which can be used as an estimator for underbidding on low value draws, was at a mean value of 1.74. The intercept decreased

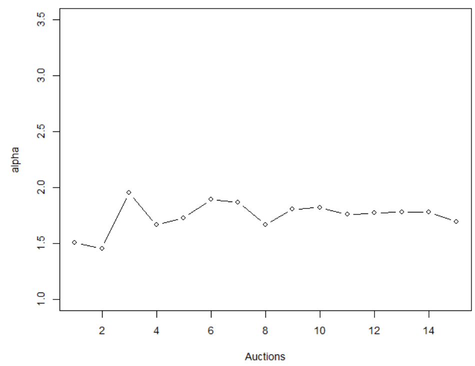


FIGURE 3.3: The the intercept α (right) across different auction runs in a session in H for the single-lot auction.

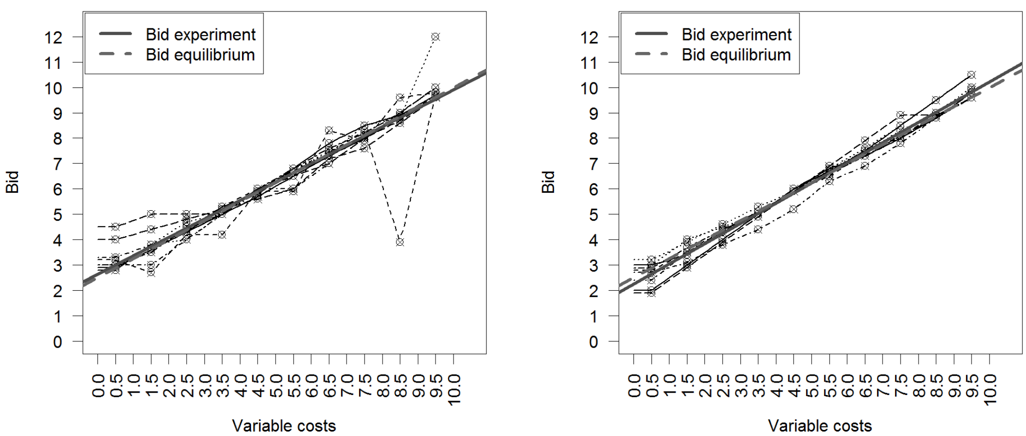


FIGURE 3.4: Scatter plot of bids and the optimal bid functions for C100 (left) and C100+ (right) for the single-lot auction.

Chow test	p-value
C100.S	0.988
C1.S	0.000
H.S	0.035

TABLE 3.4: The *p*-values of a Chow test for equivalence of the RNBNE bid function and the regression for the single-lot auction.

slightly in the last six rounds from a value of 1.81 to a value of 1.70. This can be explained by some bidders who became more aggressive on low-cost draws in order to become winners before the experiment was over. More aggressive bidding across rounds overall is also illustrated by a significantly negative, but low, coefficient $\gamma = -0.04$. We found a small but significantly negative impact of winning in the last round ($\delta = -0.06$), which cannot be explained by regret. This small negative impact can also be observed in the different split-award auctions. Note that in this paper we want to analyze when the RNBNE can explain bidding behavior in first-price auctions. This allows us to rule out explanations such as strategic complexity or wrong expectations as reasons for underbidding. The question, whether risk-aversion or rather regret determine the underbidding in our experiments may be a fruitful exercise to look at in the future.

The high MSE in treatment combination C1.S is due to a single bidder who bid substantially above the RNBNE bid function. Without this bidder, the MSE was 0.589. The average underbidding at a unit cost of 1 is 18.02% below the RNBNE bid function.

The Chow test is an econometric test of whether the coefficients in two linear regressions on different data sets are equal, which allows for another comparison of the RNBNE bid function and the regression results on the empirical data. Table (3.4) shows the p-values for the Chow test. The Chow test is based on squared residuals, and therefore, does not allow for a comparison of the regression results with the RNBNE bid function, which does not have any residuals. Treatment C100+ is, however, a good baseline for other treatments to compare against, because the treatment exhibits a high level of control for and the results are very close to the RNBNE bid function. The Chow tests show that we cannot reject the hypothesis of equivalence between the regression coefficients of the empirical bid functions of C100 and C100+ while the bid functions of C1 were significantly different from C100+. This means, even without information about the bid functions of computerized agents, the empirical bid functions in C100 are very close to C100+ and the RNBNE bid function. We will see this pattern as well in the split-award auctions. There was no significant difference of C100+ and H in spite of the underbidding observed in this treatment.

Kirchkamp and Reiß (2011) see in their experiments a median underbidding of up to 30% over the RNBNE on high value draws. In Pezanis-Christou et al. (2003), an average relative underbidding over the RNBNE prediction of 34-37% for their experiments with symmetric bidders. It is remarkable, that both Pezanis-Christou et al. (2003) and Kirchkamp and Reiß (2011) used the strategy method like we did. However, the bids were only valid for one auction and not 100 like we did in C100 and C100+. Besides, they tested sales rather than procurement auctions and and the number of competitors was different. The number of played auctions was also not the same. Hence, it is not trivial to compare the level of underbidding in their experiments with the degree of underbidding in ours. On the one hand, in Kirchkamp and Reiß (2011), two bidders competed for 1 item in 12 different auctions, on the other hand, in our treatments four bidders tried to sell the single-lot respectively 2 lots in 16 iterations . We observed on average underbidding of 18-19% for low unit costs of 1 Franc in treatments C1 and H. In the following, we show that the underbidding in treatments C1 and H will increase for split-award auctions.

As point of reference, Shachat (2009) reports high underbidding for low cost draws in reverse auctions and many outliers. This might be due to the fact that they did not use the strategy method, but bidders had to place bid for actual costs draw. Bidders could speculate which results in a deviation from the RNBNE strategy up to 40%. The common knowledge was similar to our design, since bidders knew the distribution and the corresponding range of the costs, the number of competitors and repetition. Besides, the participants got to know the amount of the winning bid after each repetition.

The underbidding in single-object reverse auctions with human bidders in H can be explained by residual risk aversion or some of the other behavioral theories that have been used to explain bidding behavior in single-object first-price sealed-bid auctions such as regret or wrong expectations about other bidders.

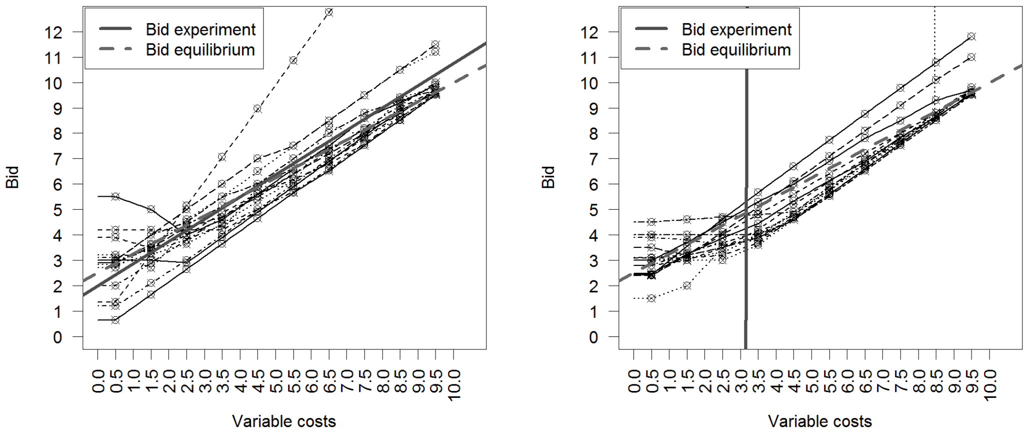


FIGURE 3.5: Scatter plot of bids and the optimal bid functions for H for the 1^{st} auction (left) and the 7^{th} auction (right) in the single-lot context.

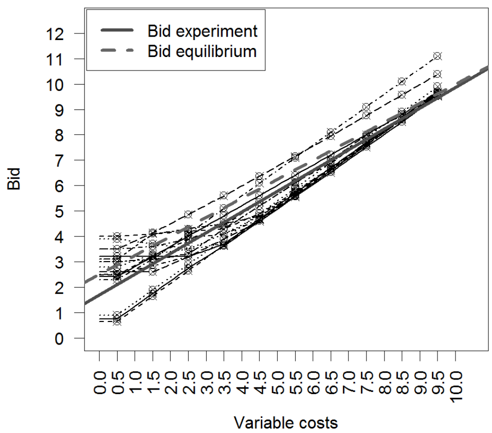


FIGURE 3.6: Scatter plot of bids and the optimal bid functions for H for the 16^{th} auction in the single-lot context.

	Large lot				Small lot				
	α	β (unit cost)	Mult. R^2	Std. error β(p-value)	α	β (unit cost)	Mult. R^2	Std. error β(p-value)	# bids/ bidders
RNBNE	**3.59**	**0.643**			**3.37**	**0.67**			
C100+.P	3.49	0.626	0.963	0.008 (0.000)	3.39	0.621	0.957	0.009 (0.000)	220/11
C100.P	3.70	0.697	0.966	0.008 (0.000)	3.67	0.680	0.977	0.007 (0.000)	260/13
C1.P	1.48	0.854	0.938	0.022 (0.000)	1.81	0.805	0.947	0.019 (0.000)	120/12
H.P	1.70	0.778	0.951	0.004 (0.000)	2.68	0.735	0.929	0.004 (0.000)	2560/16
H.P (# 1)	1.45	0.777	0.937	0.017 (0.000)	2.07	0.765	0.950	0.015 (0.000)	160/16
H.P (# 7)	1.74	0.772	0.961	0.013 (0.000)	2.79	0.722	0.940	0.016 (0.000)	160/16
H.P (# 16)	1.28	0.785	0.963	0.013 (0.000)	1.85	0.731	0.950	0.015 (0.000)	160/16
RNBNE, q=0.9	2.80	**0.721**			**3.44**	**0.67**			
C100.P9	2.16	0.753	0.972	0.009 (0.000)	2.90	0.729	0.952	0.011 (0.000)	240/12
C100+.P9	2.85	0.711	0.971	0.008 (0.000)	3.42	0.679	0.985	0.005 (0.000)	280/14

TABLE 3.5: Regression coefficients for the empirical bid functions of the parallel auction.

3.3.2 The parallel auction

The following result 2 refers to tests of the equilibrium bidding strategy in Proposition 1, while result 3 refers to Proposition 2. Complementary plots that support our results can be found in the Appendix B.

Result 2: *The RNBNE strategy explains the empirical data in C100 and C100+ in the parallel auction well. Again, like in the experiments with a single-lot, wrong expectations and strategic complexity have little impact on the bidding behavior. Also, underbidding in C1 and learning in treatments H have been observed. Again, we fail to reject Hypothesis 1, 3 and 4 but can reject Hypothesis 2.*

Support: We have added additional statistics to compare the RNBNE against the predictive power of a model with a constant profit margin and the RNBNE of a single-lot FPSB. This should help explain how sensitive the

	Large lot				Small lot			
	MSE LOESS	**MSE RNBNE**	**MSE single-lot RNBNE**	**MSE Constant Factor**	**MSE LOESS**	**MSE RNBNE**	**MSE single-lot RNBNE**	**MSE Constant Factor**
C100+.P	0.141	**0.175**	0.464	1.337	0.206	**0.260**	0.542	1.441
C100.P	0.269	**0.328**	0.406	1.037	0.187	**0.192**	0.443	1.055
C1.P	0.827	1.668	**0.948**	1.234	0.682	1.057	**0.730**	1.129
H.P	0.329	1.160	**0.449**	1.124	0.403	0.607	**0.484**	1.089
H.P (# 1)	0.578	1.107	**0.629**	1.165	0.568	0.708	**0.690**	1.059
H.P (# 7)	0.269	1.037	**0.386**	1.059	0.319	0.496	**0.424**	1.050
H.P(# 16)	0.319	1.340	**0.508**	1.223	0.453	0.750	**0.539**	1.234
C100.P9	0.312	**0.327**	0.330	0.864	0.387	**0.448**	0.736	1.090
C100+.P9	0.163	**0.235**	0.244	0.860	0.095	**0.102**	0.350	0.981

Table 3.6: MSE of the RNBNE in the parallel auction, the RNBNE of a single-lot auction, and the MSE of a constant profit margin model. The MSE of the LOESS estimate serves as a baseline to compare against.

predictions are.

The model assuming bidders had a constant profit margin had the worst MSE in all treatments because this model used the average markup of the RNBNE function across all draws as the profit margin. For the treatment combinations C100 and C100+ the RNBNE clearly had the lowest MSE (marked in bold in table (3.6)). The treatment combinations C1 and H the RNBNE of the single-lot auction has a lower MSE than the RNBNE of the split-award auction. This can easily be explained by the underbidding observed in these treatments. In a single-lot auction with the same number of bidders the competition is higher which brings down the bid prices in equilibrium below that of the RNBNE in the split-award auction. Again, the MSE for the treatment C1 is highest, which can be explained by risk aversion and the differences in how bidders respond to risk aversion. A few bidders deviated substantially from the RNBNE prediction, which led to a high MSE. In table (3.6), we have provided the MSE of all three models for the parallel auction.

The line H.P in table (3.5) describes the relevant regression coefficients of all human subject experiments where we control for bidder idiosyncrasies and the number of the auctions. The subsequent lines describe the results of the regression for the empirical bid functions in individual auctions (number 1, 7, and 16) in treatment combination H. The low intercept α together with a

	Large lot	Small lot
H	0.000	0.000
C1	0.000	0.000
C100	0.172	0.176
C100, q=0.9	0.506	0.434

TABLE 3.7: The p-values of a Chow test for equivalence of the RNBNE bid function and the regression for the parallel auction.

higher β compared to the RNBNE function indicates that there is underbidding on average on low cost draws in H compared to the computerized treatments in C100 and C100+. However, there is even more underbidding in C1.
Note that in the initial sealed-bid treatments with C100 and C100+, we have elicited the bid function for 20 unit costs from 0.5 to 10 Francs, while for the human subjects' experiments where students had to submit their bid function multiple times, we reduced this to 10 parameters. In test experiments with treatment combination C1, we did not find that this had an impact on the shape of the bid function in the experiments.
The intercepts of both C1.P and H.P are much lower than those of the RNBNE bid function for the large and the small lot. Underbidding below the RNBNE for low costs of 1 Franc on the large lot was on average 40.63% for treatment H (auction #7) and 44.79% for C1. On the small lot, we observed underbidding of 13.07% for treatment H (auction #7) and 35.27% for C1. In comparison, in the single-lot reverse auction we observed around 18-19% for both treatments.
Risk aversion can serve as a natural explanation for the underbidding in C1.P. In H.P the residual risk aversion in spite of the 16 repetitions but also other possible explanations such as regret can be potential reasons for underbidding on low cost draws.

The underbidding in these reverse auctions with human bidders in H can be explained by remaining risk aversion, regret, or some of the other behavioral theories that have been used to explain bidding behavior in single-lot first-price sealed-bid auctions. The phenomenon is similar to overbidding for large valuations in first-price sealed-bid sales auctions on single-lots, which has been reported also by Kirchkamp and Reiß (2011). Note that we conducted reverse auctions and the overbidding on large values in a sales auction might not be easily comparable with the underbidding on small values in reverse auctions that have usually been analyzed in experiments. Table (3.7) shows the p-

values for the Chow test which indicate that the null hypothesis of equivalence between the regression coefficients and the coefficients of the RNBNE function cannot be rejected for C100 and C100+.

The Chow test shows equivalence between the bid functions in C100+ and C100 for the large and the small lot. The test shows that the bid functions in C1 and H are both significantly different from C100+ (p=0.000).

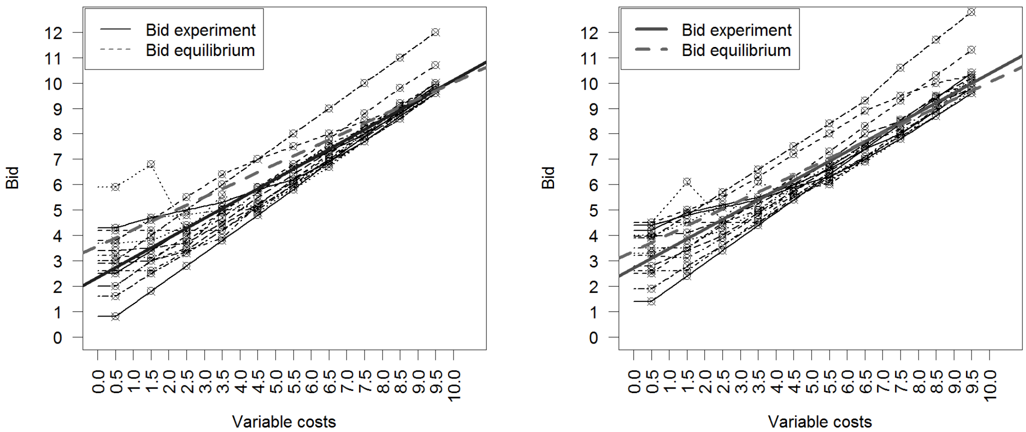


FIGURE 3.7: Scatter plot of bids and the optimal bid functions for H on the large lot for the 1^{st} auction (left) and the small lot (right) for the parallel auction (q=0.7).

Result 3: *Bidders' learning is shown in the initial two auctions of a session in H. In the last auctions, some bidders started to decrease their bids on the small lot.*

Support: Figure (3.9) plots the intercept α across all rounds to better understand underbidding relative to the RNBNE. The intercept α was low around a mean level of 1.56 and decreased slightly in the last rounds for the large lot.

In contrast, the intercept for the small lot was at 3.14 in round 2 after the initial round of learning and came down to a value of 1.84 in round 16 indicating more and more underbidding on low cost draws in the small lot. Bidders competed aggressively on the large lot and tried to achieve higher payoffs on the small lot in the initial rounds. In the last five rounds there was increased underbidding also on the small lot. Also the coefficient of r in the regression was significant and negative for the large and the small lot (-0.0167 and -0.0146,

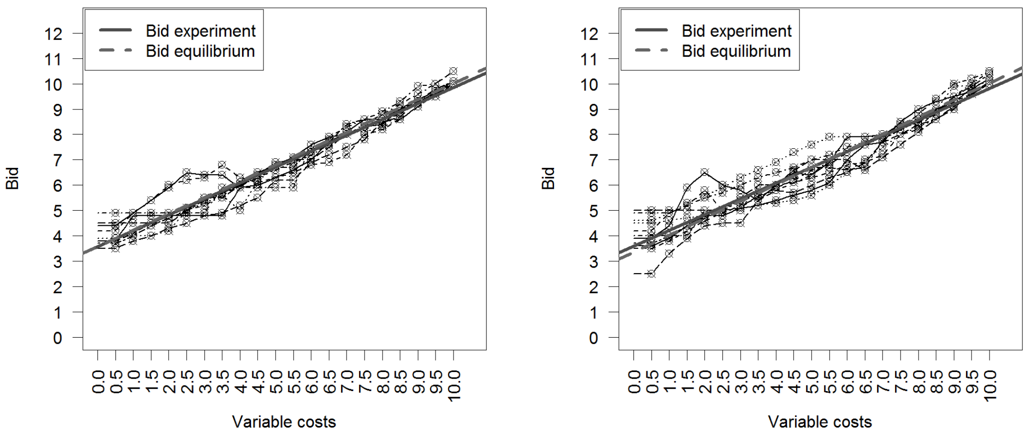


FIGURE 3.8: Scatter plot of bids and the optimal bid functions for C100+ on the large lot (left) and for the small lot (right) for the parallel auction (q=0.7).

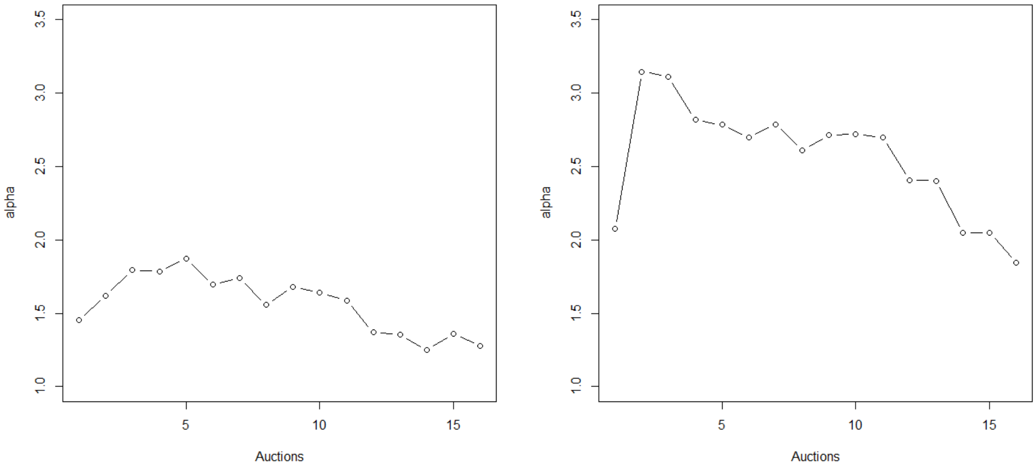


FIGURE 3.9: Intercept α for the large (left) and the small (right) lot across different auction runs in a session for the parallel auction.

resp.) indicating more aggressive bidding across rounds. As in the single-lot auction, there was a small but significant positive impact of winning in the last round $\delta = -0.09$, which could rather be explained by joy of winning than regret. Also Kirchkamp and Reiß (2011) found significant learning in the first two out of 12 rounds of single-lot auctions.

Result 4: *The correlation between the markups of bidders in the large and in the small lot was high, and on average the markup in the small lot was significantly higher than in the large lot as, theory predicts.*

Support: We found the markups between the large and the small lot to be highly correlated (H (ρ=0.981), C1 (ρ=0.968), C100 (ρ=0.977), and C100+ (ρ=0.973)). In other words, bidders with a high markup on the large lot also have a high markup on the small lot. The differences in the markup between the large and the small lot in all treatments were significant throughout (paired t-test, α=0.01). This means that bidders' behavior was consistent with the RNBNE strategy in both, the large and the small lot and they understood that they faced less competition in the small lot.

Discussion: Overall, the results from the computerized experiments C100+.P and C100.P confirm rational bidding behavior according to the theory. Wrong expectations or strategic complexity do not seem to impact bidding behavior much. Underbidding in C1.P on low cost draws can again be explained by risk aversion. This underbidding was higher than in the single-lot auction, in particular in the large lot. We conjecture that bidders tried to win the large lot with low prices, because it promised a higher total payoff with 70 as well as 90 units.
Risk aversion can also serve as one of the reason for underbidding in H.P. Bidders were again aggressive on the large lot, but they started with a higher bid on the low cost draws on the small lot. However, in the last rounds the bidding also became aggressive on the small lot with lower bids on the low cost draws.

Result 5: *As q increases, bidding becomes more (less) aggressive for the large lot (small lot), as theory predicts (Proposition 2). Only for the small lot, where the differences between the equilibrium bid function are small, the theoretical prediction does not hold.*

Support: For the large lot the intercept in q=0.9 is lower for C100 and C100+ and both regression lines are close to the equilibrium bid function (see table (3.5)). The equilibrium bid function for q=0.9 is lower than for q=0.7 until high unit costs between 8 and 9 monetary units. This is reflected in the

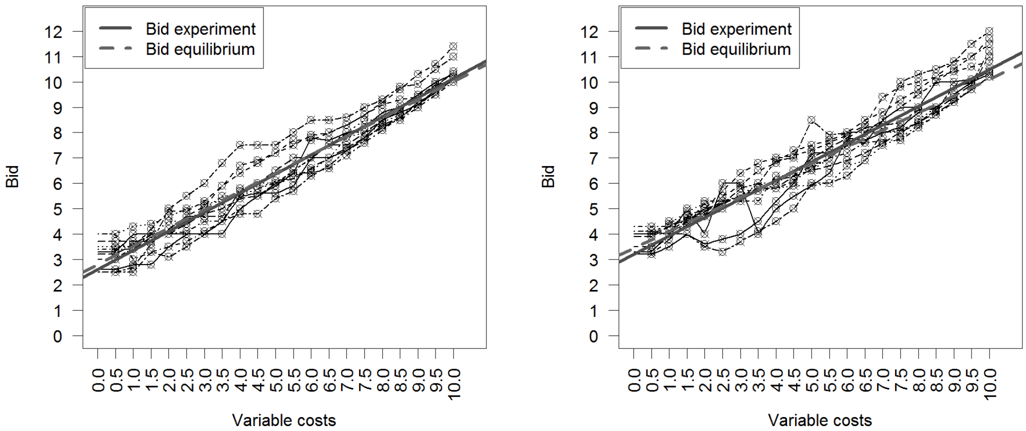


FIGURE 3.10: Scatter plot of bids and the optimal bid functions for C100 on the large lot (left) and for the small lot (right) for the parallel auction (q=0.9).

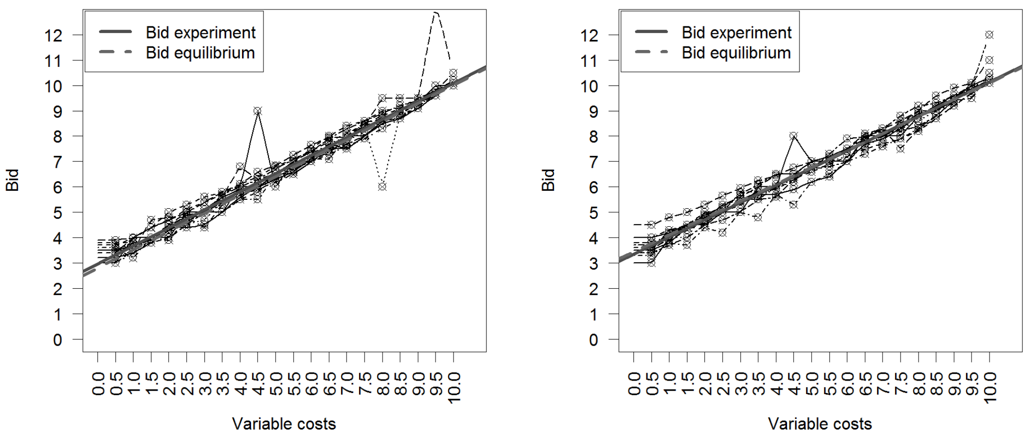


FIGURE 3.11: Scatter plot of bids and the optimal bid functions for C100+ on the large lot (left) and for the small lot (right) for the parallel auction (q=0.9).

regression lines of C100+, where both regressions intersect at a unit cost of 8. In C100, the regression line for q=0.7 is always above q=0.9, i.e., bidders bid more aggressive in q=0.9 throughout.

For the small lot the equilibrium bid function for q=0.9 is always below q=0.7 by a small number of 0.08. Also in C100+ the regression line for q=0.9 is slightly below q=0.7, in C100 it is the opposite. The differences between the C100 and the C100+ regression line are less than 1 monetary unit, however. You can see these differences also if you compare the figures (3.10) and (B.3) respectively (3.8) and (3.11).

3.3.3 The Yankee auction

In addition to the parallel auction, we also analyzed how well equilibrium bidding strategies explain bids in the different treatment combinations in the Yankee auction. The strategic complexity is higher, because bidders do not know if an aggressive bid will actually win the large lot, and if they are not winning the large lot, they might have won the smaller lot with a higher bid.

Again, we provide the results in table (3.8) and all relevant scatter plots. Result 6 refers to the equilibrium bidding strategy in Proposition 3, while Result 7 refers to Proposition 4. We have included the MSE for the single-lot RNBNE and that of a constant profit factor model in table (3.8). In the Yankee auction, the RNBNE model had the lowest MSE in treatments C100+.Y, and C100.Y. For H.Y and C.1 (w/o the outlier) the single-lot RNBNE had a lower MSE, which can again be explained by the fact that the single-lot RNBNE model leads to higher competition with the same number of bidders and lower equilibrium bid price, which better fits the average behavior of risk-averse bidders.

Result 6: *The RNBNE strategy explains the empirical data in C100 and C100+ in the Yankee auction well. This suggests that wrong expectations and strategic complexity have little impact on the bidding behavior, even in this strategically more complex split-award auction format. In C1 we found again underbidding on low cost draws showing that risk aversion has substantial impact on bidder behavior. There was learning in treatments H, and the level of underbidding increased in the final rounds. The difference of the bid functions in H and C100+ was not significant, even though there was more underbidding in H as in the other treatments. Like for the other auction formats, we fail to reject Hypothesis 1, 3 and 4 but can reject Hypothesis 2. The impact of winning a lot in the last round was again significant ($\delta = -0.22$).*

Support: We provide the same statistics as for the parallel auction in table (3.8). The line H again describes the regression coefficients of all the bid functions with the number of the auction as an additional covariate. This additional covariate had a small negative, but significant effect on the regression (-0.0295). As in the parallel auction, we find a low intercept α together with a higher β compared to the RNBNE function in the analysis of auctions 1, 7, and 16 in H. This means, that also in the Yankee auction, bidders in H with human subjects underbid on low cost draws compared to the RNBNE function, which we cannot observe in C100 and C100+. The MSE values are comparable to

	α	β (unit cost)	Std. error β (p-value)	Mult. R^2	MSE LOESS	MSE RNBNE	MSE single-lot RNBNE	MSE Constant factor	# bids/ bidders
RNBNE	3.53	0.647							
C100+.Y	3.66	0.682	0.008 (0.000)	0.972	0.148	**0.166**	0.342	0.995	220/11
C100.Y	3.21	0.684	0.007 (0.000)	0.973	0.192	**0.213**	0.396	1.039	260/13
C1.Y	2.05	0.783	0.028 (0.000)	0.860	3.191	**3.372**	3.531	3.647	110/11
H.Y	2.49	0.756	0.004 (0.000)	0.941	0.475	0.766	**0.532**	1.062	2550/16
H.Y (# 1)	2.68	0.724	0.018 (0.000)	0.930	0.907	**0.989**	1.297	1.623	160/16
H.Y (# 7)	2.19	0.743	0.012 (0.000)	0.963	0.317	0.573	**0.360**	0.941	160/16
H.Y(# 16)	1.92	0.800	0.011 (0.000)	0.975	0.355	0.914	**0.418**	0.892	160/16
RNBNE, q=0.9	2.82	0.735							
C100.Y9	2.42	0.786	0.010 (0.000)	0.961	0.572	**0.612**	0.671	0.966	300/15
C100+.Y9	2.95	0.699	0.007 (0.000)	0.970	0.140	**0.160**	0.236	0.896	320/16

TABLE 3.8: Coefficients for average cost of the linear regression for the Yankee auction.

the parallel auction. The lowest MSE values were again achieved for C100+ and C100. C1.Y has also a significantly lower intercept that can be attributed to risk aversion. In C1.Y, there was a clear outlier, a bidder who submitted very high bid functions leading to a high MSE of 3.372. Without this bidder the MSE was 1.024, which we included in brackets.

The Chow test, summarized in table (B.1), yields that there is no significant difference between the bid functions in C100+ and C100 (p=0.985), and between C100+ and H (p=0.770), but there is a difference between C100+ and C1 (p=0.000). The comparison between C100+ and H provides evidence for the predictive accuracy of the RNBNE for human subject experiments, even though we do find underbidding on low cost draws here as well. Underbidding below the RNBNE for low costs of 1 Franc was on average 29.78% for treatment H (auction #7) and 32.18% for C1. This was less than in in the parallel auction.

Result 7: *There was also learning of bidders in the initial auctions of a session in H for the Yankee auction.*

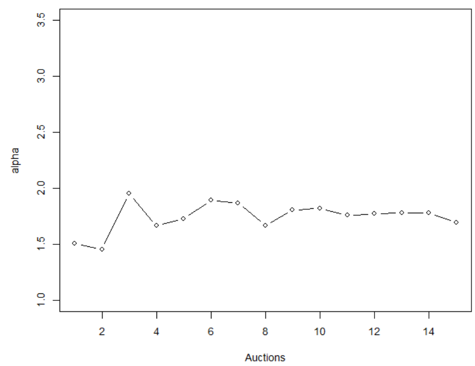


FIGURE 3.12: The intercept α across different auction runs in a session in H for the Yankee auction.

Support: Figure (3.12) shows the intercept for all 16 auctions showing an increasing trend in the first six auctions. We conjecture that the increased strategic complexity has led to a longer learning period.

The regression coefficient for the number of the auction in a session was also significant and negative at γ=-0.04, showing that across the auctions bidders became slightly more aggressive. A look at the development of the increment α across the 16 auctions in treatment H reveals that the level of underbidding below the RNBNE bid function on low cost draws increased. At the same time the coefficient β of the unit cost parameter increased at levels above the coefficient of the RNBNE bid function. In auction number 16 the average bid after the regression for unit costs of 10 Francs was 1% below the RNBNE bid, but 34.9% below the RNBNE bid for unit costs of 1 Franc only. In figure (3.12), the changes of α are shown according to the auction number.

Discussion: In the Yankee auction bidders do not know a priori if they win the large lot or the small lot with their single bid price. The high predictive accuracy of the RNBNE function in all treatment combinations is therefore an interesting result. In particular, there was no significant difference between C100 and C100+ and no significant underbidding indicating that strategic complexity had little impact. In line with what we have seen in the single-lot and in the parallel auction, we found significant underbidding below the RNBNE bid function in C1, which can be explained by risk aversion. In the treatment combinations H the level of underbidding on low cost draws increased slightly across the 16 auctions in a session.

Result 8 *As q increases, bidding becomes more aggressive for our experimental environment with fixed costs of 1 and uniformly distributed unit costs in the Yankee auction, which is in line with Proposition 4.*

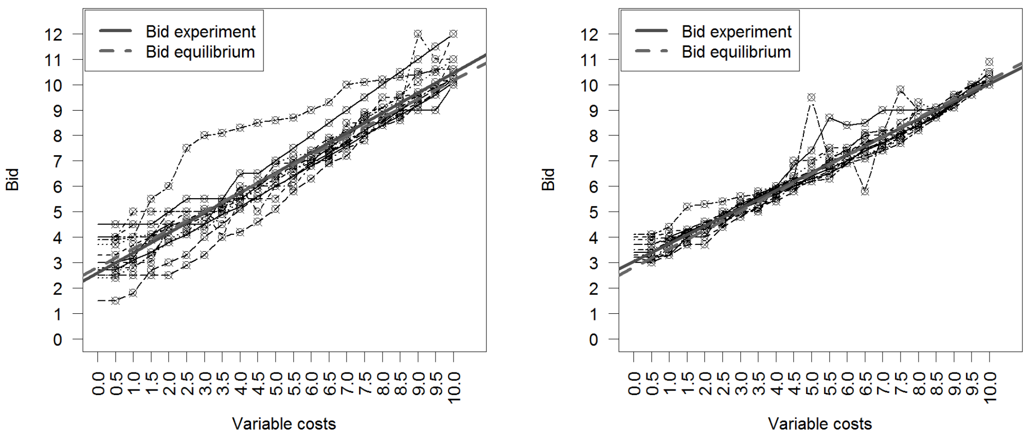


FIGURE 3.13: Scatter plot of bids and the optimal bid functions for C100 (left) and C100+ (right) for the Yankee auction (q=0.9).

Support: The intercept in q=0.9 is below that of q=0.7 (see table (3.8)). The equilibrium bid function of q=0.7 is higher than q=0.9 up to a unit cost of

Treatment	α	β **(RNBNE)**	**Std. Error** (β)	**p-value** (β)
C100+	0.139	0.980	0.006	< 2e-16
C100	-0.460	1.060	0.009	< 2e-16
C1	-2.151	1.268	0.052	< 2e-16
H	-1.867	1.188	0.005	< 2e-16

Table 3.9: Regression coefficients of the RNBNE prediction across auction formats.

9. The difference between both regression lines in C100 is small. In C100+ the regression line of q=0.9 is always below that of q=0.7. Overall, the data from the lab confirms the theoretical prediction in Proposition 4. You can also compare the figures (B.6) and (3.13).

Corollary 1 states that if bidders submitted their RNBNE bid function in a Yankee auction, then they always make a positive payoff if they win the large lot, but they could also make a loss in the small lot. Losses are more likely with high fixed costs. In our experiments fixed costs were low, and the lowest payoff that we encountered was zero. Possible losses due to high fixed costs are another phenomenon to be analyzed in the future, but losses in experiments are difficult as in most experiments it is considered unethical to have bidders pay a loss and external validity of the experiments becomes an issue.

3.3.4 Predictive accuracy across auction formats

In order to analyze the predictive accuracy of the RNBNE model across auction formats and split parameters, we have pooled all observations (Parallel and Yankee auction) within each of the four treatment combinations, as well as the observations for different split parameters (0.7 and 0.9). We have then used the RNBNE prediction as right-hand side variable for the bids in a regression. A coefficient on the RNBNE prediction close to 1 is strong evidence for the RNBNE model, and it demonstrates that subjects understand the strategic differences across the auction sessions. Again, for C100+ and C100 we find evidence for the RNBNE model, while the results in table (3.9) indicate underbidding in the treatments C1 and H.

We summarize the results across all auction formats.

- There was underbidding in treatment H. We fail to reject Hypothesis 1.

- The RNBNE strategy explains the empirical data in C100 and C100+ in the single-lot auction well. We fail to reject Hypothesis 3 and 4.
- In C1, we found underbidding on low-cost draws, showing that risk aversion has substantial impact on bidder behavior. We can reject Hypothesis 2.

3.3.5 Procurement cost comparisons

The final result of our theoretical analysis is that the expected costs of the parallel and the Yankee auction are the same. In this subsection, we report on three different metrics, allocative efficiency, the average procurement costs in a treatment, and a cost ratio, which normalizes the procurement costs by the costs of the bidders in the optimal solution. This allows for easier comparison across different cost draws in the auctions, because average costs can differ significantly due to the cost draws of individual auctions.

Allocative efficiency is defined as $E = \frac{c_1^* + c_2^* + 2K}{c_1^i + c_2^j + 2K} \in [0, ..., 1]$, where c_1^* and c_2^* are the variable costs in the efficient allocation for the large and the small lot and c_1^i and c_2^j are the costs of those bidders i and j, who won the auction. Cost ratio is defined as $C = \frac{c_1^* + c_2^* + 2K}{b_1^i + b_2^j} \in [0, ..., 1]$, where b_1^i and b_2^j describe the bids of the winning bidders i and j on the large and the small lot respectively. If bid prices in the winning allocation decrease, this ratio increases, i.e., a higher number is better for the buyer.
Table (3.10) provides the values for E, C and the average costs.

Result 9: *The parallel auction and the Yankee auction exhibit no significant differences in efficiency and cost ratio as predicted by Proposition 5.*

Support: Overall, efficiency is high in all experimental treatments. We did not find a significant difference in efficiency E and cost ratio C within the same treatment combination between the parallel and the Yankee auction using a Wilcoxon rank sum test (α=0.01). There was a significant difference in average costs for C100 and C100+, when the split was at q=0.9, but this is difficult to interpret as the cost draws were different in these auctions.

There are significant differences between the treatment combination H and C100 or C100+ for both split parameters based on a Wilcoxon rank sum test (α=0.01). H has lower efficiency and a higher cost ratio, which means a lower

	Efficiency E	**Cost ratio C**	**Average costs**
H.P, q=0.7	96.17%	83.63%	588.70
C1.P, q=0.7	99.01%	51.91%	506.26
C100.P, q=0.7	99.39%	51.63%	514.94
C100+.P, q=0.7	96.62%	71.32%	556.39
C100.P, q=0.9	97.87%	51.71%	500.86
C100+.P, q=0.9	98.79%	52.16%	494.35
H.Y, q=0.7	96.49%	79.62%	602.32
C1.Y, q=0.7	98.63%	51.66%	515.05
C100.Y, q=0.7	98.78%	51.60%	502.15
C100+.Y, q=0.7	99.24%	67.48%	584.80
C100.Y, q=0.9	98.09%	51.64%	430.63
C100+.Y, q=0.9	99.50%	52.19%	443.57
H.S	86.00%	71.33%	382.57
C1.S	99.42%	54.68%	441.53
C100.S	99.70%	54.81%	440.45
C100+.S	94.70%	57.13%	462.85

Table 3.10: Efficiency and auctioneer's costs.

cost, in both the parallel and the Yankee auction. The lower cost in H can be attributed to the underbidding that we described earlier in human subject experiments. Note that in H we have seen convergence after several auctions.

3.4 Further work

In this chapter, we tested how human bidders behave in a simple multi-item sealed-bid auction. A natural extension would be to examine the dynamic version of the parallel and the Yankee auctions. Hence, we provide suggestions how to formulate of the multi-round extensions of the two formats.

Three different dynamic procurement auctions can be found in Cramton and Ausubel (2006). In their simultaneous descending auction all the goods are purchased at the same time, each with a price associated with it. Bidders can bid on any of the items, but not on packages. Bapna et al. (2000) and Bapna et al. (2001) defined a similar mechanism as multi-item progressive auctions, where multiple units of the same product are sold to multiple bidders but each bidder cannot win more than one item. In the second auction format of Cramton and Ausubel (2006), the simultaneous descending clock auction, bidders reply with quantities according to the price. The final prices of the auction correspond to the competitive equilibria and the allocations are efficient. The difference to our parallel auction is that we have two different sized, predefined lots. Bidders know the exact amount they bid for in advance, and each bidder can submit two bids for each lot given the current prices. It is not possible to answer to the auctioneer with a suggestion for the size of the lots.

Besides, the authors discuss a two stage clock-proxy auction for complex environments, which consists of a simultaneous clock auction followed by a last-and-final proxy round similar to the CCA. Mishra and Garg (2006) analyze a multi-item generalization of descending price auctions. The different items of the multi-unit auctions can be compared to the different splits in our format. According to the authors there is no possibility for bidders to increase their surplus by aberration for their developed, greedy strategy. Interestingly, to the best of our knowledge there is no research on dynamic split-award auctions so far, though they are frequently used in practice. Therefore, we fill this gap by introducing the dynamic Yankee and parallel auction.

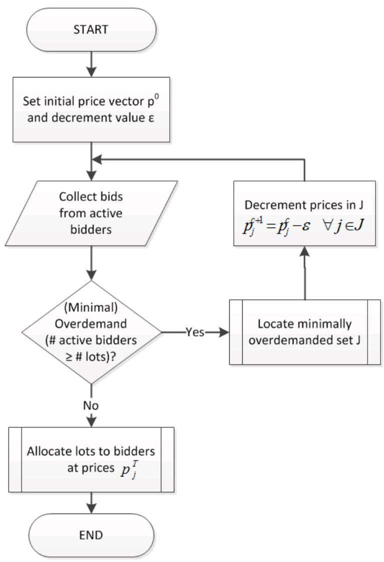


FIGURE 3.14: The sequence of the dynamic parallel auction.

An formulation of the dynamic parallel auction is visualized in figure (3.14) and described below.

There are several rounds in the ***dynamic parallel auction***. Bidders see current prices for all lots and can submit bids for any of them, but are only allowed to win at most one lot. In order to maintain eligibility, bidders have to submit at least one bid in each round; otherwise they quit the auction. If there is at least one (minimal) overdemanded set, a new round starts and prices for the lots in this set are reduced. If there is no (minimal) overdemanded set, the auction terminates. We use the definition of Demange et al. (1986) and describe a minimal overdemanded set as a set that is itself overdemanded, but none of its proper subsets is overdemanded.

The dynamic parallel auction can be seen as a reverse assignment game with a single buyer and multiple sellers. An assignment can be interpreted as an injective function $\mu : n^{'} \rightarrow m, \; and \; n^{'} \subseteq \; n$, whereas $n^{'}$ is a subset of all bidders n and m the amount of lots.

The assignment problem corresponds to a maximum weighted bipartite matching, which is a special case of the transportation problem and, in turn of the minimum cost flow problem. This problem can be reduced to a linear program (LP). Figure (3.16) summarizes the classification of the assignment problem. Related problems are job matching (Kelso and Crawford (1982)) or the college admissions and the stability of marriage (Gale and Shapley (1962)). Here, a matching of men and women has to be found such that there is no pair of a man and a woman who both prefer each other above their partners in the matching. Roth and Peranson (1999) assign medical students to hospitals for internships in the USA.

Shubik (1971) showed that the core of an assignment game is precisely the set of dual optimal solutions to the assignment optimization problem on the matrix of pairwise profits. The dual variables describe the payoff vectors of the assignment game. The existence of optimal solutions to the assignment problem and strong duality show that the set of stable payoff vectors is non-empty.

Demange et al. (1986) proof that versions of the "Hungarian algorithm" (a primal/dual method) yield this Walrasian equilibrium, i.e., a vector of linear prices. In each round, the auctioneer announces the tuple of ask prices (p^1, p^2) with a price for each lot. The exact progressive auction algorithm of Demange

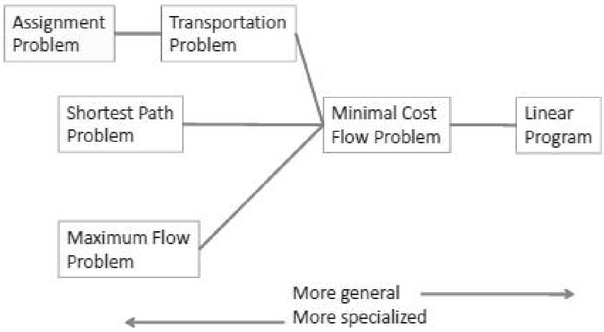


FIGURE 3.15: Classification of the assignment problem.

et al. (1986) corresponds to our dynamic parallel auction. Bidders follow a dominant straightforward strategy, i.e. they bid on those lots which maximize their payoff at the given prices. The bids can be defined as bidder's demand set $D_b(p)$, namely

$$D_b(p) = \{m : p(m) - K - c_i = max_{\eta \epsilon m} [p(\eta) - K - c_i^{\eta}]\}$$

Hereby, $p(m)$ denotes the ask price for lot m, and η any lot within m. A price is called competitive if there exists an assignment $\mu : n^{'} \rightarrow m$ such that $\mu(b) \in D_b(p)$.

Bertsekas (1981), Bertsekas (1985), Bertsekas (1988) and Bertsekas and Castanon (1989) discuss variations of an auction algorithm.

Proposition 6: *The parallel auction is a primal dual algorithm that results in VCG prices.*
Since our dynamic auction is a descending version of the exact algorithm by Demange et al. (1986), it is a primal dual algorithm that results in a core outcome [2].

Since bidders are not allowed to submit package bids, the core prices resemble the VCG prices.

Also for the Yankee auction, we formulate a multi-round mechanism.

[2] See, for more details about the "core" at chapter (4.1)

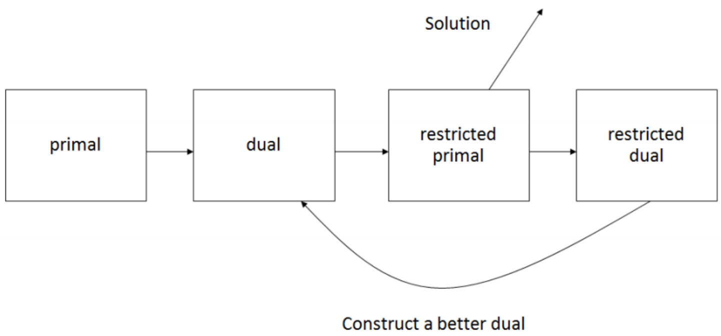


FIGURE 3.16: The dynamic parallel auction as primal dual algorithm (see Papadimitriou and Steiglitz (1998)).

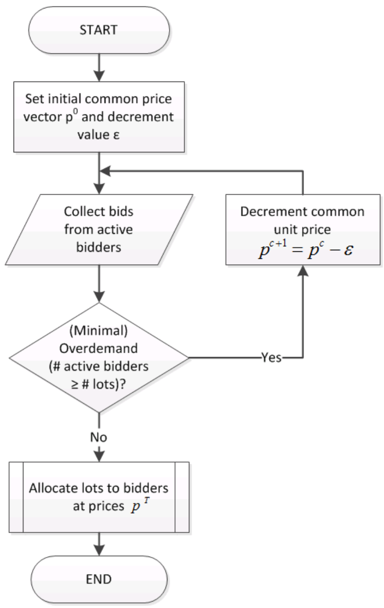


FIGURE 3.17: The sequence of the dynamic Yankee auction.

Figure (3.17) explains the mechanism well, where the unit price is the same for all lots. The current bid price can be written as: $P_0 - a \cdot t$, where P_0 denotes the initial price vector, a the fixed decrement, and t the number of decrements. If the number of active bidders is larger or equal to the number of lots $m = 2$, the auctioneer reduces the price per unit and a new round starts. Otherwise, the auction terminates. Then, the last active bidder wins the large lot and the bidder who dropped out of the auction in the last round wins the small lot. The common final ask price is the last price the $(n-1)$-th best bidder accepts. Ties are broken at random (see figure (3.17)). At every point, bidders try to maximize their payoff.

If we consider besides several lots also more than one item, the Reverse Combinatorial Clock (RCC), a reverse implementation of a CA, might be the right choice [3]. Mayer and Louca (2013) performed simulations in this context. These results should be interpreted with care, since the definition of the value models and the bidding strategies of computerized bidders determine the results decisively. Because of these and other reasons, the simulations are not presented within this thesis.

[3] See Chapter 4

Chapter 4

Combinatorial auctions

In Chapter 3, we analyzed sealed-bid auctions with two lots. In spite of the higher complexity in comparison to single item auctions, the equilibrium strategy was a good predictor for bidding behavior in the laboratory, if external effects have been controlled. We saw that strategic complexity might not serve as explanation for deviations; however, we saw, that risk aversion might affect bidders in their behavior. We emphasize that this finding only holds for this restricted setting.
In many applications like in the sales of spectrum license far more items are sold simultaneously. The value model and the auctions are much more complex - even too complex to analyze it in theory. Hence, simulations or experiments are a proper tool to find out how different auction formats might work.

We test by human subject experiments the impact of a simple "compact" versus complex “fully expressive” bid language specifically a “pay-as-bid” and “bidder-optimal core-selecting” pricing rule in sales auctions. Hence, all definitions are given in the context of forward auctions. The number of possible bids increases from two in Chapter 3 to 2,400. The main findings are published in Bichler et al. (2014b). The value model and basic theoretical considerations go back to Bichler et al. (2013a). My main contribution was the experimental part.

Spectrum auctions are often sold via combinatorial auctions (CA), whereas we introduce some theoretical background.

4.1 Combinatorial auctions

In CAs, bidders can place bids on indivisible combinations of items. By means of these "bundles" bids synergies between items can be expressed which increases economic efficiency, especially in the presence of super-additivities. Hence, a ***bid languages*** has to be defined. On the one hand, bidders should be able to express their valuations as precisely as possible. On the other hand, the message space should be restricted.

4.1.1 Bid languages

In any auction bidders express their preferences to the auctioneer by a bid language (see Nisan and Segal (2006)).

Definition 4. *An* ***atomic bid*** $b_i(S) = (S, p_{bid,i}(S))$ *is defined as a tuple of a bundle* S *of several items and a corresponding bid price* $p_{bid,i}(S)$ *which was submitted by the bidder* i*. A set of atomic bids is* ***overlapping*** *if at least one item is included in more than one bid.*

The following two definitions are often used.

- The ***additive-OR*** (***OR***) bid language allows the bidder to win any non-overlapping combination of his atomic bids.
- The ***exclusive-OR*** (***XOR***) bid language implies that the bidder can win at most one of his atomic bids.

In this chapter we use the term *bid* instead of *atomic bid.* In CAs and a number of applications in high stakes auctions for industrial procurement, logistics, energy trading, and the sale of spectrum licenses both the XOR and the OR bid language can be found. However, the OR bid language is less expressive than the XOR bid language.

A downside of the XOR bidding is that bidders have to evaluate and express $2^m - 1$ bundles, if we consider a market with m different items. This phenomenon is called ***bidders' complexity***[1].

[1]Nisan and Segal (2001) was the first to point out that for fully efficient allocations the communication requirements grow exponentially.

All bundles have to be evaluated by the bidders. This phenomenon is known as ***strategy complexity***. Bidders have to deal with the ***communicational complexity***, since they are supposed to submit bids for all bundles that generate a positive payoff in some auction formats. In addition ***valuation complexity*** summarizes the process of selecting the "right" bundle for the next bid.

Actually, it is one of the most important challenges in market design to formulate the adequate bid language and to provide sufficient space of information.
An approach to reduce bidders' complexity, is to simplify the bid language (see Perez-Richet (2011)). Milgrom (2010) proposes simplifications of bidders' message spaces that do not eliminate high-revenue equilibria. To solve the winner determination problem efficiently, the auctioneer needs as much information as possible about bidders' value models. Therefore, the right bid language is crucial to obtain a good result in terms of revenue and efficiency.
On the one hand, the bid language should be fully expressive. Bidders should be able to express their valuations completely for every possible value model. On the other hand, the bid language should be sufficiently simple to allow the bidders to represent their valuations precisely and completely for every possible value model.

Besides the above mentioned bid languages there are also many more complex concepts. A more expressive bid language is, e.g., the matrix bid language developed by Day and Raghavan (2007b) or the tree-based bid language of Cavallo et al. (2005). In our thesis, we only deal with the OR as well as XOR bid language.

4.1.2 Combinatorial allocation problem (CAP)

CAs support negotiations on multiple items, especially in the case of complementarities or substitutes. Bundle bids avoid the exposure problem, i.e., that bidders only win a fraction of their requested items.

As shown at figure (4.1), in CAs $I \in \{1, ..., n\}$ bidders are competing for subsets of $K \in \{1, ..., m\}$ indivisible non-identical items. Each bidder i has a valuation $v_i(S)$ for each subset S of any item $k \in K$. Hereby, $v_i(\emptyset) = 0$ and $v_i(S)$ is non-decreasing, i.e., $v_i(S) \leq v_i(T)$ for $S \subseteq T$. The indicator variable,

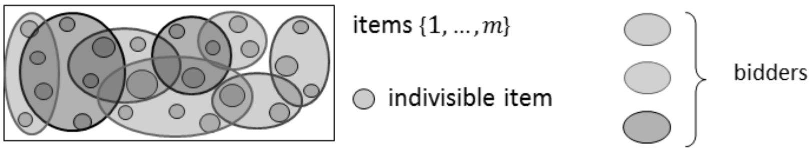


FIGURE 4.1: Items, bundles and bidders in CAs.

if bidder i places the bid on bundle S or not, is $x_i(S)$.
The ***allocation*** X is a tuple $(S_1, \ldots, S_n)$, that describes the distribution of goods to the bidders after the auction. In an allocation all bundles have to be non-intersecting and can be empty: $\forall\, i, j : S_i \cap S_j = \emptyset$.
Furthermore, we define all possible and feasible allocations by $\mathcal{X}$.
In iterative auctions, we have during the auction intermediate results, namely ***provisional allocations***, and at the end a ***final allocation***.

In this context, we also define the term ***price*** more precisely. A ***bid price*** $p_{bid,i}(S)$ is the price submitted by a bidder in an auction. The ***pay price*** $p_{pay,i}(S)$ is computed by the auctioneer at the end of the auction and paid by the winner for bundle S. As in the second-price auction, the pay price can be lower for the bidder than the price he suggested at the auction but never higher: $p_{pay,i}(S) \leq p_{bid,i}(S)$. Obviously, in first-price auctions we have $p_{pay,i}(S) = p_{bid,i}(S)$.

In order to find an *efficient allocation* in a CA that maximizes the social welfare the ***Combinatorial Allocation Problem*** (***CAP***), also called the ***Winner Determination Problem*** (***WDP***) has to be solved:

$$\max \sum_{S \subseteq \mathcal{K}} \sum_{i \in \mathcal{I}} x_i(S) v_i(S) \qquad (\textbf{\textit{CAP-I}}) \qquad (4.1)$$

s.t.

$$\sum_{S \subseteq \mathcal{K}} x_i(S) \leq 1 \qquad \forall\, i \in \mathcal{I}$$

$$\sum_{S : k \in S} \sum_{i \in \mathcal{I}} x_i(S) \leq 1 \qquad \forall\, k \in \mathcal{K}$$

$$x_i(S) \in \{0; 1\} \qquad \forall\, i \in \mathcal{I}, S \subseteq \mathcal{K}$$

The objective function maximizes the sum of valuations of the winning bundles, namely the overall revenue. In the first constraint, it is ensured that at most one bundle can be allocated to each bidder, which is a condition for the XOR bid language. The second set of constraints ensures that each item is sold once at most. For the solution of the CA, we use a CAP in the form of an integer linear program (ILP), known as (4.1) which was originally formulated by Rothkopf et al. (1998). In our work CAP always refers to the CAP-I.

The formulation of the WDP and the corresponding interpretation of the CC as LP provide the possibility to add ***allocation rules***, which is not a focus of our work, but needs to be mentioned for the sake of completeness. By these rules restriction can be formulated. For example the number of winners can be limited to a maximum of 7 or one bidder can win a maximum of 30% of the items. In this way, unintended results like monopoly or oligopoly structures can be avoided. A good example for allocation rules is the supplier quantity selection problem in Bichler et al. (2011). Here a procurement manager minimizes his procurement costs and can define a minimum/maximum number of winners, a lower/upper limit for overall quantity per winner, a lower/upper bound for overall quantity per winner and item and a lower/upper bound for overall spending per winner or group of bidders. Simulations are run to see how constraints affect the outcome.

Exact solutions to the full problem can be obtained by integer programming (see e.g. Sandholm (2006)), but scalability is a problem. Branch-and-bound, cutting-plane and branch-and-cut algorithms are alternatives. The WDP modeled as multi-dimensional knapsack problem is an instance of the Weighted Set-Packing Problem, which is known to be NP-complete. When bids are submitted on all bundles, which is rarely realistic, and certain other restrictions are met, Rothkopf et al. (1998) provide a polynomial algorithm for solving the CAP. Additionally, Rothkopf et al. (1998) state, that the WDP can be solved in polynomial time if bundles consist of a maximum of two items. This is equivalent to finding a maximum-weight matching in a graph. If the bundle size is enlarged to three or more items, the WDP is NP-hard.

To deal with the complexity, bids can be restricted so that the WDP becomes solvable in polynomial time. In Bichler et al. (2014b) and later in this thesis, we simplified the bid language and reduced the complexity, both for the bidders and the WDP. The complexity for the bidders is different from the issue of computational complexity for the auction designer, i.e., how to determine which bids are winning. Often the number of possible bids per bidder have to be capped to a few hundred in order to keep the winner-determination problem feasible.

Another approach to deal with the complexity is ***hierarchical package bidding*** (***HPB***), where bidders can only submit OR bids on those (non-overlapping) packages that are explicitly stated in the hierarchy (see Jacob et al. (2012) and Goeree and Holt (2010)).

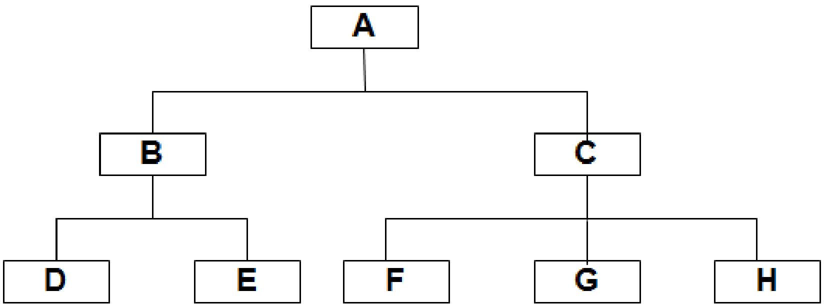


FIGURE 4.2: The tree structure in HPB.

The winner determination is strongly NP-hard in case of an XOR bid language, in spite of the tree structure which can be seen in figure (4.2). The HPB structure was applied by the US FCC in 2008 in the sales of regional 700MHz spectrum licenses. The structure can be considered as simplification of a fully expressive bid language. In the 700MHz auction, the complementarities between licenses are mostly geographic. Potential bidders are mainly interested in obtaining a nationwide coverage. For this reason, the FCC offered a nationwide package in addition to individual licenses.

An approximation of the solution would also be a solution to reduce the complexity. However, there is no polynomial-time algorithm that guarantees an approximate solution to the WDP within a factor of $l^{1-\epsilon}$ from optimal, where l is the number of submitted bids (see Rothkopf et al. (1998)) and ϵ the residuum.

4.1.3 The Vickrey-Clarke-Groves (VCG) auction

The VCG auction, also known as second-price auction, was generalized by Clarke (1971) and Groves (1973) to a generic competitive process, which includes the concept of a CA as a special case. Ausubel et al. (2006) and Ausubel and Milgrom (2006) state that the VCG payment rule has many advantages, mainly based on his dominant strategy. Hence, no bidder can obtain a better result by speculation, i.e., bidding anything else as the valuation.

After each bidder has reported his valuation $v_i(S)$ on all bundles $S \subseteq \mathcal{K}$, the auctioneer determines the revenue-maximizing allocation. Then the pay prices are computed, where the winners pay their bid price, which are reduced by

$$p_{pay,i}(S) = p_{bid,i}(S) - \big(w(C_{\mathcal{I}}) - w(C_{\mathcal{I}\setminus i})\big) \tag{4.2}$$

We explain it more detailed by the following example. Let's assume, that we have 3 bidders b_1, b_2 and b_3 and 2 items, namely A and B.

Bidder/combination	**A**	**B**	**AB**
b_1			**300**
b_2		100	
b_3	100		

TABLE 4.1: Bidders' valuations and the winning allocation in the example for the VCG payment rule.

In table (4.1) we see that b_1 submits the highest bundle bid (bold print) for both items, whereas he wins. Now his payment has to be calculated. We insert into equation (4.2) and get as VCG payment $200 = 300 - (300 - 200)$. According to Green and Laffont (1979) and Holmstrom (1979), there is no other mechanism that has a dominant strategy resulting in an efficient outcome without any additional payment to losers.

Unfortunately the VCG auction has some problems (see e.g. Ausubel and Milgrom (2006)) Here, we use the example of Ausubel and Milgrom (2006) in

Bidder/combination	**A**	**B**	**AB**
b_1	0	0	2
b_2	**2**	2	2
b_3	2	**2**	2

TABLE 4.2: Bidders' valuations and the winning allocation in the modified example for the VCG payment rule.

table (4.2) to show weaknesses. Let us again look at the same simple market with 3 bidders and 2 items but with different valuations.
Again, the efficient outcome, where A is allocated to b_2 and B to b_3, is in bold print. When we insert the values into equation (4.2) we get as VCG payment $0 = 2 - (4 - 2)$. Hence, any bidder get his item for free and the auction revenue is 0. This is the biggest problem of the VCG auction, since there is no motivation for an auctioneer to select this format when receiving ***low or zero revenue***.
Another downside is the ***monotonicity problem***, i.e., removing bidders from the auction might increase the revenue and adding bidders might reduce the auctioneer's revenue. If we remove at table (4.2) b_3, b_1 will win the bundle AB at the price of $2 = 2 - (2 - 2)$, which is the overall revenue.
There are possibilities for ***collusion***. Imagine there are complementarities and b_2 and b_3 have only the valuation of 0.5 for A or B, but still 2 for the bundle. Then, b_1 would win the bundle. However, if they collude and bid 2 instead of 0.5, they win by paying nothing. This phenomenon is called ***shill bidding***, when bidders overbid their valuation to obtain better results.

In addition, there are difficulties concerning truthfulness and privacy. In reality, bidders fear that they have to pay more if they bid their valuation. Therefore, for the implementation of an auction platform cryptographic protocols should be used to ensure fairness (see Brandt (2003)). A problem what we have seen in many experiments is that each bidder should submit all possible bundles, namely $2^m - 1$ bids. In practice, bidders do not submit bids for less profitable bundles, which are considered as zero in the winner-determination problem. This effect might lower the auctioneer's revenue significantly.

Nevertheless, the VCG auction is an important theoretical construct and used as a reference point for many auctions, especially for CAs. In many applications, there are complementarities, a situation where the main weaknesses of the VCG auction are strengthened (see Rothkopf (2007) and Ausubel and Milgrom (2006)). Therefore, it is hardly used in a real-world context.

To avoid this problem among others, the bidder-optimal core-selecting payment rule was developed. Day and Raghavan (2007a) suggested a procedure to calculate bidder-Pareto-optimal payments from sealed-bids right away. Given all total payment minimizing core points, that one is selected that minimize the sum of square deviations from the VCG payments (minimal Euclidean distance). The objective is to minimize the incentive to misreport ones valuations. Therefore, the core for package allocation problems has a competitive auction interpretation:
An individual rational allocation is in the core, if there is no group of bidders who could all do better for themselves and for the seller by raising some of their losing bids.

A good example of how core payments are computed is given by Day and Cramton (2012). This example was also shown to our participants in the experiments. Imagine an easy market with 5 bidders, b_1, b_2, b_3, b_4 and b_5, and 2 items, namely A and B.

Bidder/combination	**A**	**B**	**AB**
b_1	**28**		
b_2		**20**	
b_3			32
b_4	14		
b_5		12	

Table 4.3: Bidders' valuations and the winning allocation in the example for the core-selecting payment rule (Day and Cramton (2012)).

Valuations and the winning allocation are given in table (4.3). Since b_1 and b_2 submit the highest bids, they win both items. Now the pay prices will be reduced. If we choose the VCG payment rule, b_1 and b_2 would only pay $14 + 12 = 26$. Bidder b_3 could pay more, namely 32 and make a sub-coalition with the auctioneer. Hence, b_1 and b_2 have to pay at least 32 to avoid such problems. In the core payment rule, from the price pairs that add up to

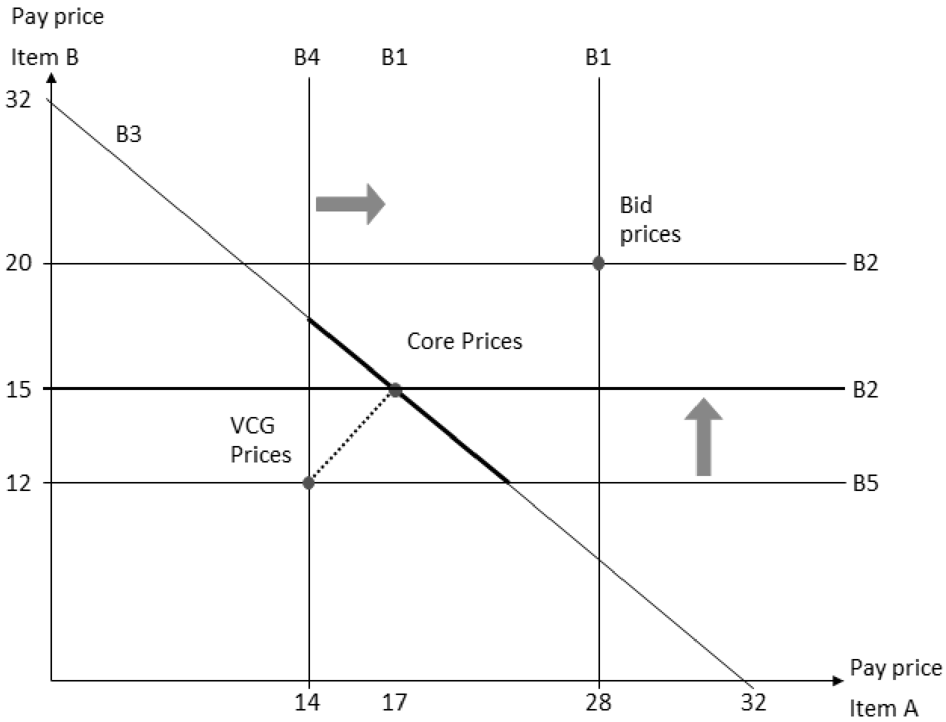


FIGURE 4.3: Exemplary computation of core payments (Day and Cramton (2012)).

32, the pair is selected that is closest to the second-prices. So, b_1 pays 17 and b_2 15. However, we have to mention that there might be some room for speculation.
Bidder b_1 will never pay more than its bid price of 28. Only when he bids less than 14, he won't win. For all bids in the range $[17, ..., 28]$, b_1 cannot reduce his pay price of 17. If his bid is higher than 14 but less than 17, he still wins, but pays less at the expense of b_2. Let us assume, that b_1 bids 15, then he could reduce his payment to 15 instead of the original 17; b_2 would have to pay 17 instead of 15. This example shows that speculation is difficult to accomplish, since you have to know others' bids, but possible.
For further details, Maldoom (2007), Day and Cramton (2012) and Day and Raghavan (2007a) should be read to understand the payment rule in detail. Hereby, an algorithm is introduced to determine a payment, which guarantees a unique outcome. The achieved prices ensure that no coalition can prefer an alternative outcome.

The VCG and the core-selecting payment rule share the revenue non-monotonicity (see Lamy (2009)), i.e., revenue can decrease with additional bids in the auction. However, the core-selecting payment rule has no dominant strategy. Hence, bidders might apply bid shading to reduce their payment, as seen in the example above. Goeree and Lien (2010b) show in a Bayesian-Nash equilibrium analysis that in a private values model with rational bidders, auctions with a core-selecting payment rule are on average further from the core than auctions with a VCG outcome. They also proof that there is no Bayesian incentive-compatible core-selecting auction, when the VCG outcome is not in the core. For a simplified setting, Goeree and Lien (2012) state that the "core selecting" payment rule may result in prices that are further from the core than VCG prices.

If auctions that use the core-selecting payment rule are defined as a complete information game, the prices resemble the VCG outcome when it is in the core. According to Day and Cramton (2012) the revenue is even higher, when the VCG outcome is outside the core. Here bidders follow a truncation strategy, where all reported values of non-null goods assignments are reduced by a non-negative constant.

4.1.4 Iterative combinatorial auctions (ICAs)

To reduce value uncertainty and increase transparency, ***iterative combinatorial auction*** (***ICA***) are frequently used. In ICAs the auctioneer collects bids from all bidders, evaluates them and provides feedback. There are different kinds of feedback possible, but at least the new ask prices have to be reported. In addition, provisional allocations, a bid history about own and others' submitted bids might be reported. The prices are increased until the demand equals supply. In such a tatônnement process, which was firstly described by Marie-Esprit-Léon Walras, a *Walrasian equilibrium* can be achieved. This result is per se Pareto optimal and therefore, efficient.

As in other formats bidders should be motivated to bid truthfully, which can be done by low ask prices. However, we have to note that is not a dominant strategy to express his valuation, since strategy proofness is not ensured. Among others Milgrom and Weber (1982a) and Elmaghraby and Keskinocak (2002) show, that ICAs perform better than sealed-bid mechanisms when there are no private valuations. Porter et al. (2003a) state “Experience in both the field and laboratory suggest that in complex economic environments iterative auctions, which enhance the ability of the participant to detect keen competition and learn when and how high to bid, produce better results than sealed-bid auctions”.

As with other dynamic auctions, the ICAs take place in different ***rounds***. At the beginning of a new round, bidders receive their updated feedback. After each round new prices and provisional allocations are computed.
Generally, bidders report their demand depending on the given ask prices. In some implementations of the ICAs, ***jump bids*** are possible. These bids are usually much higher than the current price level. Auctions that allow jump bids terminate faster, but bidders might apply strategies like signaling (see Cramton et al. (2006a)), which effects the efficiency negatively. Bidders signal by high bids even in an early auction stage that they are willing to win certain items. By this strategy, bidders can implicitly communicate between each other and share the items between each other.
Different price formats, i.e., linear, non-linear, and non-linear personalized prices are applied in ICAs (Xia et al. (2004)).

Linear (additive) prices, describe a structure, where the price for a combination of items is exactly the sum of the price for each single item. In contrast, ***non-linear*** ask prices are known as ***bundle*** prices, because the price for a bundle is different from the aggregation of the different unit prices. Prices are ***anonymous*** if the price is the same for every bidder, whereas ***discriminatory*** or ***personalized*** ask prices are dependent on the participant.

Personalized prices are only common if a XOR bidding auction is used, which is the case in CAs. The problem is that bidders might see personalized prices as unfair, since the value for similar items can differ significantly. Additionally, the computational effort increases linearly to the number of participants. In OR bid languages anonymous prices are always sufficient since bidders cannot express bundle bids and it does not matter who actually wins.

Linear prices provide many advantages. Obviously, they are easy to explain; each bidders can understand it easily and compute the prices for a combination of items intuitively. The auctioneer can also provide price updates to the bidders quickly. Kwon et al. (2005) conclude that bidders can get a market overview with respect to competitors and possible bundles quickly with linear prices, which often leads to high efficiency. However, the problem is that such prices are not accurate enough and can also not reflect synergies that might be in bidders' valuations due to the environment. For example, there might be situations in that the calculated bundle price is too high. Hence, a bidder might not bid since the ask price is above his valuation. But due to his valuation, he might be the bidder in the efficient allocation.

Parkes (2001) and others state that non-linear prices should be preferred in ICAs, because they support competitive equilibrium prices. Furthermore, many ICAs with non-linear prices are analyzed in game theory with the outcome that they result in an efficient outcome if bidders apply their straightforward strategy. However, the problem remains that such a price structure is difficult to communicate and understand. Which pricing format should be chosen depends strictly on the needs and the context.

We have seen that non-linear personalized prices are often requested; however, the CAP-I supports linear anonymous dual prices which can obtained from the corresponding dual problem. A weakness in this case is that the optimal solutions of primal and dual problems might be not the same when integrality constraints are added, which affects the duality gap. The CAP-I does not enable bundle bids and non-linear prices.
Therefore, Bikhchandani and Ostroy (2002) developed the CAP-III (4.3). They introduce the additional variables δ_X, which measure the "weight" of every allocation $X \in \mathcal{X}$. Correspondingly, in the second constraint we have

now pairs of bidders and bundles. Each bidder can only win a single bundle.

$$\max \sum_{i \in \mathcal{I}} \sum_{S \subseteq \mathcal{K}} v_i(S) x_i(S) \qquad (\textbf{\textit{CAP-III}}) \qquad (4.3)$$

s.t.

$$\begin{aligned} x_i(S) &= \sum_{X : X_i = S} \delta_X && \forall\, i \in \mathcal{I}, S \subseteq \mathcal{K} \\ \sum_{S \subseteq \mathcal{K}} x_i(S) &= 1 && \forall\, i \in \mathcal{I} \\ \sum_{X \in \mathcal{X}} \delta_X &= 1 && \\ 0 &\leq x_i(S) && \forall\, i \in \mathcal{I}, S \subseteq \mathcal{K} \\ 0 &\leq \delta_X && \forall\, X \in \mathcal{X} \end{aligned}$$

The first constraint ensures that the weight of bidder i who receives S matches the sum of weights over all allocations where bidder i gets the bundle S. The third constraint is formulated to set the total weight of all selected allocations to one. In the remaining constraints, negative weights or assignments of bundles to a bidder with a negative weight are excluded.

4.1.5 Performance metrics

There are several metrics to measure the performance of an auction mechanism. In the following, we describe the most important ones in detail. The social welfare is usually measured by (allocative) efficiency, whereas a value of 100% describes the best result. Auctioneer's revenue measures the distribution of the earnings between bidders and the auctioneer (see for example Riley and Samuleson (1981)).

The ***bidder payoff*** $\pi_i(S, \mathcal{P}_{pay})$ is the result of a bidder i who wins an item or bundle S. It is computed by the difference of valuation and the pay price.

$$\pi_i(S, \mathcal{P}_{pay}) = v_i(S) - p_{pay,i}(S)$$

For rational, risk-neutral bidders, their independent private valuation defines the upper limit for a possible bid in a sales auctions. In procurement costs bidders might not accept a price that is lower than their production costs.

The ***auctioneer revenue*** as well as the ***procurement costs*** is the sum of all pay prices:

$$\Pi(X, \mathcal{P}_{pay}) = \sum_{i \in \mathcal{I}} p_{pay,i}(S_i)$$

Therefore, the total revenue of the auctioneer and all bidders in the final allocation X with the final pay prices $\mathcal{P}_{pay}$ can be summarized as:

$$\Pi(X, \mathcal{P}_{pay}) + \pi_{all}(X, \mathcal{P}_{pay}) = \\ = \sum_{i \in \mathcal{I}} p_{pay,i}(S_i) + \sum_{i \in \mathcal{I}} (v_i(S_i) - p_{pay,i}(S_i)) = \sum_{i \in \mathcal{I}} v_i(S_i) \tag{4.4}$$

The formulation for reverse auctions is vice versa.

Allocative efficiency can be measured as the ratio of the value of the final allocation X to the value of the efficient allocation X^* (Kwasnica et al. (2005)). Therefore, the efficiency depends only on the allocation not on prices and the bidder who values the item the most will win the auction (McAfee and McMillan (1987)).

$$E(X) := \frac{\sum\limits_{S \subseteq \mathcal{K}} \sum\limits_{i \in \mathcal{I}} x_i(S) v_i(S)}{\sum\limits_{S \subseteq \mathcal{K}} \sum\limits_{i \in \mathcal{I}} x_i^*(S) v_i(S)} \in (0, ..., 1]$$

We define the ***auctioneer revenue share*** by

$$R(X) := \frac{\sum\limits_{S \subseteq \mathcal{K}} \sum\limits_{i \in \mathcal{I}} x_i(S) p_{pay,i}(S)}{\sum\limits_{S \subseteq \mathcal{K}} \sum\limits_{i \in \mathcal{I}} x_i^*(S) v_i(S)} \quad \in [0, E(X)] \subseteq [0, ..., 1]$$

If the allocation remains the same, increasing bidder revenue decreases the auctioneer revenue the same amount.

Besides these two most important performance metrics, low transaction costs for bidders, transparency, fairness et cetera (Pekec and Rothkopf (2003)) are also important.
For the auctioneer or if you run simulation, the duration of an auction is also decisive, which is known as ***Speed Of Convergence***. Here, the time as well as the amount of rounds is important. The duration depends on the (minimum) increment, i.e., how much the prices are updated after each round, if there is overdemand. The auctioneer has to master a trade-off. If the increment is too large, the auction will terminate quite quickly, but efficiency might be lost, because bidders cannot submit bids accurately depending on their valuation accurately. We set the increment in that way, that the auctions terminated always in average in less than 30 rounds, which is quite fast.
Other factors that determine the speed of convergence are the activity rules and the start prices. Our stacked activity rule motivated the bidders to submit as many bids as possible, but did not motivate for too aggressive bidding. The start prices are set at the lower limit of potential value draws. However, we have to note, that this might not be possible in practice when valuations are unknown.

Another important issue is the ***robustness*** of an auction format. It describes how stable an auction format is under different circumstances. This can hardly tested by simulation, since by predefined assumptions you cannot identify problems that might arise. Therefore, we run experiments which might be a better tool in this context, since you cannot predict by simulations precisely how humans behave.

4.2 Auction formats

In our work, we focus on auctions that are frequently used in practice for the sales of spectrum licenses. Hereby, we refer to Bichler et al. (2013a), Mayer and Shabalin (2013) and Bichler et al. (2014b).

4.2.1 The simultaneous multi-round auction (SMRA)

The ***simultaneous multi-round auction*** (***SMRA***) is a generalization of the English auction for more than one item. This iterative mechanism "was first introduced in 1994 to sell licenses to use bands of radio spectrum in the United States" Milgrom (1998, p. 1). The auction consists of multiple rounds during which bidders submit bids simultaneously for any item they want. Each item has his individual price. The bidding continues until no bidder is willing to raise the bid on any of the items. Each bidder wins the item where he is the best bidder and pays his bid (Milgrom (2000)).

The degree of information, the price update and the activity rule depends on the implementation of the auction format. In some versions all the information collected during the rounds is made public. This can be, for example, the number of active bidders and the bid history, i.e., all submitted bids of any bidder. Sometimes only the best bid for each item is known to the participants.

New bids have to exceed the current market price by a predefined minimum increment. In some versions, bidders can increase their bids as much as they want. Bidders might signal their preferences by using the trailing digits of the bid price to transmit information (see Niemeier (2002) and Weber (1997)). Therefore, in practice, the price update is often restricted to predefined levels at which value a new bid can be.

In addition, it is very important to define bidders' possible activities. It should be prevented, that some bidders speculate and wait for other participants to shade their preferences. This behavior can cause delays in the auction and lead to an inefficient outcome when some bidders do not enter the auction or do not submit all the bids they are interested in. To avoid these problems, ***eligibility rules*** can be defined. By these rules the number of items a bidder is allowed to bid in the current round is determined. At the beginning of an auction, a bidder usually gets full eligibility so that he might bid on any item. From the first round on the eligibility is non-increasing and depends on the number of different bids in the round before. The advantage of eligibility rules is that bidders are motivated to bid proactively from the first round on, because lost eligibility can never be recovered. As a consequence, bidders' participation will decrease as the auction proceeds. Bidders might stop bidding when the ask prices rise above their valuations.
Bichler et al. (2013a) implemented a "stacked" activity rule. At the beginning each bidder was eligible to bid on all items at sale. In the first three rounds bidders were required to use only 50% of their eligibility to maintain all eligibility points for the next round. From the fourth round on, bidders had

to use 100% of their eligibility.

There is limited theoretical research on the SMRA. If bidders have substitute preferences[2] and bid straightforwardly, then the SMRA terminates at a Walrasian equilibrium (Milgrom (2000)), i.e., an equilibrium with linear prices (Gul and Stacchetti (1999); Kelso and Crawford (1982)). In case of substitute valuations the marginal product of any set of bidders exceeds the sum of the marginal products of its members. Straightforward bidding means, that bidders only bid on these items that maximize the payoff given the market prices. However, Milgrom (2000) has shown that with more than three bidders and at least one non-substitute valuation no Walrasian equilibrium exists.

The SMRA generates several disadvantages and strategical problems for bidders (Cramton (2013)). Brusco and Lopomo (2002) demonstrate the possibility of collusive demand reduction equilibria in the SMRA. In addition, in order to maintain eligibility bidders temporarily bid for packages they are not interested in which can provide less efficient outcomes. Bidders can also use signaling such as jump bidding to cooperate in SMRA.
In case of substitutes and complements, bidders run the risk of winning only a part of a complementary collection of items in an auction without package bids. This phenomenon is known as ***exposure problem***.

A simple example describes the problem. Assume a bidder, who has a valuation of 1 for the items A and B; however, due to complementarities his valuation is 3 for the bundle of A and B. If he aims to win the bundle, he might bid more than 1 for each item. If prices get higher than 1 and he wins only one item, he will make a loss.
Many experiments show the negative impact of the exposure problem on the performance of the SMRA (Brunner et al. (2010); Goeree and Lien (2010b); Kagel et al. (2010); Kwasnica et al. (2005)). Goeree and Lien (2010a) analyzed a Bayes-Nash equilibrium of SMRA considering complementary valuations. They proved that due to the exposure problem, the SMRA may result in non-core outcomes. The revenue of the auctioneer decreases depending on the number of bidders similar to the Vickrey-Clarke-Groves auction (VCG) (see Ausubel and Milgrom (2006)). CAs avoid the exposure problem, since

[2] Good definitions about bidders' preferences can be found within Bikhchandani and Ostroy (2002)

bidders can submit bids on indivisible combinations of items.

Some bidders might use budget binding in the SMRA, i.e., bind budgets of other budget-constrained bidders, resulting in high prices for everyone. Bidders might maintain their eligibility in part by parking in spots other bidders are not interested in, and then move to true interests later. Waivers and bid withdrawals open up more options for the bidding strategy. We have seen this strategy in the recent Czech auction. Furthermore, bidders make clear that they are difficult to outbid and resell the blocks after the auction. But, the auctioneer could forbid resale after the auction.

4.2.2 The combinatorial clock (CC) auction

The ***Combinatorial clock*** (***CC***) auction was originally proposed by Porter et al. (2003b). In this multi-unit auction several homogeneous units of heterogeneous items are sold simultaneously and bidders can bid on partial quantities.
The CC auction starts with sufficiently low linear ask prices. Each bidder submits a bid, where he expresses the amount of each item he wants to buy given the current ask prices. Normally, bidders can only accept the current prices and not submit jump bis. After each round the prices for overdemanded items, i.e., where the demand exceeds supply, are increased and the winner determination problem, the CAP, has to be solved. All bids remain active throughout the auction. The bids that are submitted at the current ask prices are called ***standing bids***. Therefore, the number of standing bids includes all bids from the current round t and those standing bids from the previous round $t-1$, for which the ask price did not change. Each bidder with one or more standing bids is ***standing***.
Different activity rules can be applied for the CC. One alternative is given by Porter et al. (2003b), which says that demand in items cannot increase and is restricted by the current amount of requested units within an item. Ausubel et al. (2006) state that only the overall quantity across all items is decisive. For our experiment we chose this rule. If all bidders active in the last round are included in the allocation, the auction terminates. Otherwise, the prices on those items that have not been allocated to an active bidder are increased and the auction continues.

The CC is quite simply to understand for the bidders due to the intuitive rules. Additionally, price discovery works quite efficiently, transparency is increased and there are hardly any possibilities for bidders to collude. The main advantages are that the exposure problem is prevented by bundle bids and that strategies like jump bidding and signaling are not possible. Because of these and other reasons, the CC is frequently used in practice. A detailed discussion about CAs can be found in Bichler et al. (2010b).

However, there are also some downsides. Bidders can only accept the current prices and not state the bids more precisely. In addition, there is no equilibrium strategy known, that can be a baseline for bidding behavior, since the CC is too complex to analyze theoretically. Gul and Stacchetti (1999) have proven, that there is no ascending auction format known which results in an efficient outcome using linear prices. Also, bidders might have incentives for demand reduction. Bichler et al. (2010b) have even shown that there might be zero efficiency with straightforward bidding and quite low efficiency with powerset bidding, i.e., bidders bid on all items that generate positive payoff. To avoid some of these and other problems, the Combinatorial Clock Auction with a core payment rule was developed.

4.2.3 The two-phase combinatorial clock auction (CCA)

After having considered the CC, we now take a closer look at a two-phase CA format, the ***combinatorial clock auction*** (***CCA***), which is tested in the laboratory by Bichler et al. (2013a) and is our point of reference.
Ausubel et al. (2006) and Cramton (2009) proposed a early version of this format. Maldoom (2007) published a mechanism which is now used in spectrum auctions across Europe. This part of the study is based on his proposal.

The first phase of this auction consists of a CA to enable price discovery and transparency. In the second phase a sealed-bid auction is held to obtain results in core outcomes with high efficiency.
In the primary bid rounds (first phase), bidders submit their bids depending on the current market prices. If there is overdemand within an item or band, prices are increased by a fixed increment. This process continues until there is no overdemand. Bidders can only submit a bid on one package per round,

which is different from earlier proposals of Cramton (2009) and Ausubel et al. (2006). The right payment rule can motivate bidders to bid truthfully, i.e., bid their true valuation. In the supplementary bids round (second phase), bidders can submit multiple bids on arbitrary bundles, whereby the bid price is limited by **the anchor activity rule**[3]. This rule prevents bidders from holding back their demand in the first round. It is implemented to motivate them on their payoff maximizing item from the first round on in the clock phase. The non-increasing eligibility points activity rule induces the bidders to stay active in the first phase.
The anchor rule has the following underlying logic.

If a bidder wants to bid on a bundle X, which is not the last bundle from the first phase, the round have to be found in which the bidder had enough activity points to bid on X. This round is called is the anchor round. It determines on which bundle the bidder bid instead. This bundle is called the anchor combination. Therefore, the bidder preferred anchor combination to the bundle X at prices of the anchor round. This statement remains valid for the rest of the auction. Hence, the highest price which the bidder can bid on bundle X is limited by the sum of the highest bid on the anchor combination and the price difference between X and the anchor combination at the prices of the anchor round.
For the winner determination, all bids are considered for selecting the revenue maximizing allocation, which can be submitted in any phase. In the CCA the XOR bid language is used.

The core-selecting payment rule was actually developed for the CCA, mainly to avoid the problems due to the Vickrey-Clarke-Grove (VCG) prices (see Ausubel and Milgrom (2006)).
In the first round of the CCA bidders are motivated to bid straightforward, in the second round to bid truthful. Bidders are supposed to bid on all bundles that have a positive valuation.
To generate straightforward bidding, the anchor rule is implemented so that for all bids submitted in the first round, they can bid on every bundle in the supplementary bids round at their true valuation (see Bichler et al. (2013a)). The incentives for bid shading are reduced by the closest-to-Vickrey core-selecting payment rule.
Due to that fact the law of one price is not valid, since bidders might pay

[3] see for details Bichler et al. (2013a)

different prices for the same items. This criterion is quite often important for efficient markets and is seen as fairness among the participants which is often seen desirable in market design (Cramton and Stoft (2007)). Papai (2003) states that in this way the goal of envy-freeness of an allocation for general valuations is violated. Such a situation occurred in the recent Swiss auction, where two bidders obtained nearly the same spectrum licenses, but the payment differed at more than 100 million Swiss Franc. It is very difficult to justify this outcome to the companies and the public.

Let's assume a simple market with two bidders, b_1 and b_2, and two units of item A to underline the problem.

Bidder/combination	**1*A**	**2*A**
b_1	**5**	
b_2	**5**	9

TABLE 4.4: Bidders' bids and the winning allocation for two units of the item A.

At table (4.4) we see, that each bidder wins one unit, but bidder 1 pays \$4 and the bidder 2 pays zero. Due to the asymmetry of bidders the price for the same item differs.

Additionally, spiteful bidders have to be considered in real-world auctions, since bidders might prefer an outcome where their opponents get fewer earnings. Suppose that there is b_3 in the above example, who has a good estimate, what b_1 and 2 b_3 are willing to pay for the individual units so that he can safely submit a bundle bid of \$3 for $2 * A$. Now, bidder 2 would actually have a payment of \$3 instead of zero.

Morgan et al. (2003) and Brandt et al. (2007) analyzed situations when bidders did not behave as (expected) utility maximizers. They showed that the revenue equivalence theorem of the first-price and the second-price sealed-bid auction is violated with spiteful bidders, since the VCG results in higher revenue with spiteful bidders. Bichler et al. (2013a) provided examples that the CCA provides possibilities to submit spiteful supplementary bids with no risk of actually winning such a bid, if all blocks are sold after the primary bid rounds and the standing bidders only want to win their standing bid in the supplementary bids round with a small bid increment.

Another issue for auctioneers in ascending auction formats is tacit collusion, i.e., bidders cooperate with each other and reduce demand jointly to ensure that they pay relatively low prices for what they win. Bajari and Yeo (2009) report that in real-world auctions, tacit collusion is a common phenomenon. In SMRA, bidders see the others' actions and therefore, can learn about others' intention. Brusco and Lopomo (2002) analyzed theoretically how bidders can observe others behavior and coordinate their actions. The CCA reveals much less information after each round, and bidders only know if there is still overdemand, which makes tacit collusion harder.

4.3 Experimental design

First, we describe the value model before we continue with the treatment structure and the experimental procedures. Our value model does not model a certain situation in a specific country. It is a generalization of the sales of spectrum licenses as it occurs in many countries.

4.3.1 Real-world value models

By the beginning of the 21^{th} century UMTS spectrum licenses have been allocated worldwide. A good review is made by Klemperer (2002). He reported that most of the countries applied auctions; however in France and Poland, beauty contests still took place. In 2000 and 2001 Austria, Germany, Italy, Netherlands, Switzerland, UK, Belgium, Denmark and Greece sold their licenses via auctions. Since the real valuation of each bidder is not made public, the efficiency could not be measured. The revenues ranged between from £650 per capita in the UK to only €20 per capita in Switzerland. Mainly due to the high competition - 13 companies competed for 5 licenses - the revenue was so high in the UK. All of the countries except Denmark used the SMRA auction, which generated a value of €95 per capita. Generally, the revenue in all auctions was quite high since there was a hype for the 3G sector. Del Monte (2003) stated that the participants paid far too much for the licenses and a winner's curse could be recognized. The telecommunication companies overestimated the technology and spent too much money, which led to less investment for basic services within the countries. Also the exposure problem worsened the situation for the companies.

Hence, CAs became more and more popular and finally, in 2008, the FCC allowed package bids for the sales of 700MHz spectrum licenses. To avoid the ***threshold problem***, i.e., many small providers having to cooperate to get competitive towards a large bidder, the HPB auction was used, which generated almost $ 20 billion revenue.

In the German 4G auction in 2010 four bidders, Deutsche Telekom (DT), Vodafone (VF), Telefonica O2 (O2), and Eplus (E+) competed for 41 blocks in four different bands, namely 0.8 GHz, 1.8 GHz, 2.1 GHz, and 2.6 GHz. Each band was divided into paired (10 MHz) or unpaired spectrum (5 MHz) blocks. Every bidder aimed for at least two adjacent blocks to realize synergies. The complexity was increased since the players already owned licenses in the 1.8 GHz and 2.1 GHz bands based on prior allocations.

Each band can support different technologies that implement voice or data services, e.g., GSM, UMTS, LTE, WiMAX, etc.. Frequencies in 0.8 GHz respectively 2.6 GHz are mainly used for LTE in Germany. DT and E+ also use 1.8 GHz for LTE. With just a little bit of theoretical background on radio waves, it is obvious that different frequencies of the bandwidths which were sold impact the way blocks can be used. A frequency of 800MHz is comparatively low and therefore allows for wide reach at medium speed. The 2.6GHz band, on the other hand, promises a higher transfer rate but requires more cell towers to cover a certain area. Therefore, the combination of blocks from both bands allows telcos to provide full 4G coverage across the country while handling the peak load in densely populated urban areas.

The German 2.6 GHz band reflects the value model "Base"' analyzed at Bichler et al. (2013a). The spectrum is divided into blocks for the use of Frequency Division Duplex (FDD) and Time Division Duplex (TDD). FDD means that the transmitter and receiver operate at different carrier frequencies. It is mainly used for ADSL, VDSL, most cellular systems, UMTS/WCDMA, IEEE 802.16 and WiMax. TDD is the application of time-division multiplexing to separate outward and return signals. It emulates full-duplex communication over a half-duplex communication link. Typical area of application are the UMTS 3G supplementary air interfaces TD-CDMA for indoor mobile telecommunications, DECT wireless telephony, Wireless local area networks and Bluetooth, IEEE 802.16 WiMAX, etc..

Most of the revenue was generated by the sales of licenses in the 2.6 GHz spectrum, You see the allocation according to Bundesnetzagentur (2010) at figure (4.4)[4].

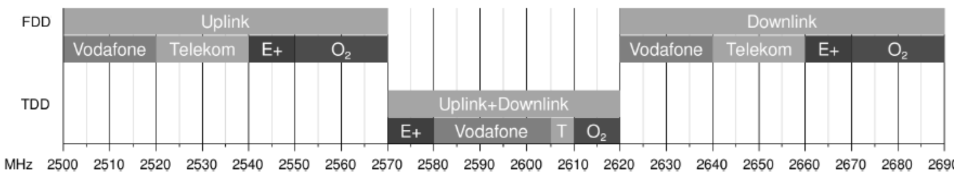


FIGURE 4.4: The final allocation of the German 4G auction in 2010 of the 2.6GHz band.

The whole auction took 27 days during which 224 rounds have been played. The total revenue was according to the Bundesnetzagentur €4.4 billion. VF got 12 blocks for €1.4 billion, O2 11 blocks for €1.4 billion, DT 10 blocks for €1.3 billion and E+ 8 blocks for €0.3 billion.

The first CCA took place in the UK in 2008, where 17 licenses have been sold. However, the bidders submitted only between 0 and 15 out of $2^{17} - 1$ possible bids in the supplementary phase, which is too less to get an efficient solution. According to Cramton (2008) a single bidder won all the licenses with a bid of £20 million, but he had only to pay £8.334 million due to the payment rule. The Switzerland also held a CCA in 2012. According to BAKOM (2012) 61 licenses in the 800MHz, 900MHz, 1.8GHz, 2.1GHz, 2.6GHz were sold. The Netherlands auctioned 41 separate licenses in the 800MHz/900MHz/1.8GHz/1.9GHz/2.1GHz/2.6GHz bands (see Minister van Economische Zaken (2012)). In the spectrum auction in Canada, 98 licenses were sold. We have to note here that even with 30 licenses the complexity is higher than 1 billion.

In the Austrian auction in 2013, the Rundfunk und Telekom Regulierungs-GmbH (2013) sold 28 blocks for the 0.8 GHz, 0.9 GHz and 1.8 GHz band to

[4]The original figure can be found at *http://de.wikipedia.org/wiki/LongTermEvolution*

three providers, namely A1Telekom Austria, T-Mobile Austria and Hutchison. Bidders could participate by entering their bids on a web platform. All blocks were sold in units of paired blocks of 2x5MHz, which means that each block included 5MHz of uplink and downlink. The whole auction took 22 days. Altogether, 216 bids were submitted during the 72 rounds in the clock phase. In the supplementary phase, additional 4032 bids were submitted, which resulted in high revenue (around €2 billion) and probably an efficient allocation. From the whole market share of licenses, 44.2 % was allocated to A1 Telekom Austria, 30.9% to T-Mobile Austria and the remaining 24.9% to Hutchison.

Another important application for the CCA was the British 4G auction in 2013, where the 0.8 GHz and 2.6 GHz band was sold [5]. Seven bidders, namely, Vodafone, Telefonica, EverythingEverywhere, Hutchison 3G, Niche Spectrum Ventures, MLL Telecom and HKT Company competed for the licenses. Each of the companies won at least one license. As expected, the most valuable target - a pair of 0.8 GHz blocks for building a nationwide network with maximum reach - was won by the two big providers Vodafone and Telefonica. Both in the 0.8 GHz and 2.6 GHz band, 2x5MHz and 2x10 MHz paired spectrum were sold. In addition, 2x20 MHz paired and 5MHz unpaired spectrums was auctioned in the 5 GHz. The CCA achieved only 2.23 billion GBP revenue. This was far below below the expectations, which led to an investigation by the UK National Audit Office [6].

4.3.2 The value model

The value model used in our experiments tries to model the German auction in 2010[7]. However, the structure is similar in almost each country.

In this paper we will draw on the multi-band value model used in earlier experiments of Bichler et al. (2013a), which has four bands with 6 licenses each (see figure (4.5)). This value model reflects quite closely the German market, where 4 bidders also competed for licenses within 4 bands. We can directly compare our results with the older ones.

[5]See for details http://stakeholders.ofcom.org.uk/spectrum/spectrum-awards/

[6]see http://www.theguardian.com/technology/2013/apr/14/4g-auction-national-audit-office

[7]The data is published at http://www.bundesnetzagentur.de

A1	A2	A3	A4	A5	A6
B1	B2	B3	B4	B5	B6
C1	C2	C3	C4	C5	C6
D1	D2	D3	D4	D5	D6

FIGURE 4.5: The design of the value model.

Within a band, each individual block has the same value for bidders. For example, item A1 has the same value as A5 for a bidder. Therefore, bidders had to evaluate $7^4 - 1 = 2400$ different packages. In practice, the complexity is even much higher. For example, in the Canadian auction, 98 licenses were sold.

The structure of the value model and the distribution of the block valuations of all bands are known to all bidders, i.e., it is common knowledge. In particular, band A is of high value to all bidders and bands B, C, and D are less valuable. Bidders receive base valuations for items in each band. Base valuations are uniformly distributed: v_A was in the range of $[100, ..., 300]$ while v_B, v_C, and v_D were in the range of $[50, ..., 200]$. Furthermore, bidders have complementary valuations for bundles of blocks within bands, but not across bands. In all bands, bundles of two blocks resulted in a bonus of 60% on top of the base valuations, while bundles of three or more blocks resulted in a bonus of 50% for the first three blocks. For example, if the base value was 100, then the valuation for two blocks was 320, for three blocks 450, and for four blocks 550. Although the value models resemble characteristics of actual spectrum sales, this was not communicated to the subjects in the lab to maintain a neutral framing. Also in practice, synergies are important and crucial for a company's success. Some high speed services can only be offered if more than 1 license is won.

4.3.3 Bid languages

It is one of the most important tasks in market design to design the right bidding language. Under the fully expressive bid language (see figure (4.5)), bids can be placed on any of the 2,400 different packages with the understanding that at most, one of the bids can win (XOR). This causes a high complexity

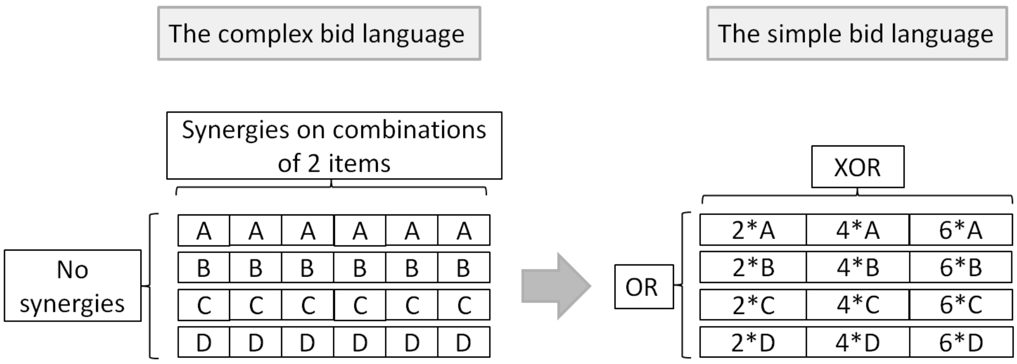


FIGURE 4.6: The design of the compact bid language.

for the bidders. The first simplification at figure (4.6) is that we do not distinguish between blocks within a band. Hence, we note each block within a band only with the name of the band. Quite often, there are synergies for adjacent blocks within a band. For example to provide a LTE standard in large cities, 2 or more blocks within the 2.6 GHz band are important. If providers establish a nationwide network, adjacent licenses in the 0.8 GHz are necessary. These synergies are not common between bands. In many countries, the situation concerning the synergies is like those in our value model. In addition, blocks in different bands are often sold simultaneously.

Under the compact bid language, bids can be submitted on 2, 4, and 6 lots only in each of the bands and at most one of the bids within a band can be win (XOR). However, a bidder can win multiple bids in different bands, i.e. we use an OR bid language across bands. Overall, bidders can submit $3 * 4 = 12$ bids in each round, and win a maximum of 4 bids (one bid per band), see figure (4.6). As in practice, in our value model there are no cross-band synergies since such synergies, are less pronounced than those within a band for many spectrum auctions. If this would be the case, another simplification might be the better choice. As already mentioned in the motivation, choosing the right bid language is actually one of the most crucial parts for auctioneers or governments. Although the bid language and the value model might differ in the field, the experiments allow us to estimate the differences in efficiency compared to an XOR bid language. However, our work can give estimates for decision makers.

4.3.4 Treatment structure

We analyze two variations, simple (S) and complex (C), of both, the bid language and payment rule. In particular, we consider a compact bid language versus a fully expressive bid language, and a pay-as-bid versus a bidder-optimal core-selecting payment rule. That means on the one hand, an intuitive and easily understandable concept that has some downside in theory. On the other hand, a fully expressive bid language and a core-selecting payment rule is good in theory, but is difficult to understand for humans. We tested both ascending (A) and sealed-bid (SB) auction formats. The different treatments are denoted F_{LP} where $F = A, SB$ denotes the format and the subscripts $L = S, C$ and $P = S, C$ indicate the bid language and payment rule respectively.

Treatment	Auction format	Bid language	Payment rule	Auctions
1 ($SMRA$)	ascending	single-item	simple	16
2 (A_{CC})	two-stage	complex	complex	16
3 (SB_{SC})	sealed-bid	simple	complex	16
4 (SB_{SS})	sealed-bid	simple	simple	16
5 (SB_{CS})	sealed-bid	complex	simple	16
6 (SB_{CC})	sealed-bid	complex	complex	16
7 (A_{SC})	ascending	simple	complex	16
8 (A_{SS})	ascending	simple	simple	16

TABLE 4.5: The treatment structure.

The treatments are summarized in figure (4.5). For example, the combinatorial clock auction, using the expressive bid language and complex payment rule, is defined as A_{CC}. SB_{SS} denotes a sealed-bid auction with a compact bid language and a pay-as-bid payment rule. The only ascending auction format with a fully expressive bid language we consider is the A_{CC} (and not A_{CS}) since it is the incumbent standard.[8] Instead of the A_{CS} we include the SMRA, which used to be the standard and also has a simple pay-as-bid payment rule and a (super) compact bid language, i.e., OR bidding within and across bands.

[8]Ascending auction formats with an XOR bid language, a pay-as-bid payment rule and non-linear and personalized ask prices have already been tested in the lab Scheffel et al. (2011), but the number of auction rounds renders them impractical for larger auctions with more than 10 items.

In the sealed-bid formats bidders can submit their bids in a single round. After the round is over, the winner-determination problem is solved and the pay prices are computed.
In contrast, the ascending auctions consist of an unknown number of rounds and at the start of each round ask prices for all licenses are announced. Based on these ask prices, bidders report whether they are interested in 0, 2, 4, or 6 licenses in each of the four bands. If there is overdemand in at least one band, a new round starts with higher ask prices for the bands with excess demand. Prices in the first round are set to 100 for items in the A band and to 50 in the B, C, and D bands. The price increment in the A band is 20 while in the B, C and D bands it is set to 15. A bidder has to submit at least one bid in each round to bid again for bundles in the next round. When there is no more overdemand in any of the bands, the winner determination problem is solved considering all bids submitted during the entire auction. If the computed allocation does not displace an active bidder from the last round the auction terminates, otherwise the price is incremented in those bands where a bidder was displaced.[9]

4.3.5 Procedures and organization

We used the same sets of value draws ("waves") across treatments to reduce performance differences due to the random draws. Each wave was used to run four different auctions, which when combined define one session. We ran **between subjects** experiments with four bidders in each session. The experiments were conducted from June to December 2012 with subjects from computer science, mathematics, physics, and mechanical engineering. The subjects were recruited via e-mail. Each subject participated in a single session only.

The sessions with the ascending auction took around four hours and the sealed-bid auctions between 1.5 and 2.5 hours. At the start of each session, the environment, the auction rules and all other relevant information was explained to the participants. The instructions were read aloud and participants had to pass a test before they were admitted to start the experiment.

A spreadsheet tool was provided to subjects to analyze payoffs and valuations in each round. This tool showed a simple list of available bundles, which could be sorted by bundle size, bidder individual valuations, or payoffs based on

[9] A theoretical analysis of this auction format can be found in Bichler et al. (2013b).

current prices in the ascending auction formats. At the start of each auction, subjects received their individual value draws, information about the value distributions and their synergies for certain bundles. Each round in the ascending auction took 3 minutes. The time given to the subjects in the sealed-bid formats varied between 20 and 25 minutes (although subjects could always ask for more time when needed).

After all four auctions were completed, subjects were paid. The total compensation consisted of a €10 show-up fee and an auction reward, which was calculated as a €3 participation reward plus the auction payoff converted to Euros at a 12:1 ratio. Negative payoffs were deducted from the participation reward. To compensate for the different durations of the ascending and sealed-bid auction formats, and for the differences in earnings stemming from the payment rules, we paid two out of four randomly drawn auctions in A_{SC}, three out of four in A_{SS}, 1.5 out of four auctions in SB_{CS} and SB_{SS}, and one out of four auctions in SB_{CC} and SB_{SC}. (To pay 1.5 auctions means that the first auction that was drawn was paid fully and for the second auction only half the payoff.) On average, each subject earned €70.94 in A_{SC} and €69.75 in A_{SS}, €37.69 in the sealed-bid auction with compact bid language (SB_{SC}, SB_{SS}) and €42.16 in the sealed-bid expressive auction (SB_{CC}, SB_{CS}).

4.4 Experimental results

In the following, we report first high level performance metrics. Then, we continue with detailed bidding behavior.

4.4.1 Efficiency and revenue

We compare auction formats in terms of ***allocative efficiency*** E, and ***revenue distribution*** R, which shows how the resulting total surplus is distributed between the auctioneer and the bidders. For the pairwise comparisons of these metrics, we use the rank sum test for clustered data by Datta and Satten (2005) to reflect that the auctions were conducted in sessions with the same set of subjects.

Result 10: *(i) Formats with a compact bid language are more efficient than those with a fully expressive language. To some extent the efficiency loss with a fully expressive bid language is due to the fact that items remain unsold,*

Auction	E	R	Unsold licenses
$SMRA$	98.51%	81.96%	0
A_{SS}	95.92%	86.62%	0
A_{SC}	97.26%	78.96%	0
A_{CC}	89.33%	37.41%	1.25 (5.2%)
SB_{SS}	94.33%	91.05%	0
SB_{SC}	97.21%	77.28%	0
SB_{CS}	88.56%	89.62%	0.82 (3.4%)
SB_{CC}	91.76%	65.53%	0.31 (1.3%)

TABLE 4.6: Aggregate measures of auction performance.

Coefficients	Estimate	Pr($>|t|$)
Intercept	0.9759	$< 2e-16$
XOR bid language	-0.0728	$1.36e-15$
Pay-as-bid payment rule	-0.0104	0.165
Auction format	-0.0081	0.279

TABLE 4.7: Impact of bid language, payment rule, and auction format on efficiency (adjusted $R^2 = 0.4239$).

which does not happen with a compact bid language. (ii) Among the formats with a fully expressive bid language, there are no efficiency differences. (iii) Among the formats with a compact bid language, only the SMRA yields significantly, albeit not substantially, higher efficiency.[10]

Result 10 is illustrated in figure (4.7) and table (4.6). The intuition behind the efficiency loss with fully expressive bid languages is that few bids among the 2,400 possible bids are selected. The environment is too complex for bidders to select the right bids. Therefore, auctions with many bundles suffer from "too less bids" (see Cramton (2013)).
The winner determination algorithm assigns zero value to all packages not bid for, which distorts the optimal allocation especially when the submitted bids create a fitting problem.

Somewhat surprisingly, the SMRA comes out ahead despite the substantial

[10] In more detail, SMRA $\succ^* A_{SC} \sim SB_{SC} \sim A_{SS} \sim SB_{SS} \succ^* SB_{CC} \sim A_{CC} \sim SB_{CS}$, where $\sim$ indicates an insignificant order, $\succ$ indicates significance at the 10% level, $\succ^*$ indicates significance at the 5% level, and $\succ^{**}$ indicates significance at the 1% level.

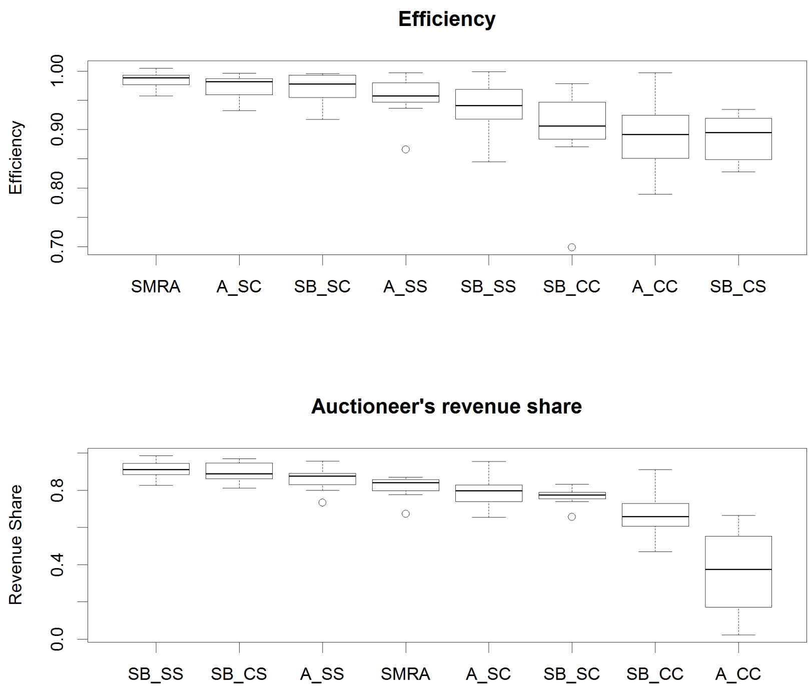


FIGURE 4.7: Efficiency and Revenue in the different auction formats.

complementarities within bands. Bidders did a good job in dealing with the resulting exposure risk, with high-value bidders taking more exposure risk and low-value bidders less.

Coefficients	**Estimate**	**Pr(> $\|t\|$)**
Intercept	0.6656	$< 2e-16$
XOR bid language	-0.1738	$3.93e-14$
Pay-as-bid payment rule	0.1794	$7.58e-13$
Auction type	0.1435	$2.89e-09$

TABLE 4.8: Impact of bid language, payment rule, and auction format on auctioneer's revenue (adjusted R^2=0.5827).

A multiple linear regression confirms the impact of bid language (compact or fully expressive) on efficiency, while the payment rule (core-selecting or pay-as-bid) and the format (ascending or sealed-bid) have no significant effect (see table (4.7)).

Result 11: *Formats with a pay-as-bid payment rule yield higher revenue than those with a core-selecting payment rule. Among the formats with a pay-as-bid payment rule, only the SMRA yields significantly and substantially less revenue. Among the formats with a core-selecting payment rule, those with a fully expressive bid language yield significantly and substantially less revenue.*[11]

Support for result 11 can be found in figure (4.7) and table (4.6). The higher revenue for pay-as-bid sealed-bid auction formats might be explained by risk aversion. Bidders often preferred a "safe" earning to a high profit. In the complex payment rule, bidders often had to pay less than their actual bid, which results in a lower revenue. Each of the auction parameters affects the auctioneer's revenue. In table (4.8), you can have a look at the the impact of the auction format, bid language, and payment rule. After having presented the high level results, we continue now with the detailed biding behavior behavior in both the sealed-bid and the ascending format. The detailed analysis for the $SMRA$ and the A_{CC} can be found in (Bichler et al. (2013a)).

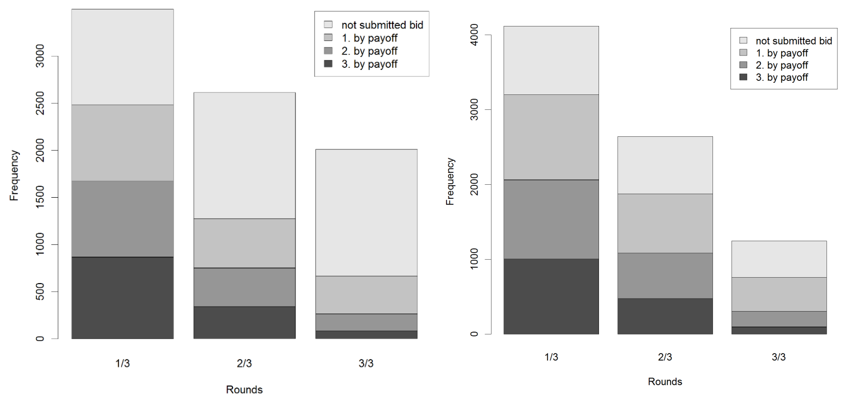


FIGURE 4.8: Distribution of bids by payoff in the A_{SS} (left) and A_{SC} (right) auction.

4.4.2 Bidder behavior in ascending auctions

Result 12: *Bidders in an ascending auction with a compact bid language select their bundles mainly based on payoff. Bidders did not only bid on their*

[11]In more detail, $SB_{SS} \sim SB_{CS} \sim A_{SS} \succ^* \text{SMRA} \succ A_{SC} \sim SB_{SC} \succ^* SB_{CC} \succ^* A_{CC}$.

highest valued bundles, but on 72.9% of all bundles with a positive payoff. The payment rule did not have an impact on bundle selection. A fraction of 7.83% of all bids were above value in the A_{SC} auction compared to only 0.32% in the A_{SS} auction. In the supplementary phase of the two-stage combinatorial clock auction (A_{CC}) only a small fraction (0.06%) of the 2,400 possible bids is submitted.

Note that in the clock phase of the combinatorial clock auction, bidders are only allowed to submit a single package bid per round. Figure (4.8) shows how many bids were submitted on the bundle with the highest payoff (dark grey), the second and third highest payoff, and on how many bundles with a positive payoff were not bid on (light grey). The three bars summarize the distribution of such bids in the first, middle, and final third of all auction rounds (recall that the number of rounds varies across auctions). The two panels highlight that bidders did not only bid on the payoff maximizing bundle. Initially, they even submitted more bids on bundles with the second or third highest payoff. We conjecture that bidders compared valuations rather than payoffs in the initial rounds.

Bids were frequently above value with the core-selecting payment rule, which might be due to the fact that the payment is lower than the submitted bid in this case. We cannot find a difference in bundle selection depending on different bands. In figure (4.9), we see, that bidders behaved similarly in band A and C. This was also the same for band B and D.

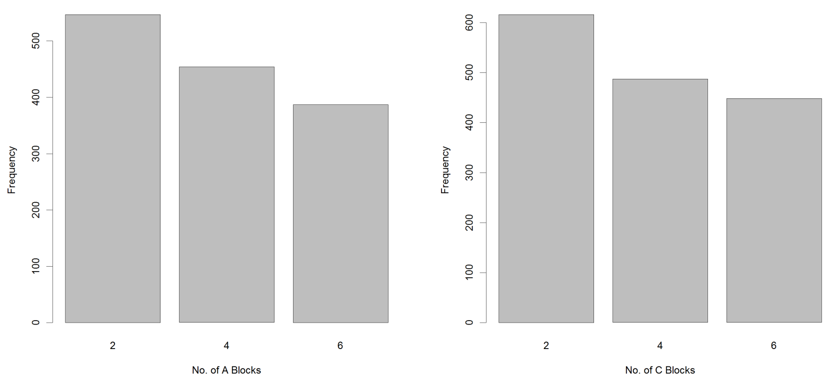


FIGURE 4.9: Bundle selection for band A (left) and band C (right).

We ranked the payoff of every bundle in each band and each round and classified them as the bundle with the highest, second highest, or third highest payoff. In addition, we used the size of the bundle as a proxy for the value of the bundle, as the largest bundle of licenses in a band has the highest value overall, followed by bundles of 4 and 2 licenses. Note that the highest synergy was for a bundle with two licenses in each band. Bidder IDs were used as additional covariates to control for unobserved heterogeneity among bidders. In addition, we used the payment rule and the round no. as additional covariates. Then we generated a table with all possible bids with a positive payoff that a bidder could submit in each round and analyzed the impact of these covariates on the bundle choice in the A_{SS} and A_{SC} using a binary logit model (see table (4.9)).

	Estimate	**Std. Error**	**z value**	$Pr(>\|z\|)$
(Intercept)	-1.7050	0.1191	-14.31	0.0000
2nd highest payoff	0.3358	0.0631	5.32	0.0000
3rd highest payoff	0.4845	0.0512	9.45	0.0000
4 licenses	0.2587	0.0685	3.78	0.0002
6 licenses	0.6630	0.0505	13.13	0.0000
Pay-as-bid	0.1329	0.1358	0.98	0.3278
Round no.	0.1563	0.0045	34.99	0.0000
Auction no. in session	0.1914	0.0174	10.98	0.0000
Bidder IDs	...	...	...	...
Null deviance	21,141			
Residual deviance	16,459			
AIC	16,535			

TABLE 4.9: Logistic regression of the bidders' likelihood to bid on a bundle.

Round number was significant, which can be explained as the number of bundles with a positive payoff decreased with an increasing number of rounds. Also the number of the auction in a session had a significant positive impact on the likelihood of selecting a bundle, which might have to do with learning effects. In contrast, the payment rule did not have a significant impact on the bundle selection. Higher valued bundles (with 4 or 6 licenses) had a positive impact on the probability of a bundle being chosen, and so did a lower payoff.

We can categorize bidders if they have drawn a high base value for a certain item compared to the opponents or not. The bidder with the highest

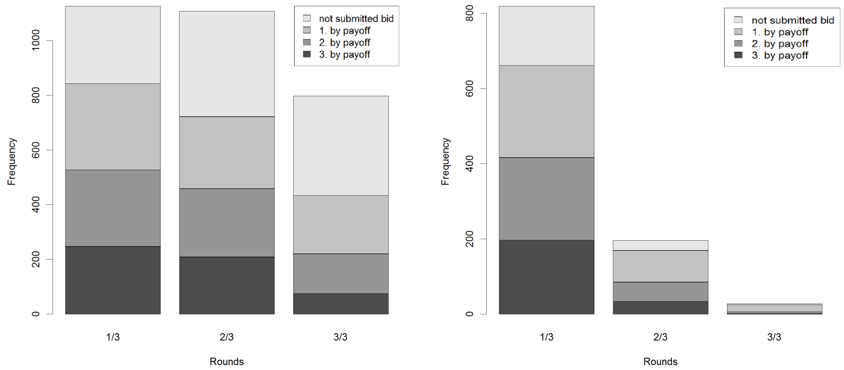


FIGURE 4.10: Distribution of bids by payoff in the A_{SC} for the strongest bidder (left) and and the weakest bidder (right).

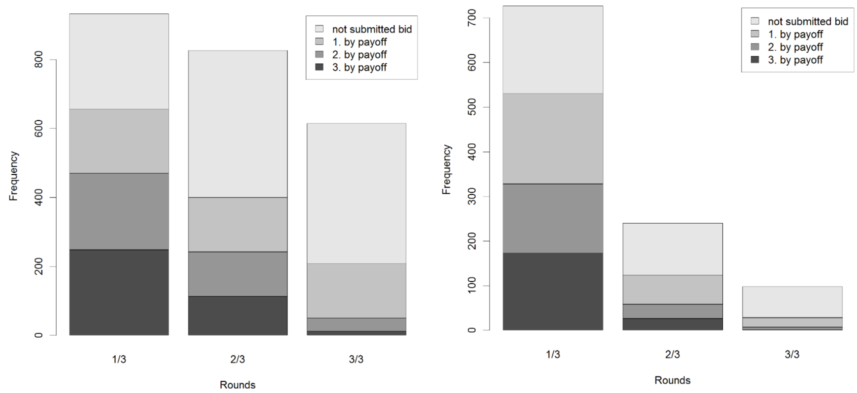


FIGURE 4.11: Distribution of bids by payoff in the A_{SS} for the strongest bidder (left) and and the weakest bidder (right).

valuation within a band is called "strongest" bidder, with the second highest one "medium strong", then "medium weak" and finally the weakest bidder. There is nothing special for the "medium strong" and "medium weak" bidder. However, at figure (4.10), we see for A_{SC} that at the beginning of an auction, when the "strongest" and "weakest" bidder are able to place bids on any bundle, they behave similarly. However, the longer the auction takes and prices increase, the number of possible bids decreases for the weakest bidder. Therefore, he bids on almost any item at the end of the auction. Conversely, the strongest bidder declines to bid on a lesser amount the longer the auction takes (see figure (4.10)). An explanation could be that he wants to concentrate

on his most preferred bundle at the end of the auction.
A similar result can be seen in A_{SS} at figure (4.11), with the difference, that the weakest bidder also concentrates in the end of the auction on his most valuable item.

4.4.3 Bidder behavior in sealed-bid auctions

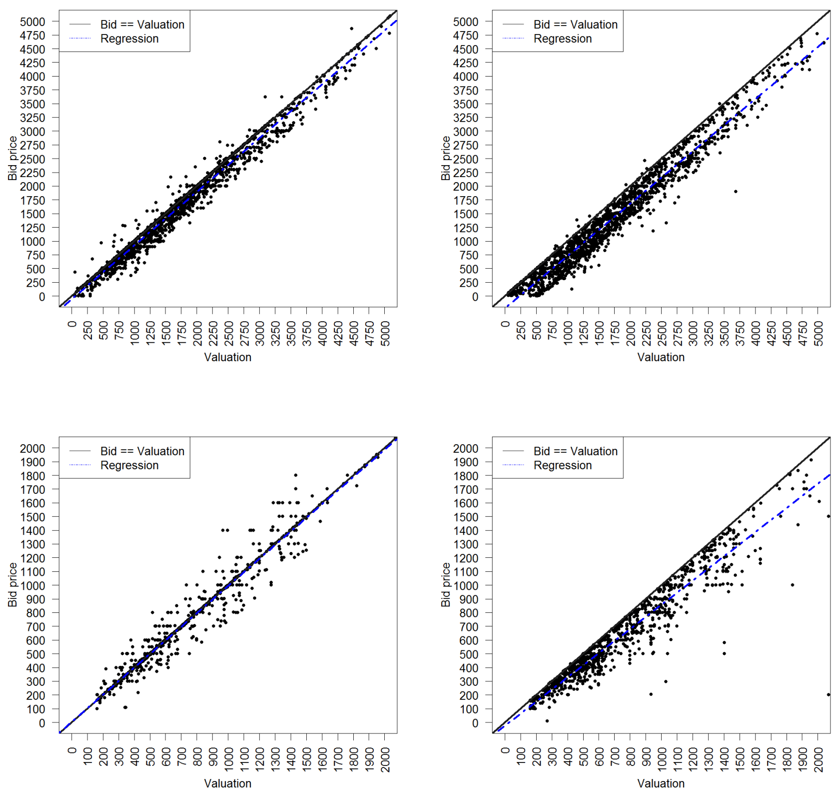


FIGURE 4.12: Bid shading in the auctions with core-selecting (left) and pay-as-bid auction (right) with a fully expressive bid language (top) and a compact language (bottom).

Result 13: *Bidders in core-selecting sealed-bid auctions with a compact bid language bid on all possible bundles. Bidders in sealed-bid auctions with a fully expressive bid language bid only on 2.42% of all 2,400 possible packages. There was more bid shading with the pay-as-bid payment rule compared to the core-selecting payment rule.*

Figure (4.12) and table (4.10) provide support for this result.

We also estimated a linear regression with valuation as a covariate to explain bid prices (and bidder ID to control for unobserved heterogeneity among bidders). The intercept (α) and the slope (β) of the bidding function can be found

Format	truthful	overbidding	underbidding
SB_{SS}	0%	0.99%	99.01%
SB_{CS}	0%	1.23%	98.77%
SB_{SC}	32.34%	22.05%	45.61%
SB_{CC}	18.11%	4.55%	77.34%

Table 4.10: Truthful bidding in sealed-bid auctions.

Format	α	β	p-value	adjusted R^2
SB_{SS}	0.5601	0.8834	0.0086	0.917
SB_{CS}	-0.0129	0.953	0.0033	0.986
SB_{SC}	-76.3868	0.9921	0.0056	0.975
SB_{CC}	-0.5637	0.9736	0.0029	0.986

Table 4.11: Estimated bid functions.

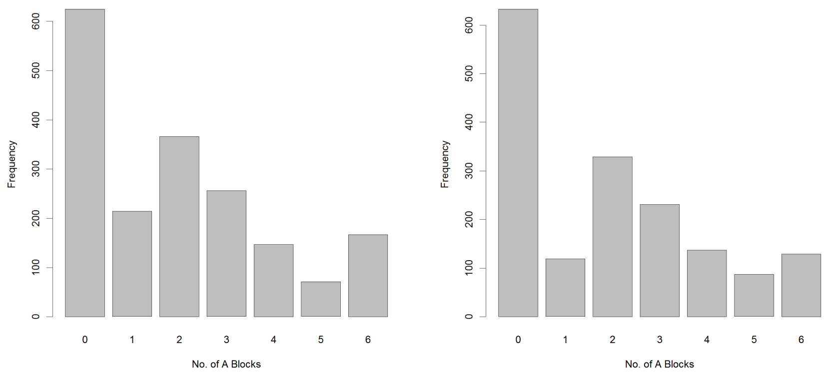


Figure 4.13: Distribution of bids by payoff in the SB_{CC} (left) and and the SB_{CS} (right).

in table (4.11). The β coefficients are lower for pay-as-bid auctions, which indicates higher bid shading for higher valuations. The estimation results are shown by the dashed lines in figure (4.12). In the formats with the simple bid language, bidders submit all possible bids. For the complex bid language, there was no difference between bands but within them. The bundle selection within a band can be seen in figure (4.13). There was also no difference depending on bidders' strength due to the large amount of possible bundles.

4.5 Further work

There are different approaches to model bidders' preferences in spectrum auctions. Many assumptions of the IPV model are violated in spectrum auctions. Frequently, bidders cannot be categorized as (ex-ante) symmetric. Although bidders are quite often defined as risk-neutral utility maximizers, this is not true in practice. In spectrum auctions, the market position will be defined for the next decade(s) and motives like spite, regret and other behavioral reasons influence the behavior. Hence, the utility might be not quasi-linear, because there are far more impact factors. Also the values are not independent, since it is of interest how many licenses opponents win. A new way might be to use an affiliated values environment. Besides, the individual budget determines bidding behavior. However, the theory does not include budget constraints.

For future work, on the one hand, bidders' working memory and possible effects on the bidding behavior could be analyzed. It is also interesting to test the Reverse Combinatorial Clock in complex procurement markets with several items and lots.

4.5.1 Cognitive limits

Participants' ***working memory*** could be measured by experiments. According to Baddeley (1983) and Baddeley and Hitch (1994) the working memory describes the temporary storage of data in connection with the performance of other cognitive tasks. In our context, differences in bidding behavior depending on individual working memory are of interest.

Using a pretest, we could measure the working memory and then test if there is a correlation to the auction performance. However, it has to be proven whether the outcome of two separate experiments can be transformed.
Chen et al. (2011) tested the impact of working memory on the performance in double auctions. Over 500 subjects had to take five working memory tests before entering the auction. They showed that a high working memory capacity leads to a better auction outcome. Chen et al. (2009) analyze if cognitive ability affects the auction outcome. They conclude that individual cognitive capacity has (positive and significant) influences on the performance

in profits in certain markets.

However, we have to interpret these results with care because ***information overload*** might be due to several reasons.
Anderson et al. (1996) conclude that a limit of cognitive capacity cannot be defined by an exact number since it is depending on the context. Just and Carpenter (1992) assume that individual differences in working memory are the dominating effect, whereas universal results cannot be obtained. Other psychologists follow the theory that there is a fixed capacity humans can deal with, but the actual limit is different (Miller (1956) and Halford et al. (1998)). Schweickert and Boruff (1986) suppose that the cognitive limit is based on the race between decay of memory traces and rehearsal.
Oberauer and Kliegl (2006) and Barrouillet et al. (2004) support the interference model. The mutual degradation of memory traces that are held in working memory simultaneously is, according to that theory, the most important reason for cognitive limits.

In future work interference between some attributes can be examined. The similarity between items might influence the bidding behavior, e.g., bidders might better remember goods within, but not outside the same band. As a consequence, it can hardly tested by laboratory experiments up to how many possible bids, the bidders may submit the "right" bids respectively and can evaluate different alternatives.

Another possibility other than the measurement of working memory is ***diffusion tensor imaging***.
Here we can check if professional traders who take part in an experiment behave better than other human subjects since they are familiar with information overload. The same analysis could be performed by a longitudinal design, where human bidders are trained during a long span of time. Before, during and after training certain areas of the brain are measured to find out possible changes. Depending on different kinds of training the performance, i.e., in our context the selection of the "right" bundles, gets better or not. A similar approach is done by Adomavicius et al. (2009).

Dalén et al. (2013) test how humans deal with a different amount of information when they deal with the electricity consumption in private households.

They define three treatments, with a high, medium and a low degree of information. Then, the participants solve a complex knapsack problem, since they have to maximize the value of using an item while considering the electronic consumption. They conclude that an intermediate degree of information generates the best results, since people can still define their preference quite precisely but are not overloaded with (too) much information.

Following this method we could define different bid languages for a value model. A simple language has to be formulated which is theoretically bad, but practically simple. This might not be very efficient from a theoretical point of view. A complex language in turn is good in theory, but practically bad, what has negative effects on the efficiency. Therefore, a language with medium complexity might provide the best practical efficiency.
In addition, bidders' stress could be measured by scanning the skin conductivity to find out a correlation of stress and performance. In this case, a pretest might be helpful to show that bidders stress increases by the amount of possible bundles. The hypothesis would be that a treatment with a medium degree of information results in the best outcome.

4.5.2 The reverse combinatorial clock auction

As already mentioned in chapter (3.4) the ***reverse combinatorial clock*** auction (***RCC***), the reverse implementation of the CC might be proper in case of a multi-item multi-lot procurement environment. An important issue in reverse combinatorial auctions is setting the start price. In forward auctions, the initial price vector is set as zero to guarantee a feasible start solution. Conversely, the start price in a reverse auction should be set at ∞ to obtain prices in the equilibrium. However, this is not practicable, since the auction duration would be too long. Therefore, we can choose the start price sufficiently high, i.e., on the upper limit of the cost interval, so that even bidders with high costs could take part in the relevant auction. In practice, this is very difficult since bidders' valuations and in this context the costs are not know up front. In each round bidders submit bundle bids based on the current unit prices. If a lot in any item is demanded by multiple bidders, it is overdemanded and its unit price is reduced. This process continues until there is no overdemanded lot in any band. Then, in case of termination, the auction ends and the procurement cost minimization allocation is computed based on all submitted bids in each round.

For the procurement context the CAP-I has to be adapted, since now not the overall value is maximized, but the overall production costs and auctioneer's payment, i.e., the procurement costs, are minimized. Therefore, we replace in the reverse auction $v_i(S)$ by $c_i(S)$, since we do not consider fixed costs for now. Again, $c_i(\oslash) = 0$ and $c_i(S)$ is non-decreasing, i.e., $c_i(S) \leq c_i(T)$ for $S \subseteq T$.

$$
\begin{aligned}
&\max \sum_{S \subseteq \mathcal{K}} \sum_{i \in \mathcal{I}} -x_i(S) v_i(S) \equiv \\
&\equiv \min \sum_{S \subseteq \mathcal{K}} \sum_{i \in \mathcal{I}} x_i(S) c_i(S) && (\boldsymbol{CAP\text{-}I\text{-}REV}) \qquad (4.5)\\
&\text{s.t.} \\
&\sum_{S \subseteq \mathcal{K}} x_i(S) \leq 1 && \forall\, i \in \mathcal{I} \\
&\sum_{S : k \in S} \sum_{i \in \mathcal{I}} x_i(S) \geq 1 && \forall\, k \in \mathcal{K} \\
&x_i(S) \in \{0; 1\} && \forall\, i \in \mathcal{I}, S \subseteq \mathcal{K}
\end{aligned}
$$

In the resulting allocation each bidder can win at most one bundle bid and pays the given bid price. The second set of constraints is modified and ensures that each item is purchased at least once.
This constraint is actually a problem which might lead to infeasibility. We can solve this problem with artificial OR-bids. The assumption is that at the price of these bids, the procurement manager can buy products on the market. Hence, a feasible allocation always exists.

Chapter 5

Conclusions and outlook

In this thesis we tested bidding behavior in multi-item auctions by laboratory experiments with different levels of complexity. We found out that bidders are able to derive the equilibrium bid prediction in a simple setting with two items and intuitively add the right markups to their cost if we control for risk aversion, regret, and other behavioral influences in experiments against computerized agents. Hence, the RNBNE strategy can act as a guideline for practitioners. Moreover, in multi-object auctions with several items, a compact bid language can recover most of the efficiency losses compared to a fully expressive combinatorial auction.

First, we analyzed two split-award auctions with two lots. These game theoretical auction mechanisms for sealed-bid procurement auctions are a fundamental part of this work. The sealed-bid Yankee and the sealed-bid parallel auction are regularly used in procurement practice. We obtained closed-form Bayes Nash equilibrium bidding strategies and several interesting model implications.
Given the recent experimental literature on single-lot first-price auctions, however, we wanted to find evidence that human subjects are actually able to derive their equilibrium bid functions even without these added complexity. The two lot split-award auction is particularly interesting as it is cognitively more complex than single-lot auctions, but less challenging than first-price combinatorial auctions, where a Bayesian Nash equilibrium strategy is not yet known.
Experimental work on the first-price sealed-bid auction has shown a consistent pattern of overbidding in sales auctions. There is far less work on reverse

auctions. Different reasons for over- or underbidding, such as risk aversion, regret, wrong expectations about own and others' bids and the complexity of deriving the RNBNE bid function have been discussed in literature since decades. Hence, it is questionable whether RNBNE strategies are a good predictor for split-award procurement auctions. The complexity is much higher than in single-lot reverse auctions. In our contribution we bridge the gap, in that there has been almost no experimental work testing RNBNE predictions for multi-object auctions in the lab.

We provide the results of lab experiments with different levels of control. The experiments against computerized bidders are meant to limit the influence of risk aversion as far as possible. Interestingly, there is no significant difference between the average bid function of bidders in the lab and the RNBNE bid function. This is new compared to earlier experiments of first-price sealed-bid auctions, and we attribute the result to our experimental design. Our experiments provide evidence that bidders are able to mimic their RNBNE bid function even in strategically complex split-award auctions.

We also provide results of repeated human subject experiments which resemble procurement auctions in the field. We found underbidding for low cost draws compared to the RNBNE bid function, which typically increased in the latter auction rounds. The level of underbidding is comparable to what we found in single-lot reverse auctions. Still, the RNBNE bid function provides a fairly good approximation of the average bid function of bidders in the lab. When taking some level of underbidding into account, the RNBNE bid function can be a helpful guideline for practitioners.

The results should also be interpreted with care. Even though we provide evidence that expected utility maximization can serve as a meaningful model to explain bidder behavior in two-lot auctions, this does not necessarily carry over to more complex multi-lot or combinatorial auction environments with many lots or items. Experiments have shown, for example, that a main driver for inefficiencies in larger combinatorial auctions with 18 items is the restricted bundle selection of bidders in the lab (Scheffel et al. (2012) and chapter (4.4)). This is in line with Kurz-Milcke and Gigerenzer (2007), who argue that when small worlds are studied, optimization can well guide human decision behavior. If there are more items and more complex cost functions, simple heuristics and cognitive biases rather than expected utility

maximization might dominate bidder behavior. Therefore, our contribution can only be a first step in modeling and understanding bidder behavior in split-award procurement auctions.
There are various ways to develop the model further. Asymmetry and risk aversion are two obvious extensions. Also, more complex cost functions could be modeled.
In addition, a regret parameter could be added to our model as it is done in Davis et al. (2011).

Another possibility would be that we do not focus on a predefined split and so widen the scope. That means on the one hand that the auctioneer can decide after the auction on sole sourcing or a split-award outcome. On the other hand, the true value of the split parameter is not known to the participants before the termination. A model might be possible where the buyer selects between single and dual sourcing based on an assurance of supply related criterion. This uncertainty will influence the suppliers' bidding strategy and behavior. The procurement costs for the buyer might be as low as in a pure single source strategy because he can decline to pay any premium to assure supply. However, it will affect the supply chain in a long-term view if only one supplier provides the full amount. A monopoly structure might be generated, which can result in higher procurement costs in the future and eventually cause disruptions in supply.

Second, we tested human behavior in a complex environment with many possible bundles. Bichler et al. (2013a) analyzed the CCA which has been introduced in the past few years by regulators worldwide to sell spectrum licenses. Increasingly, the auction is being used for multi-band auctions which allows bidders to submit bids on thousands of packages. Recent research showed that the auction format suffers from communication complexity and with larger multi-band value models, the efficiency can be substantially lower than that of a SMRA. Regulators face a trade-off between the exposure problem and communication complexity, which both negatively impact efficiency. This trade-off arises with all combinatorial auctions that use a fully XOR expressive bid language.
That raises the question whether regulators can find a design to mitigate the exposure problem and the communication complexity to achieve high efficiency.

Therefore, we developed a bid language that drastically reduces the number of possible bids that a bidder can submit. First, the bid language assumes that bids in different bands are additive and like in SMRA bidders can win bids in multiple bands in each round. The remaining exposure problem might often be manageable for bidders.[1] In addition, we allowed bidders to submit bids only on packages of 2, 4, or 6 licenses. Bidders can only win one of these packages per band. This reduced the number of bids a bidder could submit in each round to 12. The experiments showed that much of the efficiency losses of the CCA could be recovered with ascending or sealed-bid auction formats and a compact bid language.

Still in our value model, SMRA came out with the highest efficiency, as bidders handled the exposure problem well. Although, the synergies in our value model were substantial, this result might not carry over to other applications, where the exposure problem could outweigh the simplicity of SMRA. We do not aim to propose a specific bid language to be used in spectrum auctions. The design of the right bid language is actually one of the most important questions in market design. It should help bidders to express their preferences, but at the same time limit the number of parameters a bidder needs to specify his preferences. Surprisingly, this topic has received little attention in the design of spectrum auctions in the field.

Apart from the bid language, regulators have a number of other design choices that might matter. Arguably, the auction format (ascending or sealed-bid) and the payment rule (pay-as-bid or bidder-optimal core-selecting payments) can play a significant role in the efficiency of an auction. These topics have been central issues in auction design. In addition to the bid language, we also analyzed these design choices. Our experiments showed that indeed bidders bid close to their true valuation in core-selecting auctions, while they shaded their bid in pay-as-bid auctions. Both the payment rule and the auction format had a significant impact on revenue, but not on efficiency. In some applications, bidders might have much more information about their competitors than what we assumed in the lab, and such information can provide possibilities for speculation and resulting inefficiency in a CCA (see Goeree and Lien (2012) and Bichler et al. (2013a)). The choice of the payment rule and the auction format therefore depends on the information available to bidders in an application and the design goals of the regulator.

[1] There could also be a possibility for bidders to specify either-or-constraints to avoid winning packages that are substitutes in the bid language.

Appendix A

Experimental instructions

In Appendix A, we present the experimental instructions that have been used to prepare the participants. After having explained all the rules and shown examples we asked pre-questions to ensure a deep understanding and ran test auctions to identify possible problems.

A.1 Experimental instructions for split-award auctions

We have run several experiments in the split-award context (see chapter (3.2)). Now, we provide examples of the bidder instructions for the parallel auction. The text was identical across the various treatments, but some numbers differed according to the specific treatment combination. For example, in C1 the bid function was only used in a single computerized auction, whereas in C100 and C100+ it was reused in 100 auctions.

A.1.1 Computerized experiments

This is an experiment on decision making. The following instructions are simple, and if you follow them carefully and make good decisions, you may earn a considerable amount of money.

During the experiment your payoff will be in experimental Francs that will be converted into Euro at the end of the experiment at the following rate:

16 Experimental Francs = 1 Euro

Payments will be made privately at the end of the experiment. If you have a question at any time, please raise your hand and the monitor will answer it. We ask that you not talk with one another for the duration of the experiment. On your desks you should have a checkout form, a pen, and a copy of the consent form.

Your Experimental Task

In each round of today's session you will be bidding against three computerized competitors. The computerized competitors have been programmed to bid in a way that would maximize their expected earnings when they bid against likewise programmed competitors. Their bidding strategies are only based on the cost draw, the distribution of costs, the fixed costs and the number of competitors, which are public to all bidders.The bids of the computerized bidders have also been determined, and they cannot be affected by your decisions today.

At the beginning of the experiment, you will receive a sheet of paper on which you will see a list of 20 numbers. Each number is between 0 and 10 Experimental Francs (randomly drawn with equal probability) and has been rounded to one decimal place. Each number represents a possible unit cost that you may have to produce a fictitious commodity. The process of selecting possible unit costs is exactly the same for everyone.

You can either win a contract on a small lot with 30 units of the commodity or on a large lot for 70 units of the commodity. You can bid on both lots. The unit costs determine the total cost for the small and large lot, which you can also find on the sheet. For each of your 20 possible cost values, you should write down a bid for the small lot and a bid for the large lot in the space provided on the sheet of paper for the small and the large lot. Then, bids are connected with a line to determine bids for all possible variable costs. We will call this your bid function. After all of the participants have chosen their bids for each of the 20 possible cost values, the lists will be collected.

The bids function will then be used in **100 auctions,** where you compete against the three computerized agents in each round. The strategy of the computerized agents does not change across the different auctions. However, in each of these auctions, your variable costs and also those of your competitors will be randomly drawn from a uniform distribution between 0 and 10.

The bidder in each auction with the lowest bid for each lot wins this lot and pays the exact amount of his or her bid. If a single bidder wins both lots, he will get the large lot and the second best bidder on the small lot will win this lot. In the case of a tie, the winner will be determined randomly by the software. Winners in an auction will earn the difference between their bid and their true costs. If you are not a winner, you will not earn any money. You will be paid an average of your winnings in the 100 auctions. After the auction you will participate in a brief survey.

Before you submit the bid sheet, you should think about your bid strategy for

1. High and low cost draws, and
2. The small and the large lot.
3. Would your strategy change, if a certain bid was only valid for 1 and not for 100 auction?

Results of both sessions will be e-mailed to you together with information about how much money you have won. You will not learn information about other bids in the auction, just whether you won or you lost. Are there any questions?

A.1.2 Human subject experiments

This is an experiment on decision making. The following instructions are simple, and if you follow them carefully and make good decisions, you may earn a considerable amount of money.

During the experiment your payoff will be in experimental Francs that will be converted into Euro at the end of the experiment at the following rate:

16 Experimental Francs = 1 Euro

Payments will be made privately at the end of the experiment. If you have a question at any time, please raise your hand and the monitor will answer it. We ask that you not talk with one another for the duration of the experiment. On your desks you should have a checkout form, a pen, and a copy of the consent form.

Your Experimental Task

In each round of today's session you will be bidding against three other human bidders. These bidders will be determined randomly in each of 16 rounds from the pool of participants.

At the beginning of the experiment, you will receive a sheet of paper on which you will see a list of 10 numbers. Each number is between 0 and 10 Experimental Francs (randomly drawn with equal probability) and has been rounded to one decimal place. Each number represents a possible unit cost that you may have to produce a fictitious commodity. The process of selecting possible unit costs is exactly the same for everyone.

You can either win a contract on a small lot with 30 units of the commodity or on a large lot for 70 units of the commodity. You can bid on both lots. The unit costs determine the total cost for the small and large lot, which you can also find on the sheet. For each of your 10 possible cost values, you should write down a bid for the small lot and a bid for the large lot in the space provided on the sheet of paper for the small and the large lot. Then, bids are connected with a line to determine bids for all possible variable costs. We will call this your bid function. After all of the participants have chosen their bids for each of the 10 possible cost values, you can upload the sheet on a server. In the auctions, your variable costs and also those of your competitors will be randomly drawn from a uniform distribution between 0 and 10, and the computer determines the bids based on the randomly drawn costs. Next you will be randomly matched to three of the other players in the room and the bids of all bidders will enter the auction. The bidder in each auction with the lowest bid for each lot wins this lot and pays the exact amount of his or her bid. If a single bidder wins both lots, he will get the large lot and the second best bidder on the small lot will win this lot. In the case of a tie, the winner will be determined randomly by the software. Winners in an auction will earn the difference between their bid and their true costs. If you are not a winner, you will not earn any money. After each round you get the following feedback:

1. Your own cost draw,
2. Your bid for the small and the large lot according to your bid function,
3. The bids of your competitors of both lots, and
4. If you have won or not.

Additionally, the mean and all winning bids of each round will be shown aggregated on the web-page. Please consider both the feedback of the previous round and the aggregated winning bids.

Before you submit the bid sheet, you should think about your bid strategy for

1. High and low cost draws, and
2. The small and the large lot.

Results of the whole session will be e-mailed to you together with information about how much money you have won.

Are there any questions?

After the participants read the instructions, a short presentation was given to ensure a deep understanding of the auction mechanisms and the environment. Then, in a demo auction, remaining questions have been answered.
We print here exemplary the slides for the first-price parallel auction in the treatment C100+.

A.1.3 Exemplary presentation slides

The slides are modified depending on the treatment combination.

A.1.4 Exemplary bid sheet

Here, we provide you a typical sheet, where we picked out bidders' bidfunctions.

☐ **Auction environment:**

- ☐ You and 3 computerized bidders take part in each auction.
- ☐ The total demand of 100 units is purchased under two lots.
  - ☐ Large lot: 70 units
  - ☐ Small lot: 30 units
- ☐ There is only 1 round in the auction.
  - ☐ Each bidder submits sealed bids for each lot.

☐ **Winner determination and payoff:**

- ☐ Winners are determined according to the lowest bid for each lot.
  - ☐ Each bidder is only allowed to win at most 1 lot.
  - ☐ If a bidder wins both lots, he will get the larger one.
- ☐ Tie breaking: If two or more bidders submit exactly the same bid, the winner will be determined at random!
- ☐ Your payoff = payment per lot – total costs per lot
- ☐ The currency of the auction is Franc.

☐ The fixed costs for all the bidders are the same: 1 Francs.

☐ Bidder A's variable costs are 1.0, bidder B's 2.0, bidder C's 3.0 and bidder D's 4.0.

Total Costs	small lot	large lot
Bidder A	31.0	71.0
Bidder B	61.0	141.0
Bidder C	91.0	211.0
Bidder D	121.0	281.0

Bids per unit	small lot	large lot
Bidder A	5.0	**4.0**
Bidder B	**6.0**	5.0
Bidder C	8.0	8.0
Bidder D	11.0	10.0

☐ Result:

- Bidder A is the best bidder for the large and the small lot.

  Bidder A wins the large lot and his payoff is 280 (= 4 *70) - 71 = 209.
- Bidder B is the second best bidder for the small lot.

  Bidder B wins the small lot, because bidder A has already won the large lot.

  B's payoff is 180 (= 6 *30) - 61 = 119.

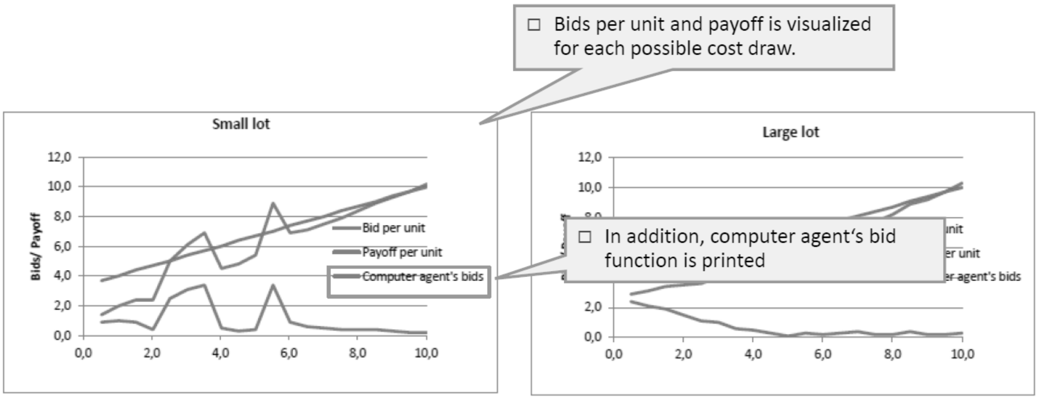
- ☐ The computerized competitors have been programmed to bid in a way that would maximize their expected earnings when they bid against likewise programmed competitors.
- ☐ Their bidding strategies are only based
  - ☐ on their cost draw,
  - ☐ the distribution of costs,
  - ☐ the fixed costs,
  - ☐ and the number of competitors, which are public to all bidders.
- ☐ Before each auction, they draw new variable costs.

- ☐ You submit bids per unit for the small and the large lot for 20 possible cost draws which are exactly the same for everyone.
- ☐ Each number represents a possible unit cost.
- ☐ Then, bids are connected with a line to determine bids for all possible variable costs.

  ⇒ We will call this your ***bid function***.
- ☐ After all of the participants have chosen their bids for each of the 20 possible cost values, the bids are collected.

- ☐ The bids function will then be used in ***100 auctions,*** where you compete against the three computerized agents in each round.
- ☐ The strategy of the computerized agents does not change across the different auctions.
- ☐ However, in each of these auctions, your variable costs and also those of your competitors will be randomly drawn from a uniform distribution between 0 and 10.

☐ In the bid sheet, you find two graphics that visualize your bid function and the corresponding payoff per unit:



☐ **Show up reward:**

☐ Each participant receives 5 EUR show up fee for participating.

☐ **Auction payoff:**

☐ Payoffs are *translated from Franc into EUR* through an exchange rate *of 1:16.*

☐ A payoff of 16 Franc will provide you a payment of 1 EUR.

☐ Negative payoffs, i.e. losses, are deducted from the payoff of all auctions and the show up fee.

General structure:

☐ **Payment = show up fee + payoff from auctions**

☐ The total payment per participant is limited to 25 EUR

☐ **Collusion and losses:**

☐ In case participants collude and communicate with each other, there will be **no payment** to these bidders and bidders can be excluded from the experiment.

☐ If you make a loss, which is not covered by the show up and the payoff of all auctions, you will be excluded from the experiment and the session will be cancelled.

☐ **Where and when will you get the financial compensation?**

☐ You will receive an e-mail with information about your payment and a date to collect it.

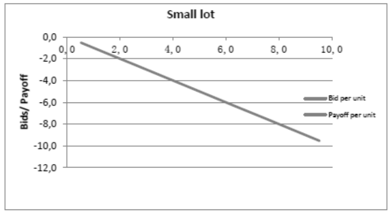
☐ The actual payment is made by the secretary of the DSS chair.

FIGURE A.1: Explanation of the auction rules for the parallel auction in treatment C100+ for q=0.7 to the participants in laboratory experiments.

name	
whole demand	100
split q	0,7
large lot	70
small lot	30
number of bidders	4

costs	
uniform distribution of variable costs:	[0...10]
fixed costs (for all bidders the same):	1

		small lot						large lot					
draw	costs	average costs	bid per unit	payoff per unit	total costs	total bid	total payoff	average costs	bid per unit	payoff per unit	total costs	total bid	total payoff
1	0,5	0,5		-0,5	16,0	0,0	-16,0	0,5		-0,5	36,0	0,0	-36,0
2	1,5	1,5		-1,5	46,0	0,0	-46,0	1,5		-1,5	106,0	0,0	-106,0
3	2,5	2,5		-2,5	76,0	0,0	-76,0	2,5		-2,5	176,0	0,0	-176,0
4	3,5	3,5		-3,5	106,0	0,0	-106,0	3,5		-3,5	246,0	0,0	-246,0
5	4,5	4,5		-4,5	136,0	0,0	-136,0	4,5		-4,5	316,0	0,0	-316,0
6	5,5	5,5		-5,5	166,0	0,0	-166,0	5,5		-5,5	386,0	0,0	-386,0
7	6,5	6,5		-6,5	196,0	0,0	-196,0	6,5		-6,5	456,0	0,0	-456,0
8	7,5	7,5		-7,5	226,0	0,0	-226,0	7,5		-7,5	526,0	0,0	-526,0
9	8,5	8,5		-8,5	256,0	0,0	-256,0	8,5		-8,5	596,0	0,0	-596,0
10	9,5	9,5		-9,5	286,0	0,0	-286,0	9,5		-9,5	666,0	0,0	-666,0



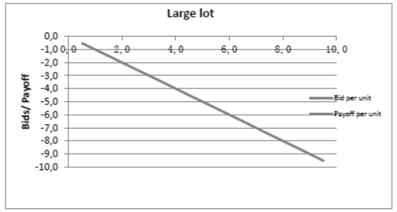


Figure A.2: Exemplary bid sheet for the parallel auction in C100 with q =0.7.

A.1.5 Screen-shots of the bidding interfaces

In each treatment in the procurement context, bidders had to submit a filled bid sheet before we ran simulations. Bidders had to upload it on our platform "procurement auction implementation" at "http://dss.in.tum.de/exper/".

FIGURE A.3: The bidding interface in the procurement context.

A.2 Combinatorial auctions

For our experiments with the combinatorial auctions we used different instructions than for the split-award auctions.

A.2.1 Exemplary instructions

The bidders were instructed as follows. At the beginning, the auction rules were explained and examples provided. Especially, the complex payment was described in detail. Afterwards, anyone could read the instructions by his own and ask questions. As soon as all participants have been familiar with the auction rules, we introduced them into the software platform. In order to ensure a deep understanding of the auction format and the environment, a test auction was played before the start of the experiment.
Below the auction rules of the A_{SS} and the S_{CC} are presented. The introduction differed according to the specific treatment combination. Due to its complexity the core selecting payment rule was introduced by an example that is based on Day and Cramton (2012).

Similar to Bichler et al. (2013a) we prepared the slides in German, since all participants were native German speakers.

Aufgabe der Teilnehmer in diesem Experiment:

- Sie werden an **4 Auktionen** teilnehmen
- Das gesamte Experiment wird **ca. 4 -5 Stunden dauern**
- Ihre aufgewendete Zeit und ihr Erfolg in den Auktionen werden **finanziell entgolten**
  - **Je erfolgreicher Sie sind desto höher fällt die Kompensation aus**
- Jeder Bieter wird **einzeln** in den Auktionen teilnehmen
  - **Während dem gesamten Experiment ist keinerlei Kommunikation unter den Teilnehmern erlaubt**
- Das Experiment wird mit Hilfe der einer web-basierten Auktionsplattform (MarketDesigner) durchgeführt

Rahmenbedingungen der Auktion:

- In jeder Auktion nehmen **4 Bieter** teil
- Es werden **24 Güter** in einer Auktion mit mehreren Runden versteigert
- Sie erfahren nichts über die Gebote der anderen
- Die Güter verteilen sich auf **vier Bereiche** (A, B, C und D)
  - In jedem **Bereich werden 6 Güter** versteigert
  - Innerhalb der Bereiche sind die Güter nicht zu unterscheiden
- Der Gewinn eines Bieters in einer Auktion ergibt sich ausschließlich aus dem Wert der Güter, die er gewonnen hat, abzüglich der zu zahlenden Preise: **Gewinn = Wertigkeit – Preis**
  - Die Aufteilung der restlichen Güter auf andere Bieter hat keinen Einfluss auf seinen Gewinn
- Deshalb gilt generell: Jeder Bieter versucht **möglichst viele Güter** in allen Bereichen **zu möglichst niedrigen Preisen** zu gewinnen
- Die Auktionswährung ist **Franc**

Bereich A:

A01	A02	A03	A04	A05	A06

Bereich B:

B01	B02	B03	B04	B05	B06

Bereich C:

C01	C02	C03	C04	C05	C06

Bereich D:

D01	D02	D03	D04	D05	D06

Grundwertigkeiten

- Die **Grundwertigkeit für A-Güter wird aus dem Intervall [100; 300] zufällig gezogen**
- Die **Grundwertigkeit für B-, C- und D-Güter wird aus dem Intervall [50; 200] zufällig gezogen**

Boni

- Mehrere Gütern innerhalb eines Bereichs werden mit einem Bonus belohnt
- Kombinationen von **2 Gütern** erzielen einen **Bonus von 60%** auf die Grundwertigkeiten
- Kombinationen von **3 Gütern** erzielen einen **Bonus von 50%** auf die Grundwertigkeiten
- Zusätzliche Güter bringen keinen weiteren Bonus. Diese erzielen nur die Grundwertigkeit
- Beispiel für die Grundwertigkeit von 100 im Bereich D:

Anzahl Güter in D	Grundwertigkeit	Bonus	Gesamtwertigkeit
1	1 * 100 = 100	-	100
2	2 * 100 = 200	60% * 200 = 120	320
3	3 * 100 = 300	50% * 300 = 150	450
4	4 * 100 = 400	50% * 300 = 150	550
5	5 * 100 = 500	50% * 300 = 150	650
6	6 * 100 = 600	50% * 300 = 150	750

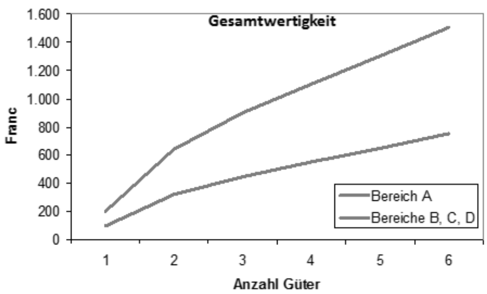
- Im Experiment kann nur auf 2er, 4er, 6er Bündel geboten werden.

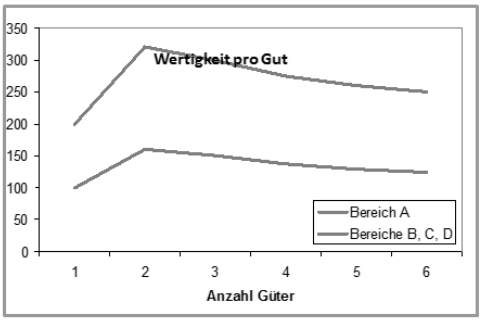
Verhältnis von Wertigkeiten in den Bereichen:

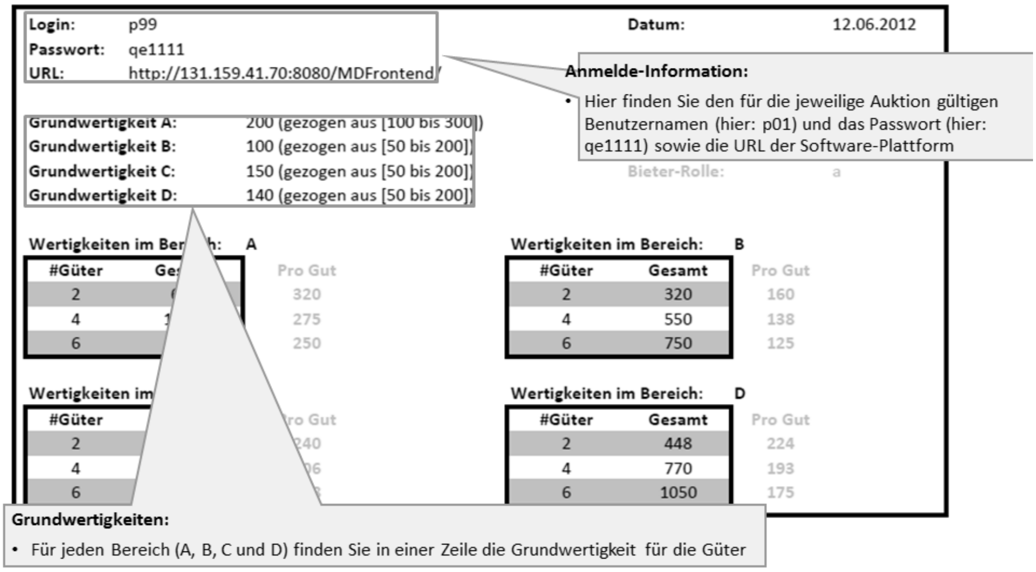
- Das Grundwertigkeiten-Intervall von Bereich A liegt mit [100; 300] über dem der Bereiche B, C und D mit [50; 200]
- Durch die Boni für 2er- und 3er-Kombinationen steigen die Wertigkeiten pro Gut zuerst an und fallen dann mit steigender Güterzahl wieder

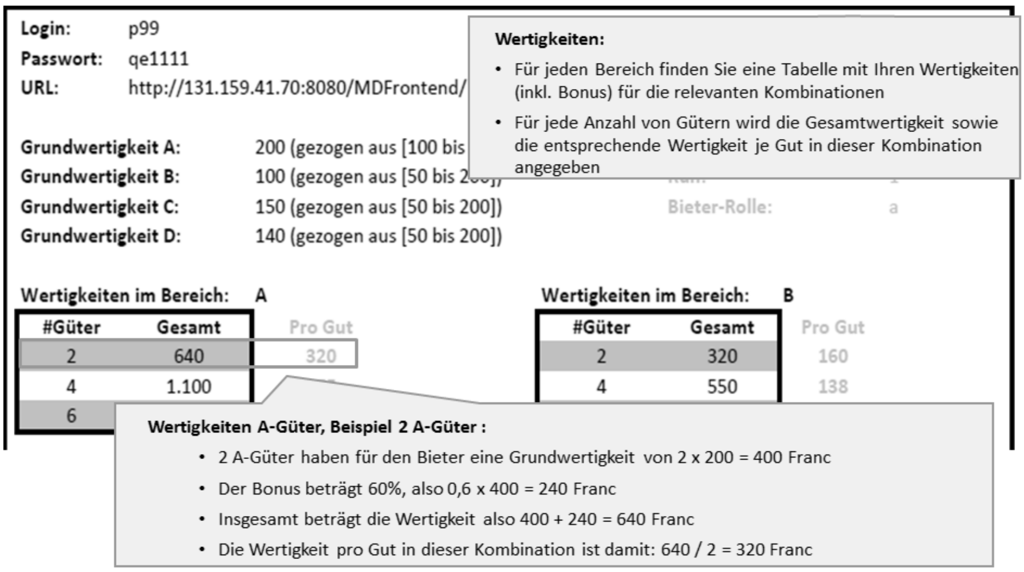
Beispiel:

- Grundwertigkeit A-Bereich: 200 Franc
- Grundwertigkeit B-Bereich: 100 Franc






Login: p99
Passwort: qe1111
URL: http://131.159.41.70:8080/MDFrontend/
Datum: 12.06.2012
Anmelde-Information:
Hier finden Sie den für die jeweilige Auktion gültigen Benutzernamen (hier: p01) und das Passwort (hier: qe1111) sowie die URL der Software-Plattform
Grundwertigkeit A: 200 (gezogen aus [100 bis 300])
Grundwertigkeit B: 100 (gezogen aus [50 bis 200])
Grundwertigkeit C: 150 (gezogen aus [50 bis 200])
Grundwertigkeit D: 140 (gezogen aus [50 bis 200])
Bieter-Rolle: a
Wertigkeiten im Bereich: A
#Güter
Pro Gut
2 320
4 275
6 250
Wertigkeiten im Bereich: B
#Güter Gesamt Pro Gut
2 320 160
4 550 138
6 750 125
#Güter
Wertigkeiten im Bereich: D
#Güter Gesamt Pro Gut
2 448 224
4 770 193
6 1050 175
Grundwertigkeiten:
Für jeden Bereich (A, B, C und D) finden Sie in einer Zeile die Grundwertigkeit für die Güter


Login: p99
Passwort: qe1111
URL: http://131.159.41.70:8080/MDFrontend/
Wertigkeiten:
Für jeden Bereich finden Sie eine Tabelle mit Ihren Wertigkeiten (inkl. Bonus) für die relevanten Kombinationen
Für jede Anzahl von Gütern wird die Gesamtwertigkeit sowie die entsprechende Wertigkeit je Gut in dieser Kombination angegeben
Grundwertigkeit B: 100 (gezogen aus [50 bis 200])
Grundwertigkeit C: 150 (gezogen aus [50 bis 200])
Grundwertigkeit D: 140 (gezogen aus [50 bis 200])
Bieter-Rolle: a
Wertigkeiten im Bereich: A
#Güter Gesamt Pro Gut
2 640 320
4 1.100
6
Wertigkeiten im Bereich: B
#Güter Gesamt Pro Gut
2 320 160
4 550 138
Wertigkeiten A-Güter, Beispiel 2 A-Güter :
2 A-Güter haben für den Bieter eine Grundwertigkeit von 2 x 200 = 400 Franc
Der Bonus beträgt 60%, also 0,6 x 400 = 240 Franc
Insgesamt beträgt die Wertigkeit also 400 + 240 = 640 Franc
Die Wertigkeit pro Gut in dieser Kombination ist damit: 640 / 2 = 320 Franc

1. Schritt (Höhe des Gebots bestimmen):

- Sie haben z.B. Gebote **für 4 A und 2 B-Güter** gewonnen
- Ihr Gebot für 4A beträgt **900 Franc**, für 2B **224 Francs**
- Nach der Preisregel hat sich ergeben, dass Sie einen **Preis für 4A in Höhe von 800 Francs und für 2B in Höhe von 205** zahlen müssen

2. Schritt (Wertigkeiten bestimmen):

- **A-Bereich:** Benutzen Sie die Tabelle auf der linken Seite der Wertigkeiten-Übersicht um ihre **Wertigkeit für 4 Güter** zu ermitteln (hier 1.100 Francs)
- **B-Bereich:** Benutzen Sie die Tabelle auf der rechten Seite der Wertigkeiten-Übersicht um ihre **Wertigkeit für 2 Güter** zu ermitteln (hier 320 Francs)

Wertigkeiten im Bereich: A

#Güter	Gesamt	Pro Gut
2	640	320
4	1.100	275
6	1500	250

Wertigkeiten im Bereich: B

#Güter	Gesamt	Pro Gut
2	320	160
4	550	138
6	750	125

3. Schritt (Auktionsgewinn ermitteln):

- Der zu zahlende Betrag kann unter dem gebotenen Betrag liegen(800 Francs < 900 Francs und 205 Francs < 224 Francs)
- Benutzen Sie die folgende Formel um den Auktionsgewinn zu ermitteln:
  - **Potentieller Gewinn = Summe der Wertigkeiten – Zu zahlender Betrag**
  - **Gewinn für 4A: 300 Francs = 1.100 Francs – 800 Franc**
  - **Gewinn für 2B: 115 Francs = 320 Francs – 205 Franc**
  - **➔ Ihr Gesamtgewinn beträgt 415 Francs (= 300 Francs + 115 Francs)**

Systematik:

- **Auszahlung = Anwesenheitsprämie + Auktionsgewinne** (Achtung: Strafregeln beachten!)
- **Von den 4 gespielten Auktionen werden am Ende des Experiments durch Zufall n Auktionen zur Auszahlung bestimmt** (Diese Zahl wird Ihnen vor dem Experiment bekannt gegeben)
- **Die zur Auszahlung stehenden Auktionen sind für alle Bieter gleich**
- **Pro Teilnehmer ist die Gesamtauszahlung auf 100 € gedeckelt**

Anwesenheitsprämie:

- Jeder Teilnehmer, der an allen Auktionen teilnimmt, erhält **10 € unabhängig vom Verlauf der Auktionen**

Auktionsgewinne:

- Auktionsgewinne ermitteln sich aus der **Differenz Ihrer Wertigkeiten und der gezahlten Preise**
- Auktionsgewinne werden durch einen **Umrechnungsfaktor UF** von Franc in Euro umgerechnet:
  - Der für Ihre Auktion gültige Umrechnungsfaktor beträgt 12
- Für jede gespielte Auktion erhalten Sie **3 € Auktionsprämie**
- Ihre Auszahlung hängt also maßgeblich von Ihrem Erfolg in den Auktionen ab: Je höher der Gewinn in den Auktionen, um so höher fällt Ihre Auszahlung aus

Strafregel 1 (Absprachen unter den Bietern):

- Falls der **Verdacht** besteht, dass sich Bieter abgesprochen haben, so erhalten **diese Bieter für die betroffene Auktion keine Auszahlung**

Strafregel 2 (Auktionsverluste):

- Je Auktion wird der Auktionsgewinn oder -verlust über alle Güter hinweg berechnet
- Auktionsverluste (also negative Gewinne) werden **von der Auktionsprämie von 3 € abgezogen**
- Teilnehmer können je Auktion maximal ihre Auktionsprämie verlieren

Auszahlung der finanziellen Kompensation:

- Sie werden per E-Mail über die Höhe Ihres Gewinns informiert
- Die Auszahlung **erfolgt durch das Sekretariat** des DSS Lehrstuhls

Gebote und Preise:

- Bieter geben **Gebote** für 2er, 4er, 6er Blöcke (d.h. ihre maximale **Zahlungsbereitschaft für eine gewünschte Anzahl aus A-, B-, C- und D-Gütern**) in einem Bereich ab
- Jeder Bieter kann innerhalb eines Bereiches mit maximal einem Gebot gewinnen
- Somit können insgesamt maximal 4 Gebote (ein Gebot pro Band) eines Bieters gewinnen
- Für **jeden Bereich gibt es einen eigenen Güter-Preis**, der für **alle Güter im jeweiligen Bereich gleich ist**

Ablauf:

- Die Auktion besteht aus **einer beliebigen Anzahl von Runden**
- **Die Auktion endet,** wenn **alle aktuellen Gebote aus der letzten Runde gewinnen**
- **Zu Beginn jeder Runde werden die neuen Güterpreise** (je Bereich ein Preis) **bekannt gegeben**
- **Auf Basis dieser neuen Preise entscheidet jeder Bieter** wie viele A-, B-, C- und D-Güter er zu aktuellen Preisen kaufen möchte. Er gibt ein **Gebot ab,** in dem 2, 4, oder 6 A-, B-, C- oder D-Gütern spezifiziert
- Haben alle Bieter ihre Gebote abgegeben oder ist die max. Rundendauer erreicht, so ist die Runde beendet
- Wenn **in einem Güter-Bereich von allen Bietern insgesamt mehr Güter nachgefragt wurden als vorhanden sind**, so wird der Preis des Bereiches um einen **Clock-Tick erhöht und die nächste Runde gestartet** (ein Clock-Tick im A-Bereich entspricht 20 Franc, im B-, C- und D-Bereich jeweils 15 Franc)

Aktivitätsregel:

- Ein Bieter muss **mindestens ein Gebot in der aktuellen Runde abgeben**, damit er in der nächsten Runde auch wieder bieten darf

Bestimmung der Gewinner:

- Unter allen Geboten aller Runden werden diejenigen ausgewählt, die den Gesamterlös der Auktion maximieren

Bestimmung der zu zahlenden Preise (Core-Zahlpreise):

- Die zu zahlenden Preise (Zahl-Preise) entsprechen den gebotenen Preisen (Gebot-Preisen).

FIGURE A.4: Explanation of the auction rules for the A_{SS} to the participants in laboratory experiments.

Gebote und Preise:

- Bieter geben **Bündelgebote** ab (d.h. ihre maximale **Zahlungsbereitschaft für eine gewünschte Kombination aus A-, B-, C- und D-Gütern**)

Ablauf

- Die Auktion besteht aus **genau einer Runde**
  - Sie bekommen keine Information über Aktivitäten (Gebote) von andere Bietern

Bietsprache:

- Nur eines ihrer **Bündelgebote** kann gewinnen.

Bestimmung der Gewinner:

- Unter allen Geboten werden diejenigen ausgewählt, die den Gesamterlös der Auktion maximieren

Bestimmung der zu zahlenden Preise (Core-Zahlpreise):

- Die zu zahlenden Preise (Zahl-Preise) können sich von den gebotenen Preisen (Gebot-Preisen) unterscheiden
- Der erfolgreiche Bieter zahlt nicht den Preis, den er geboten hat, sondern das geringste Gebot das sicherstellt, dass ihn kein anderer Bieter überbietet
- Die **Zahl-Preise können deshalb kleiner oder gleich aber nie größer als die Gebot-Preise** sein

FIGURE A.5: Changes in the explanation of the auction rules for the S_{CC} to the participants in laboratory experiments compared to the A_{SS}.

A.2.2 Exemplary valuation sheet

Depending on the expressivity of the bidding language, we printed different valuation sheets for the bidders. Before each auction, participants received their new valuation for each band.

Login:	p81	Test user	**Datum:**	15.12.2013
Passwort:	qe9089			
URL:	http://131.159.41.70:8080/MDFrontend/			

Grundwertigkeit A:	201 (gezogen aus [100 bis 300])
Grundwertigkeit B:	80 (gezogen aus [50 bis 200])
Grundwertigkeit C:	77 (gezogen aus [50 bis 200])
Grundwertigkeit D:	61 (gezogen aus [50 bis 200])

Wertigkeiten im Bereich: A

#Güter	Gesamt	Pro Gut
2	643	322
4	1.106	277
6	1508	251

Wertigkeiten im Bereich: B

#Güter	Gesamt	Pro Gut
2	256	128
4	440	110
6	600	100

Wertigkeiten im Bereich: C

#Güter	Gesamt	Pro Gut
2	246	123
4	424	106
6	578	96

Wertigkeiten im Bereich: D

#Güter	Gesamt	Pro Gut
2	195	98
4	336	84
6	458	76

FIGURE A.6: Valuation sheet in experiments with the simple bidding language.

A.2.3 Screen-shots of the bidding interfaces

Bidders could either bid on 12 predefined bundles or select 1 possible bundle out of 2,400. For the simple bidding language we present the whole introduction we gave to the participants. In order to avoid repetitions, we print for treatments that used the complex bid language only the slides that changed due to the increased expressivity.

Login: p82 Test user **Datum:** 15.12.2013
Passwort: qe4118
URL: http://131.159.41.70:8080/MDFrontend/

Grundwertigkeit A: 126 (gezogen aus [100 bis 300])
Grundwertigkeit B: 75 (gezogen aus [50 bis 200])
Grundwertigkeit C: 58 (gezogen aus [50 bis 200])
Grundwertigkeit D: 101 (gezogen aus [50 bis 200])

Wertigkeiten im Bereich: A

#Güter	Gesamt	Pro Gut
1	126	126
2	403	202
3	567	189
4	693	173
5	819	164
6	945	158

Wertigkeiten im Bereich: B

#Güter	Gesamt	Pro Gut
1	75	75
2	240	120
3	338	113
4	413	103
5	488	98
6	563	94

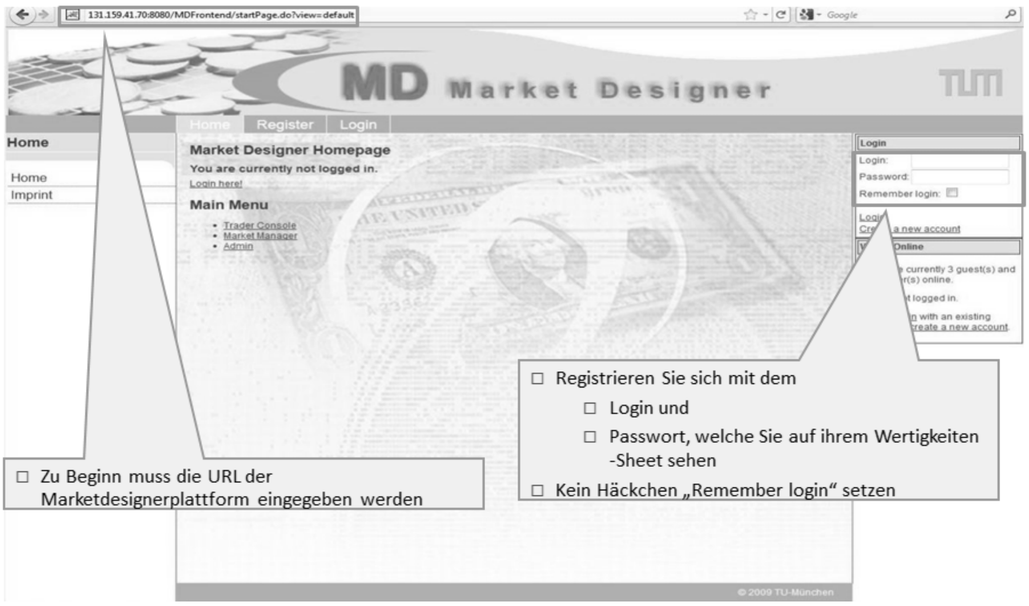
Wertigkeiten im Bereich: C

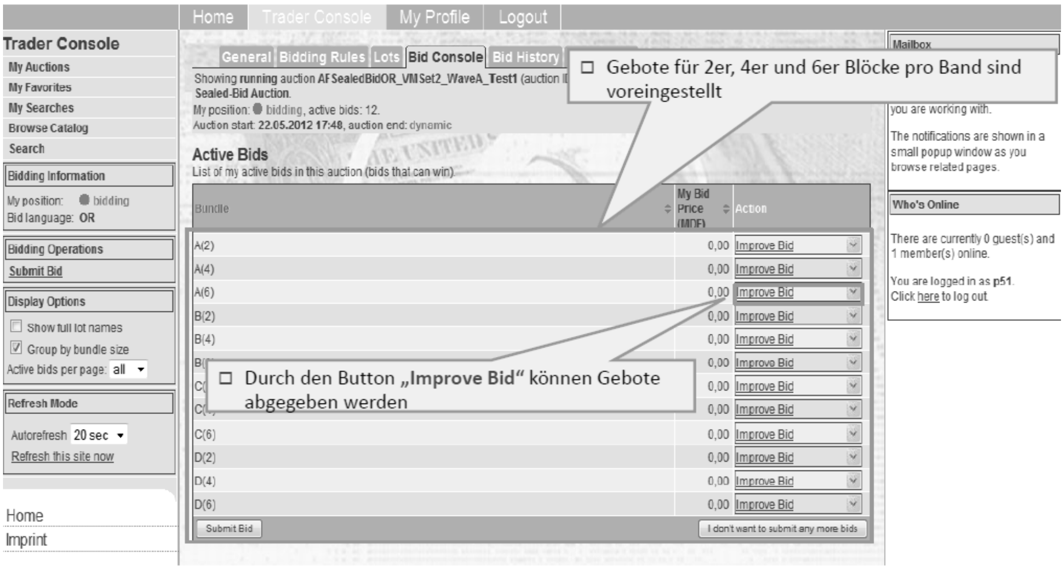
#Güter	Gesamt	Pro Gut
1	58	58
2	186	93
3	261	87
4	319	80
5	377	75
6	435	73

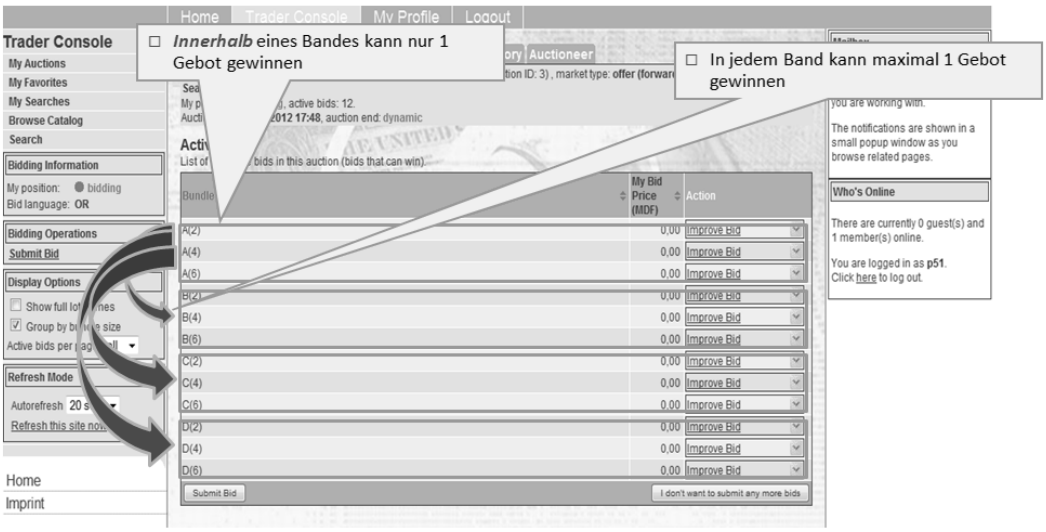
Wertigkeiten im Bereich: D

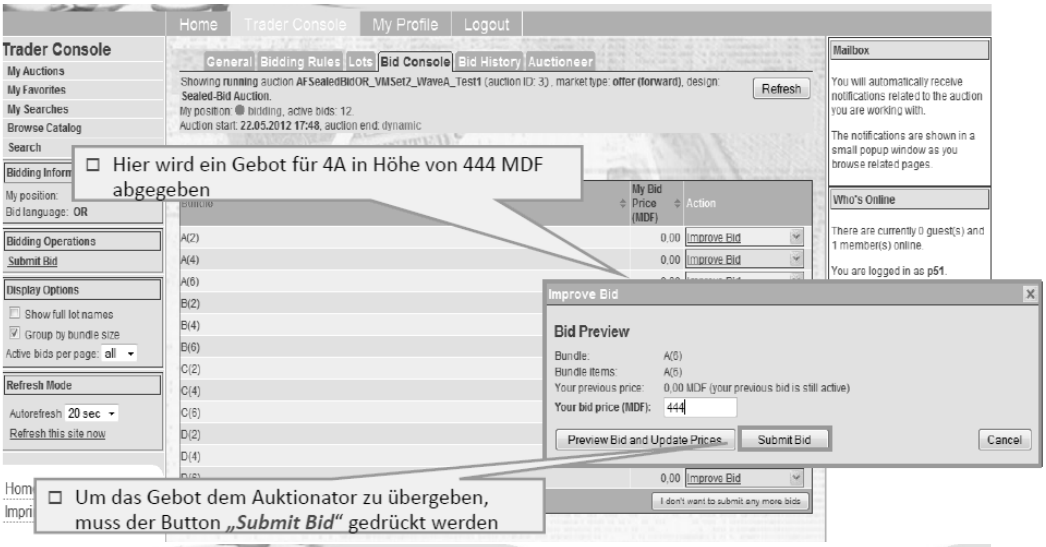
#Güter	Gesamt	Pro Gut
1	101	101
2	323	162
3	455	152
4	556	139
5	657	131
6	758	126

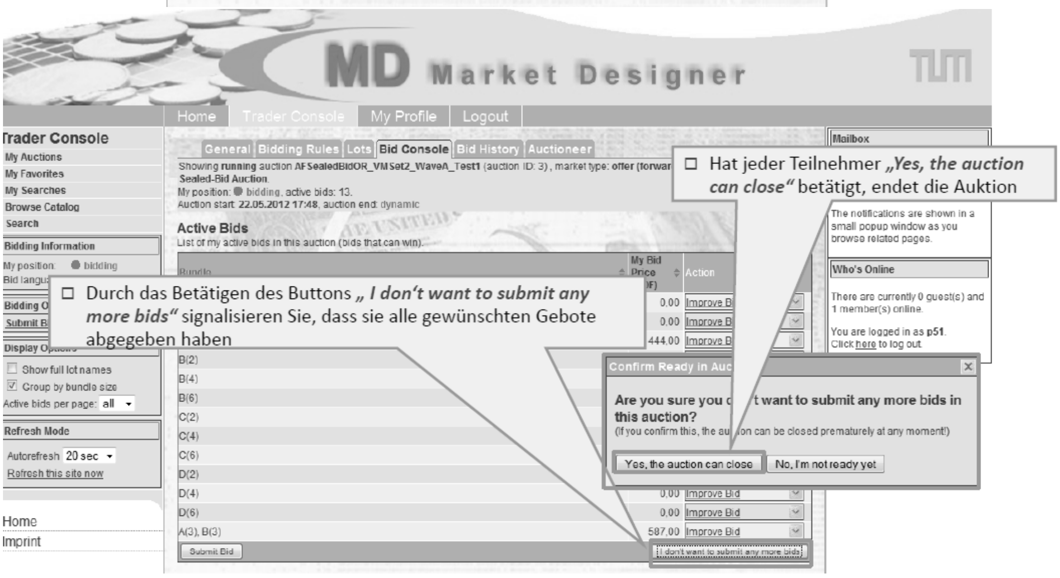
FIGURE A.7: Valuation sheet in experiments with the complex bidding language.




Gebote für 2er, 4er und 6er Blöcke pro Band sind voreingestellt
Durch den Button „Improve Bid“ können Gebote abgegeben werden
Trader Console
Active Bids
List of my active bids in this auction (bids that can win)
Submit Bid
I don't want to submit any more bids


Innerhalb eines Bandes kann nur 1 Gebot gewinnen
In jedem Band kann maximal 1 Gebot gewinnen
Trader Console


Hier wird ein Gebot für 4A in Höhe von 444 MDF abgegeben
Um das Gebot dem Auktionator zu übergeben, muss der Button *„Submit Bid“* gedrückt werden
Trader Console
Improve Bid
Bid Preview
Preview Bid and Update Prices
Submit Bid
Cancel


MD Market Designer
Hat jeder Teilnehmer *„Yes, the auction can close“* betätigt, endet die Auktion
Durch das Betätigen des Buttons *„ I don't want to submit any more bids“* signalisieren Sie, dass sie alle gewünschten Gebote abgegeben haben
Trader Console
Active Bids
Yes, the auction can close
No, I'm not ready yet

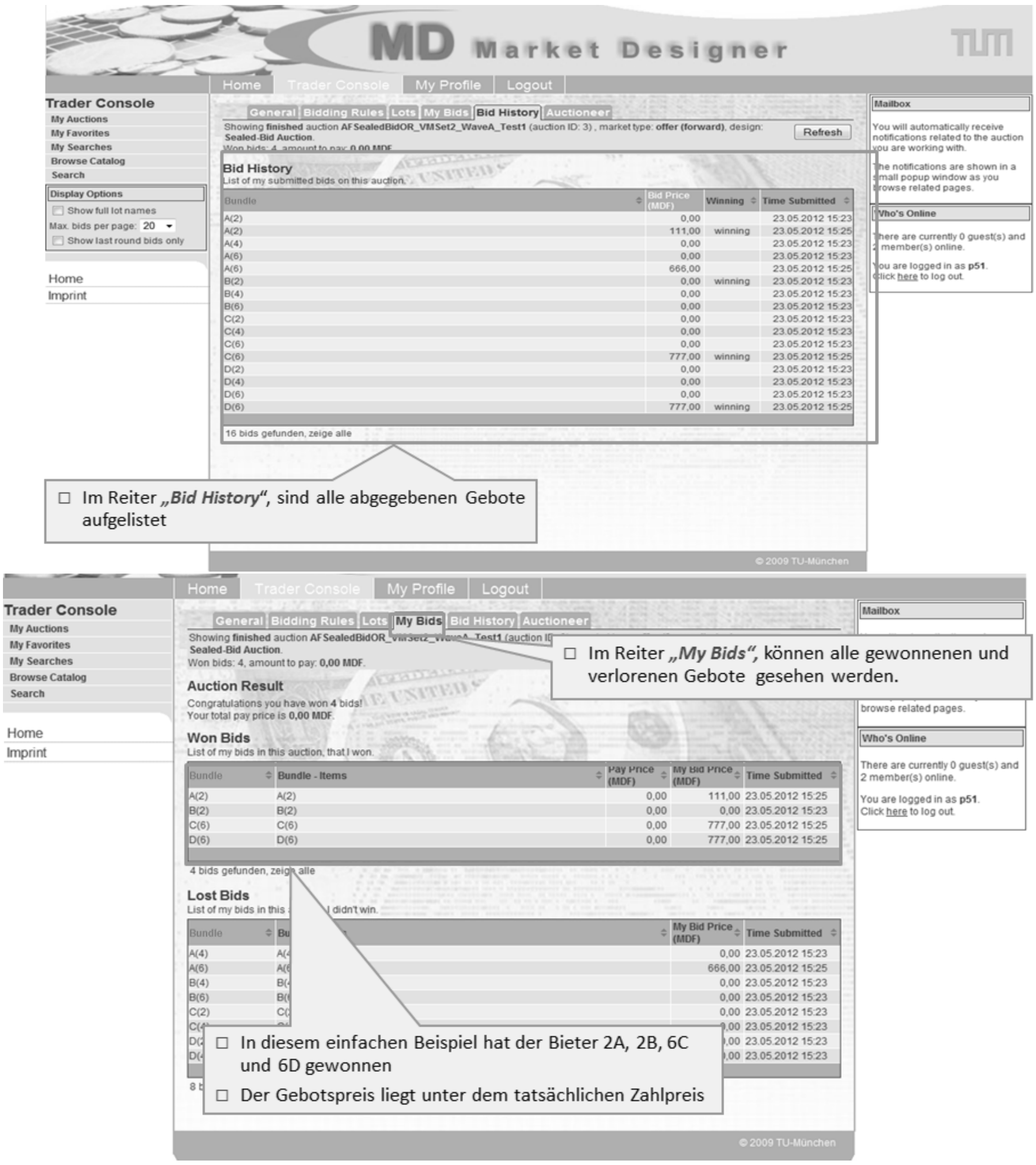


FIGURE A.8: Bidding interface with the simple bidding language.

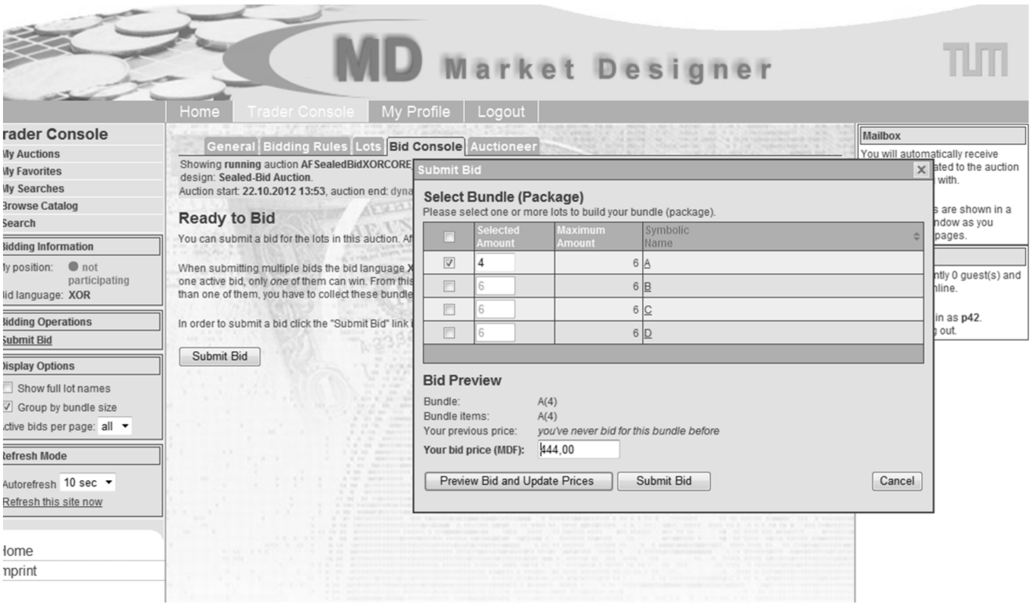


FIGURE A.9: Changes in the bidding interface with the complex bidding language.

Appendix B

Further figures and tables

In Appendix B, we present additional figures and tables that underline the results in Chapter 3.

B.1 Figures for the parallel auction

Figure (3.8) already shows the scatter plots for the first auction in treatment H. In addition, the corresponding plots for the 7^{th} and 16^{th} auction can be seen at the figures (B.1) and (B.2). The scatter plots visualize that there is learning in the first round, but no big difference between the 7^{th} and 16^{th} auction

Figure (B.3) supports result 2 and accomplishes figure (3.8). It can be seen, that there is not much difference in bidding behavior between the treatments C100 and C100+.

B.2 Figures and tables for the Yankee auction

In Chapter 3 only scatter plots of the single-lot and the parallel auction are provided. To show, that there was actually no difference between auction formats (see also table (3.9)), we print figure (B.4) as counterpart for figures (3.5) and (3.7).

Figure (B.5) accomplishes (B.2) and (3.6), (B.6) complements (B.3), (3.8) and (3.4).

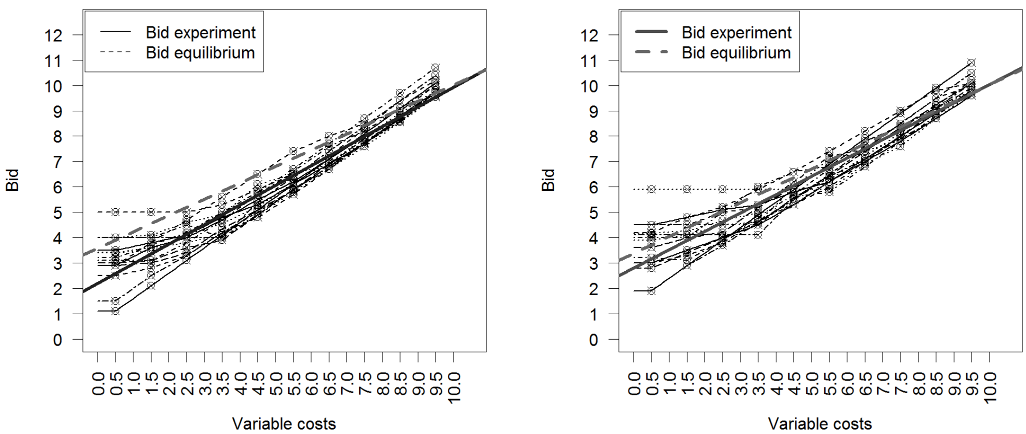


FIGURE B.1: Scatter plot of bids and the optimal bid functions for H on the large lot for the 7^{th} auction (left) and the small lot (right) for the parallel auction (q=0.7).

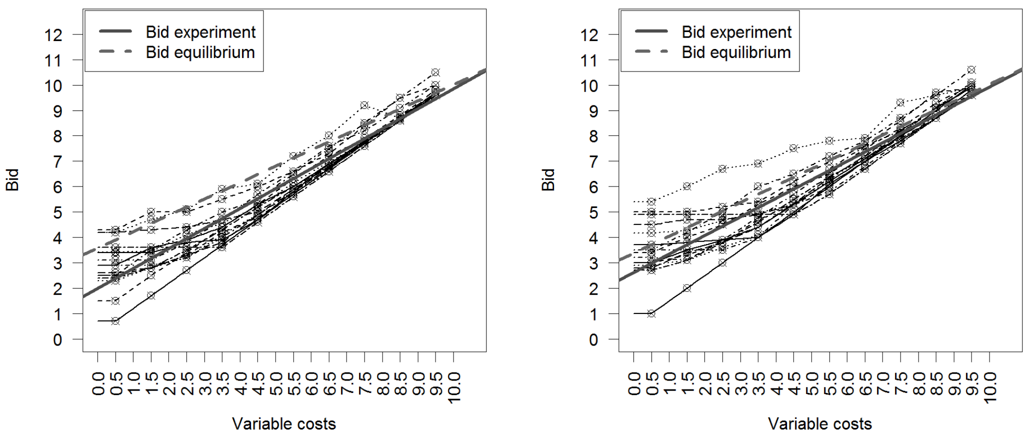


FIGURE B.2: Scatter plot of bids and the optimal bid functions for H on the large lot for the 16^{th} auction (left) and the small lot (right) for the parallel auction (q=0.7).

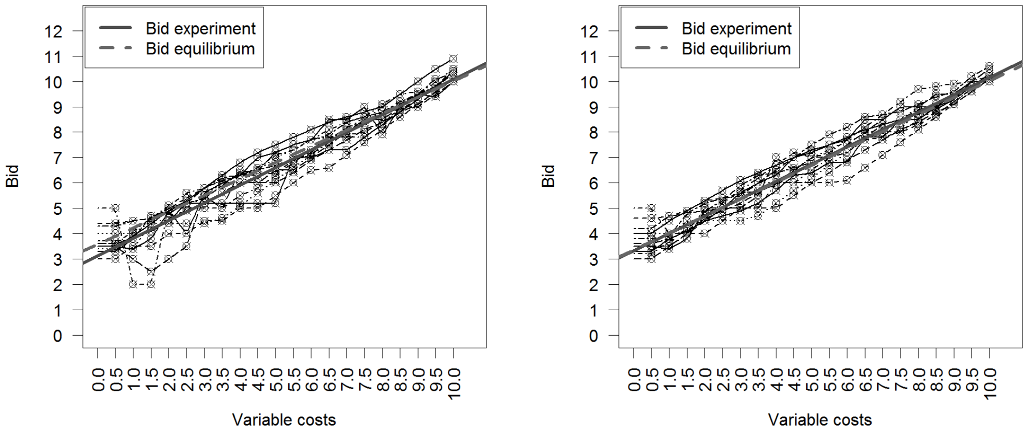


FIGURE B.3: Scatter plot of bids and the optimal bid functions for C100 on the large lot (left) and for the small lot (right) for the parallel auction (q=0.7).

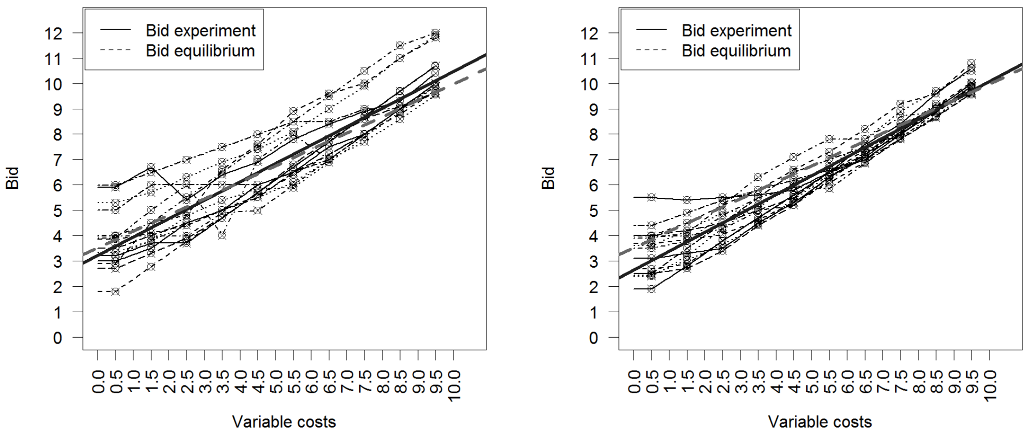


FIGURE B.4: Scatter plot of bids and the optimal bid functions in H for the 1^{st} (left) and the 7^{th} auction (right) for the Yankee auction.

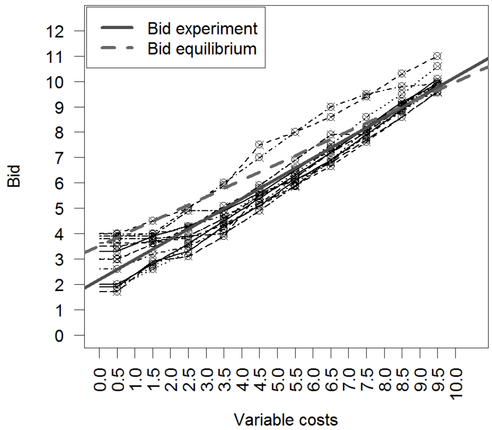


FIGURE B.5: Scatter plot of bids and the optimal bid functions in H auction for the 16^{th} auction for the Yankee auction.

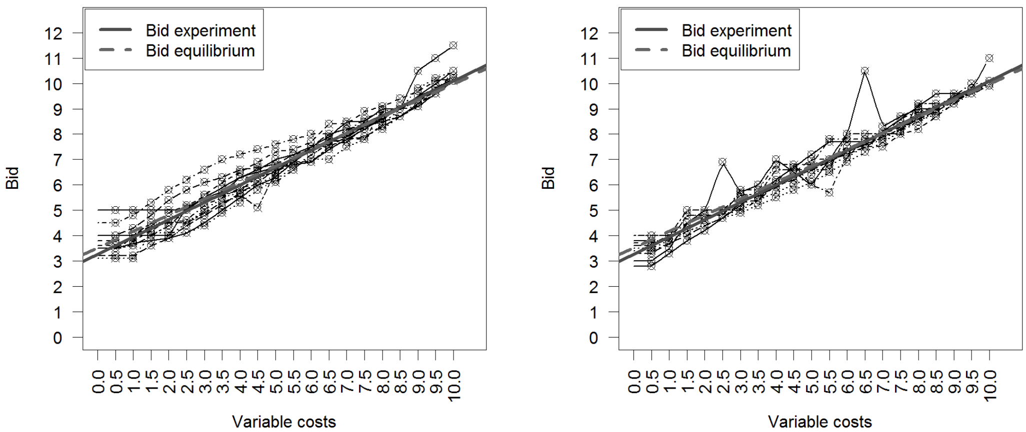


FIGURE B.6: Scatter plot of bids and the optimal bid functions for C100 (left) and C100+ (right) for the Yankee auction (q=0.7).

	p-value
H	0.770
C1	0.000
C100	0.985
C100, q=0.9	0.000

TABLE B.1: The p-values of a Chow test for equivalence of the RNBNE bid function and the regression for the Yankee auction.

The Chow test for the Yankee auction (table (B.1) provides similar results as for the single-lot (3.4) and the parallel auction (3.7).

B.3 Significance tests

In table (3.10) the high level results are shown. For these benchmarks, we did significance tests (see table (B.2)).

	H.Y, q=0.7	*C1.Y, q=0.7*	*C100.Y, q=0.7*	*C100+.Y, q=0.7*	*C100.Y, q=0.9*	*C100+.Y, q=0.9*	*H.S*	*C1.S*	*C100.S*	*C100+.S*
H.P, q=0.7	E:0.5019 C:0.186 P:0.6732						E:0.0005 C:0.0011 P:0.0000			
C1.P, q=0.7		E:0.6252 C:0.7975 P:0.2035						E:0.2023 C:0.0129 P:0.0000		
C100.P, q=0.7			E:0.4274 C:0.7176 P:0.0568						E:0.1038 C:0.0021 P:0.0000	
C100+.P, q=0.7				E:0.2286 C:0.6444 P:0.3722						E:0.2286 C:0.0262 P:0.0009
C100.P, q=0.9					E:0.1959 C:0.9805 P:0.0000			E:0.0042 C:0.0246 P:0.0000		
C100+.P, q=0.9						E:0.0112 C:0.4175 P:0.0000			E:0.0037 C:0.0177 P:0.0000	
H.Y, q=0.7							E:0.0003 C:0.0406 P:0.0000			
C1.Y, q=0.7								E:0.0425 C:0.0064 P:0.0000		
C100.Y, q=0.7									E:0.0313 C:0.0124 P:0.0005	
C100+.Y, q=0.7										E:0.4983 C:.0.1858 P:0.0007
C100.Y, q=0.9								E:0.0128 C:0.0362 P:0.2586		
C100+.Y, q=0.9									E:0.0772 C:0.0061 P:0.8952	

TABLE B.2: Significance tests (Wilcoxon rank sum tests) for a difference on all pairs of auction formats and treatments concerning efficiency E, cost ratio C and average (procurement) costs P.

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