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Efficiency, auctioneer revenue, and bidding behavior in the Combinatorial Clock Auction - An analysis in the context of European spectrum auctions

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Abstract

Magnetic radio spectrum is usually allocated by means of auctions. Mobile operators bid for spectrum licenses which are used to offer communication and data services to their customers. Such spectrum sales are among the biggest trades in terms of revenue, which makes this domain especially interesting for research in the field of market design and auctions.

For many years now, the Simultaneous Multi-Round Auction (SMRA) has been the predominant auction format for spectrum sales worldwide. SMRA is compelling due to its simple auction rules and its excellent price discovery, but bidders with complementary valuations are affected by exposure risk. This causes bidders to apply bidding strategies and various forms of signaling which jeopardize efficiency. The recently introduced Combinatorial Clock Auction (CCA) has been designed in order to give strong incentives for truthful bidding, which has high efficiency as a result (Cramton, 2009b). It has been used as an alternative to the SMRA in a number of countries.

In this thesis, we analyze the performance of CCA in comparison to SMRA and examine bidding behavior in both formats. We have conducted experiments in three different settings closely resembling the settings of European spectrum auctions. We did not find a significantly superior performance of CCA in terms of efficiency. In multiband settings, in which several spectrum bands were sold, the efficiency of CCA was significantly worse than in SMRA. Auctioneer revenue was significantly lower due to unsold items and the payment rule of

the CCA. Bidders in the CCA submitted bids for only a fraction of all possible bundles. They used simple heuristics to select bundles and focused on the complementarities of the value models. Instead of bidding their true valuation on all possible bundles, which is a dominant strategy in a pure Vickrey-Clarke-Groves mechanism, bidders bid on bundles that offered the highest synergies in their valuations. In accordance with theoretical predictions, bundle bids were either at or slightly below the valuation. Bidding behavior in SMRA exhibited strong signaling activities, such as the use of jump bids and bids on the bidders' own items, as observed in field auctions.

To improve the external validity of the experiments with unprepared subjects, we also conducted competitions. Taking account of field auction conditions, subjects in competitions participated as teams and had several weeks to prepare for the auctions. Competition results confirmed the findings from the lab experiments.

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Chapter 1

Introduction

Study nature, not books.
Louis Agassiz

Magnetic radio spectrum is a scarce resource which is required for many applications. One of the most prominent users is the telecommunications industry, since service providers require spectrum to build up networks and offer mobile voice and data services. Spectrum is considered a state property and the regulatory authority is in charge of assigning licenses for use of the spectrum to various parties across the territory of the country. Ideally, it should be put to the best use and contribute to social welfare as much as possible.

The assignment of usage rights is far from easy: The scarcity of licenses and the rapid development of faster voice and data services that consume more and more bandwidth generate a greater demand for licenses and competition for them among the service providers. The exact value of such licenses is often uncertain, even for the regulatory authorities.

Nowadays, spectrum is usually allocated through auctions. But before the first spectrum auction was held in the United States of America (US) in 1994, it was common to organize administrative hearings or lotteries to assign spectrum usage rights.

Administrative hearings require a comprehensive application by interested telecommunication service providers. The high costs involved with such an application can deter smaller companies from applying. The administrative process of selecting the applicants that will receive licenses is then a quite tedious and often lengthy process because the concept of the intended usage, the funding, and legal issues have to be evaluated (Hoffman, 2011). Applicants often perceive this process as non-transparent and the results as unfair. The goal of finding the best use of the spectrum for the society is undermined, since applicants with more direct influence on the process or with better lobbying might have an advantage over better applicants. For this reason, such administrative processes have often been called ***beauty contests***. Court processes have often been fought over the assignment of licenses due to this lack of transparency in the assignment process. In the field of telecommunication services, where technological standards are developing at an increasing pace, administrative processes appear to be too slow and are thus less attractive for the assignment of spectrum licenses.

Another approach for assigning licenses, which has been used, e.g., by the FCC,[1] are ***lotteries***. All applicants are placed in one pool and the licenses are randomly assigned. This process has the advantage of being quick but there is no or only limited control over the quality of applicants. Thus, many bidders applied without the intention of actually using the licenses. Their intention was to sell them immediately after the lottery for a more or less riskless profit. Hoffman (2011) reports on a group of dentists who made a profit of several million US dollars by selling a single license right after such a lottery. Speculations of that kind led to geographic fragmentation and delayed introduction of a nationwide mobile telephone service in the US (Milgrom,

[1] Federal Communication Commission, the regulatory authority in the US.

2004). Of course, this was not acceptable to the US government since a lot of revenue was lost for the taxpayers and licenses were not allocated for best use, i.e., efficiency was low.

After this experience, the US Court decided to allocate spectrum through an auction and requested that the FCC define the auction rules. Among other goals, the auction design should foster competition, earn acceptable revenue, and promote efficient use of the spectrum (Hoffman, 2011). Scientists were consulted and made suggestions for the auction design, lab experiments were conducted, and eventually the ***Simultaneous Multi-Round Auction (SMRA)*** format was designed. The rules were first proposed by Milgrom, Wilson, and McAfee. In 1994, the FCC was the first to run an SMRA to sell spectrum usage rights. With some rule adjustments, it has been used in many spectrum auctions worldwide since then and accounts for revenues in excess of 200 billion US dollars (Cramton et al., 2006b).

The SMRA design is a non-combinatorial auction format that assigns all licenses for sale at the same time. It has quite simple rules but it poses several problems for the bidders, most importantly exposure risk and aggregation risk. In SMRA, bidders can bid only on individual items and not on packages. Bidders with synergistic valuations for packages of items, e.g., for several licenses required to build a network, risk winning only a fraction of the desired license set at prices reflecting the synergies of the larger bundle. There is no dominant strategy for bidders telling them how to bid in such an auction independent of the bidding of competitors. Bidders have to develop a tactic or strategy to bid in the auction. This has led telecommunication service providers to set up bidding teams and seek advice from experts and consultants. In SMRA, bidders with a better strategy might win against bidders with a higher valuation for the licenses. This contradicts the regulators' goals of efficiently allocating the spectrum.

Therefore, auctioneers have tried to amend the auction rules. For example, withdrawals have been suggested, allowing bidders to step back from a won license when the new combination is not attractive anymore. But withdrawals give bidders the possibility to apply tactics, i.e., bidders can submit high bids on the preferred blocks of their competitors to raise their payments. If the case arises that they are not outbid, they can withdraw their bid.

Another problem arises from the technical properties of radio spectrum. The spectrum blocks, i.e., the units of spectrum for sale, within one band are more or less identical for the use of service providers. Major differences exist only for blocks of different bands. For bidders in the auction, it is difficult to decide how to bid. In 2010, Germany auctioned off 360 MHz of spectrum from several bands within one auction, called the German Super Auction (Niemeier, 2002). The German regulatory authority (Bundesnetzagentur) decided to offer abstract blocks of spectrum within each band. While the intention was to facilitate bidding for the service providers, this again opened up several new possibilities for auction tactics. Bidders could bid on blocks which are not the cheapest among identical abstract blocks to send signals to competitors. From many such experiences, one lesson learned is that even small rule changes in the mechanism can have a great impact on bidding behavior and the auction outcome.

Cramton (2009b) suggested a new auction format, the Package Clock, also called the ***Combinatorial Clock Auction (CCA)***. It is a combinatorial design allowing bidders to submit all-or-nothing package bids. So there is no exposure risk anymore. Its rules give bidders strong incentives to bid their true valuations and to refrain from applying any bidding strategies, which eventually should lead to high efficiency.

The CCA has already been applied to spectrum sales (section 1.2) with varying degrees of success. There are no published lab experiments for this new format that we know of. This is quite surprising given the huge amounts of money at stake in spectrum auctions.

The goal of this thesis is an experimental analysis of the performance and the bidding behavior connected with the CCA in realistic settings of spectrum sales and a comparison of CCA and the de facto standard SMRA. We found that the CCA performance was not superior to that of SMRA in terms of efficiency in a smaller setting and that in multiband settings it was even worse. Bidders in the CCA did not report their true valuations, but followed rather simple heuristics, which can be compared to satisficing behavior. Addressing the external validity of the lab experiments, we also conducted competitions in which subjects participated in teams and had more preparation. This resembled the situation of bidding teams in the field. The results from the competitions confirmed the findings from the lab.

1.1 The domain of spectrum sales

Radio spectrum can be divided into several bands of frequencies which are used to implement voice or data services, e.g., the 0.8 GHz band for GSM, the 2.0 and 2.1 GHz bands for UMTS, and the 2.6 GHz band for WiMAX or LTE.[2] Typically, spectrum usage rights are sold in blocks of 5 MHz. Some technologies for mobile communication services (e.g., LTE) require paired spectrum, i.e., one block for uplink and another for downlink. Thus, paired spectrum encompasses two blocks to accommodate this. Other technologies, such as WiMAX, use a single block for up- and downlink. The corresponding spectrum is called unpaired spectrum and is sold per block.

Within the same band, spectrum blocks can be considered identical. Some factors such as pending law trials or interference at country borders can cause

[2] GSM, UMTS, LTE, and WiMAX refer to technological standards of communication services. LTE (Long Term Evolution) and WiMAX (Worldwide Interoperability for Microwave Access) are standards to offer mobile services of the fourth generation. UMTS (Universal Mobile Telecommunications System) and GSM (Global System for Mobile Communications) are third- and second-generation standards which are currently in use.

minor differences in value among blocks of the same spectrum band. For this study, such effects can be ignored and blocks can be treated as identical. Each band can be considered as one item with multiple units, i.e., the number of blocks within this spectrum band. We call such an environment a multi-unit setting.

Determining the value of spectrum can be quite complex. The technology implemented by the mobile service provider determines the type and the quality of services to be offered to end customers. The more revenue a provider can expect from the market, the more attractive the business case is, and the higher the resulting valuation of the spectrum licenses. Since the valuation is based on expected revenue, there is some inherent ***value uncertainty*** in all value estimates.

The characteristics of the technologies to be implemented and the specifics of the mobile services market add to the complexity of determining valuations: For example, LTE reaches peak performance when it is implemented on four adjacent spectrum blocks. The respective business case and the valuation of the four blocks are therefore quite high. An LTE-implementation on two blocks promises only less than half the value. Therefore, the valuation of four blocks is higher than twice the valuation of two blocks, i.e., they have a synergistic value (the licenses are ***complements***, see section 2.1.1). But the opposite effect can also be observed: The value of two blocks in the 1.8 GHz band on top of two blocks in the 2.1 GHz band might be lower than the combined value of their single valuations. This can be the case if a bidder wants to implement, e.g., UMTS in only one of these two bands.

In addition, a sufficiently large geographic footprint might be necessary for a viable business plan, law trials might add additional uncertainty and risks, licenses might come with the regulatory obligation to cover white spots[3] first.

Due to the complexity and the necessity for telecommunication service

[3] White spots are geographical regions not covered sufficiently with voice or data services.

providers to obtain licenses in spectrum sales, they invest considerable effort and money to prepare for spectrum auctions.

1.2 Combinatorial auctions for spectrum sales

Combinatorial auction formats allow bidders to submit bundle bids, i.e., indivisible all-or-nothing bids on a set of items. Bidders can precisely state their valuations including super-additivities (***complements***) and sub-additivities (***substitutes***). Thus, there is no exposure risk, which is the risk of winning only a fraction of the required bundle.

But the design rules for combinatorial auctions raise new challenges. The choice of the bidding language is crucial: If any non-overlapping combination of a bidder's bids can win (***OR bidding language***), the bidder might end up with more items than required. If at most only one of his bids can win (***XOR bidding language***), the number of required bids can be impracticably high. Especially in larger settings, which are encountered in spectrum sales, the computational complexity is a serious concern. The number of possible bundles grows exponentially in the number of items for sale. With n items for sale, the number of all possible bundles is $2^n - 1$ if the bidder does not care about the allocations of competitors. For realistic settings with several items, it is almost impossible and impracticable to bid on all bundles. With twenty items, there are already more than one million possible bundles. This is also difficult for bidders, who incur costs in determining the valuation of bundles and in communicating their preferences (Cramton et al., 2006b).

The winner determination among all submitted bids and the allocation of bundles to winners is a complex task which is NP-hard. Due to the advent of information technology, the computational complexity can be handled and combinatorial auction designs have evolved.

In recent years, academia has discussed and analyzed various combinatorial auction formats. The **Vickrey-Clarke-Groves (VCG)** auction (section 2.6.1) is such a combinatorial auction format that offers attractive properties. VCG applies a second-price rule, which gives a discount to each bidder representing the additional value the bidder adds for the auctioneer. Through this rule, bidders have an incentive to reveal their true valuations, which supports efficient auction outcomes. While the VCG is still a point of reference for theory, it comes with many practical limitations (section 2.6.1.2). One of the most prominent shortcomings is that VCG outcomes do not necessarily lie in the *core* if bidders' valuations exhibit complementarities. This means that the prices winning bidders have to pay can be so low that there are losing bidders who wanted to pay more than the winners (section 2.4.3). Especially in sales of public goods, such as spectrum usage licenses, this is hard to explain to the public. Therefore, auction designs have been proposed that ensure auction outcomes in the core.

While SMRA has been the predominant auction format to sell spectrum licenses worldwide, some combinatorial auctions have recently been conducted. One prominent example is the Hierarchical Package Bidding format (HPB) that was applied in auction 73 to sell parts of the 700 MHz band in the US in 2008. HPB allows bidders to choose from a set of pre-defined bundles which are hierarchically structured (Goeree and Holt, 2010).

Also, the Simultaneous Clock or (single-stage) Combinatorial Clock (Porter et al., 2003) has gained popularity. It is a round-based design which offers ask prices (clock prices) in each round, and bidders respond with their demand at current prices by submitting bundle bids (section 2.6.2.1). Recently, the Combinatorial Clock Auction (Cramton, 2009b) has been proposed, which builds on the concept of the Simultaneous Clock and expands it with a sealed-bid phase to improve final outcomes (section 3.2). It uses a core-selecting payment rule to avoid the problems connected with the VCG. Its activity rule provides strong incentives to bid truthfully and, as a result, higher levels of ef-

Country	Year	Auction format	Revenue (Euro million)	Population (million)	Euro/ MHz/Pop
Norway	2007	SMRA	29	4.8	2.95
Sweden	2008	SMRA	226	9.1	13.01
Finland	2009	SMRA	3.8	5.3	0.33
Netherlands	2010	CCA	2.6	16.5	0.12
Denmark	2010	CCA	137	5.5	13.08
Germany	2010	SMRA	345 (only 2.6 GHz)	81.9	2.21
Austria	2010	CCA	40	8.3	2.50

Table 1.1: European 2.6 GHz band auctions
(Source: www.kbspectrum.com)

ficiency. Although there are no published results of any experimental analysis, this design was used to sell the 2.6 GHz spectrum band in the Netherlands, Denmark, and Austria, while other countries have stuck to SMRA. Table 1.1 provides an overview of the European sales of the 2.6 GHz band.

Cramton (2009b) refers to the design as Package Clock. In the field, an implementation of dotEcon was used (Maldoom, 2007) which describes this auction format as ***Combinatorial Clock Auction (CCA)***. We stick to this term as well.

1.3 Related literature

There is substantial literature on spectrum auction design (Banks et al., 2003; Cramton, 1997, 2009b; Klemperer, 2002; Plott, 1997; Plott and Salmon, 2004; Porter and Smith, 2006; Weber, 1997). Especially in recent years, combinatorial formats with core-selecting payment rules like the CCA have been analyzed heavily (Day and Milgrom, 2007; Goeree and Lien, 2010b; Lamy, 2009).

There are strong experimental results in comparisons of SMRA and combinatorial auction designs that suggest that combinatorial formats lead to higher efficiency when bidders' valuations exhibit complementarities (Banks et al., 1989, 2003; Brunner et al., 2010; Goeree and Holt, 2010; Kwasnica et al., 2005; Ledyard et al., 1997; Porter et al., 2003; Scheffel et al., 2011).

One strand of experimental literature on spectrum auctions tries to analyze and explain specific strategic situations as they have occurred in particular auctions either game-theoretically, experimentally, or based on data from the field (Bajari and Yeo, 2009; Ewerhart and Moldovanu, 2003; Grimm et al., 2003; Klemperer, 2002; Plott and Salmon, 2004). For example, some authors have attempted to understand why two companies bid very aggressively in the German UMTS auction in 2000 without being able to overbid other bidders. Hoffman (2011) provides an excellent survey of recent developments in spectrum auction design.

Another strand that analyzes the mechanisms used in spectrum auctions is based on related, but simplified settings in the lab (Abbink et al., 2005; Banks et al., 2003; Brunner et al., 2010; Goeree and Holt, 2010; Seifert and Ehrhart, 2005). Abbink et al. (2005) found differences in results between experiments with experienced and inexperienced students. Sutter et al. (2007) performed experiments with individuals and teams in the context of European spectrum auctions and found differences in the results: Teams stayed longer in an auction and paid significantly higher prices. Although teams made smaller profits, the efficiency was higher with teams.

A number of experimental studies have compared different combinatorial auction formats (Cramton et al., 2006a) and analyzed the conditions under which combinatorial auctions are superior to SMRA. In an early study, Ledyard et al. (1997) compared SMRA with a sequential auction and a combinatorial auction with various value models. They found that all three formats perform well with homogeneous items, but SMRA outperforms the sequential auction for heterogeneous items and the combinatorial auction is best suited in environments with value complementarities. Also, the experiments conducted by

Banks et al. (1989), Banks et al. (2003), and Kwasnica et al. (2005) show that package bidding is superior in environments with super-additivities.

Brunner et al. (2010) recently compared a standard SMRA with a Simultaneous Clock (different to the two-phase design of the CCA used in our experiments, see section 2.6.2.1) and an FCC format that augmented an SMRA auction to allow for package bids. They also found that package bidding yields an improved performance when complementarities are present. Accordingly, the Simultaneous Clock provided the highest efficiency and the highest seller revenues. The Simultaneous Clock has also been analyzed for other domains such as emission trading (Porter et al., 2009). Experimental results on the performance of the CCA with a sealed-bid phase have not been published yet.

The Hierarchical Package Bidding (HPB) format which has been developed for spectrum auctions in the US was compared to SMRA and Modified Package Bidding (a format with pseudo-dual linear prices) by Goeree and Holt (2010). By reducing the exposure risk for large national bidders, HPB outperformed the other two auction formats in terms of efficiency and auction revenue. Interestingly, combinatorial auction formats with linear, item-level prices have achieved high levels of efficiency in the lab (Brunner et al., 2010; Goeree and Holt, 2010; Kwasnica et al., 2005; Porter et al., 2003, 2009; Scheffel et al., 2011). Scheffel et al. (2011) compared linear-price combinatorial auctions to auction formats with non-linear, personalized prices for which an ex-post Nash equilibrium bidding strategy is known, but found that bidders failed to follow their equilibrium bidding strategies. Chen and Takeuchi (2010) analyzed the VCG mechanism and an efficient ascending combinatorial auction (iBundle (Ausubel and Milgrom, 2006a; Parkes, 2001)) in the lab, and found the latter to be more efficient.

1.4 Research objectives

SMRA has been analyzed theoretically (e.g., Brusco and Lopomo (2008)) and tested experimentally in the lab (e.g., Brunner et al. (2010); Kwasnica et al. (2005)). No experimental results have been published for the CCA, but it has already been implemented in the field. The first results from the Netherlands, the UK, and Denmark are mixed.

One goal of this study is to analyze the performance of the CCA in realistic spectrum settings encountered in European spectrum sales and compare it to that of SMRA.

Very often, lab experiments simplify realistic field conditions for the setting in the lab. In order to extract a single effect, the setting is reduced to rather small numbers of bidders and items or unrealistic assumptions are placed on the valuations. While this enables the analysis of single effects, the transfer of findings back to the field is difficult. In this study, the field settings are imitated as closely as possible.

The European 2.6 GHz spectrum auctions serve as an example. The setting is almost identical among the European countries because there is a mandatory European spectrum plan for the 2.6 GHz band. Therefore, the setting in the lab, i.e., the number of bidders and lots on sale, as well as the value models of mobile operators and the auction rules are modeled as closely as possible on these auctions. In addition, two multiband settings were analyzed in which several spectrum bands were sold simultaneously. Such settings are discussed, e.g., in Switzerland. We applied different types of complementarity structures, decreasing and increasing in the bundle size, as well as identical and differing among bidders in order to allow for different strategic environments for bidders (section 5.1.1.4).

Another goal of this work was to analyze the bidding behavior in CCA. There are no known equilibrium strategies for the CCA. VCG is the only incentive-compatible mechanism, and with the payment rule of the CCA there is no dominant strategy. Bidders have to decide on which bundles and how much to bid. In this study, we use experiments to analyze bidding behavior in the lab (section 4).

Auction mechanisms have traditionally been analyzed with game theory and computational simulations. ***Game theory*** assumes rational individuals that optimize their personal wealth. In well-defined economic settings, game-theoretic models study the existence of strategy equilibria. Often, these models work well for simple settings, but require strong assumptions, e.g., of the structure of valuations, which are hardly met in the field. For larger settings and complex market mechanisms, the space for bidding strategies and options becomes very large and game theory is pushed to its limits. Assuming a certain pattern of bidder behavior, ***computational simulations*** can help to analyze auction outcomes for various settings and to create a point of reference for auction performance. Bidding behavior cannot be analyzed with either of them. In ***lab experiments***, an economic setting is artificially created and unprepared subjects are observed while participating in the auction. The setup, auction rules, and instructions for participants are crucial for the experiment. Section 4 discusses a methodological framework to set up a controllable and manageable lab environment and to ensure internally and externally valid results (Smith, 1982).

As described above, prior research in spectrum auctions indicates that there are differences in behavior between teams and individuals (Sutter et al., 2007), as well as between inexperienced and experienced bidders (Abbink et al., 2005). To approximate the level of bidder preparation of mobile operators in spectrum auctions, this study compares the results of the lab experiments to those in ***competitions*** in which subjects prepare for a longer time period, have access to additional information and literature, and participate in teams.

1.5 Contributions

The SMRA has been the predominant auction format for spectrum sales worldwide since it was first applied in the US in 1994. SMRA is a non-combinatorial auction format in which bidders face the exposure problem. This has initiated the design of fully combinatorial auction formats. In 2008, the British regulatory authority decided to allocate spectrum through a CCA. Since then, the CCA has been used in a number of countries to sell spectrum licenses with mixed success. It was designed for high efficiency and to incentivize truthful bidding (Cramton, 2009b). While SMRA has been analyzed theoretically and tested experimentally, only little knowledge is available about CCA's efficiency properties and typical bidding behavior in relevant environments.

This thesis analyzes the performance of CCA in comparison to SMRA and examines bidding behavior in both formats. While attractively simple, theoretical models are often based on assumptions not met in the field. Experiments with unprepared subjects in a controlled lab environment can complement such models.

We conducted experiments (i) in a base setting which closely resembles the 2.6 GHz auction setting in several European countries and (ii) in two variants of multiband settings resembling a comparably more complex environment, in which different spectrum bands are sold simultaneously.

The results of our work do not indicate a significantly superior performance of CCA in terms of efficiency in the base setting. In the multiband settings, in which bidders had comparably more possible bundles to choose from, the efficiency of CCA was significantly lower than that of SMRA. The low number of bundle bids submitted in both auction phases, combined with the core-selecting payment rule of the CCA, resulted in very low auctioneer revenue compared to SMRA, and also compared to a CCA simulation in which bidders submitted bids on all possible bundles. SMRA does not adequately address synergies in bidder valuations, but bidders revealed their value for individual blocks. Therefore, unsold blocks were not an issue and efficiency was rather high.

Bidding behavior in CCA resembled that of bidders in the field, in that they submitted bids for only a fraction of all possible bundles. Bidders used heuristics to restrictively select bundles, which can best be explained by bounded rationality and satisficing. Instead of bidding the true valuation on all possible bundles, which is a dominant strategy in a pure VCG mechanism, bidders bid on bundles that offered the highest synergies or had the perceived highest chances of winning. In accordance with theoretical predictions, bundle bids were either at or slightly below the valuation.

Bidding behavior in SMRA exhibited strong signaling activities, such as the use of jump bids and bids on bidders' own blocks, as observed in field auctions.

A major characteristic of this work is the realistic setting in the lab experiments. By implementing the rules of the field auctions and by closely recreating the economic setting, meaningful results are obtained that are applicable to spectrum auctions in Europe. The crucial factor of complementarities was varied to create different strategic environments for bidders. In order to further improve the external validity of the experiments, we also organized competitions. As in auctions in the field, we let subjects in competitions participate as teams and prepare for the auctions. Bidding strategies in SMRA were used more wisely and with better success in the competition than in the lab. CCA bidders followed a bundle selection and bidding strategy similar to that in the experiments with unprepared subjects. Again, the final auction outcomes do not indicate a significantly superior performance of CCA in terms of efficiency.

This thesis is based on the research projects I have carried out with Professor Martin Bichler and Dr. Pasha Shabalin. Parts of this thesis have been presented at conferences and submitted to journals. The corresponding sections of this thesis are in large part the same as in the articles. Specifically, the work on the external validity of lab experiments and the pre-study on competitions in chapter 4 were submitted to the *Jahrestagung der experimentellen Wirtschaftsforschung 2010* and presented in Luxembourg. The results of the principal lab experiments for the comparison of the CCA and the SMRA were presented at the Conference on Auctions, Market Mechanisms, and their Applications (AMMA) 2011 in New York, and submitted for publication as Bichler et al. (2011). The paper is currently under review. Parts of these submissions correspond to section 1.3, chapters 3, 5, and 6. Of course, all errors, misinterpretations, and inconsistencies in this thesis remain my own.

1.6 Outline

The rest of this thesis has the following structure:

Chapter 2 provides the required theoretical background and definitions. It discusses the economic environment of spectrum auctions and approaches for the determination of winners and required payments. It introduces combinatorial auction formats, including the Vickrey-Clarke-Groves auction, and performance measures used to evaluate the outcome of auctions.

Chapter 3 formally defines the auction formats SMRA and CCA, which were used in the lab experiments.

Chapter 4 introduces lab experiments as a methodology to analyze bidding behavior in auctions and separates it from game theory and computational simulations. It addresses issues of internal and external validity of lab experiments in the domain of spectrum auctions and proposes competitions with teams of prepared subjects as a complement to traditional lab experiments with unprepared bidders.

Chapter 5 compares the performance of CCA and SMRA and analyzes the bidding behavior in both auction designs. The lab experiment uses settings closely resembling the European 2.6 GHz setting and multiband settings in which several spectrum bands are sold. It uses different value models to cover a range of environments with different complexities and numbers of available bundles for bidders. In addition, it reports on competitions conducted in the exact same settings and compares the results.

Chapter 6 concludes the thesis and discusses areas of future research.

Chapter 2

Design of combinatorial auction mechanisms

Price is what you pay.
Value is what you get.
Warren Buffett

Auctions answer the most fundamental questions in economics regarding a trade: Who should be assigned the goods on sale and at what prices? (Cramton et al., 2006a) There is hardly one auction design that fits all needs, so various auction designs try to answer these questions. Depending on the environment and the domain, a particular design may be more suitable than others. An environment is characterized by the number of market participants, i.e., the sellers and buyers, the number and type of items (or goods) on sale, the preferences of all participants, the private information the parties have about preferences, etc.

In many domains, bidders might have quite complex valuation structures for bundles or packages of individual items. A logistics service provider might value a round-trip route higher than the sum of the two single trips, since he can avoid an unloaded drive, or a mobile operator might value a bundle of licenses covering all regions of a country higher than the sum of individual regional licenses. So bidders might want to express such valuations within an auction instead of bidding only on individual items.

Combinatorial auctions allow bidders to express their preferences for bundles in a detailed manner. Bidders can bid on packages or bundles of items rather than only on individual items, which allows them to exactly state preferences. In the recent past, various industries and application fields have adopted combinatorial auctions, e.g., for bus route assignment (Cantillon and Pesendorfer, 2006), truck load transportation (Caplice and Sheffi, 2006), industrial procurement (Bichler et al., 2006), assignment of airport departure and arrival slots (Ball et al., 2006), or the allocation of spectrum usage licenses (Cramton, 2009b). Enabling bidders to exactly state package valuations helps improve efficiency and revenue. Determining the valuations themselves can be a challenging task because bidders might have to perform complex calculations and develop business cases. Ideally, the market design should handle the combinatorial complexity of the market setup and bidders should focus on the valuation so that no strategies are required for bidders to arrive at a desirable outcome.

Depending on the purpose and the setting of the auction, different goals may apply: Fairness, transparency, and an efficient assignment might be more relevant in the sale of public goods while revenue or low procurement costs might be the focus of industrial applications. Since these goals are often contradictory, market designers have to weigh them when designing auction mechanisms.

Within a given environment, an auction design encompasses the rules (i) to determine the winners of the auction, i.e., who gets assigned which items (section 2.3), and (ii) to determine the payments required from the winning bidders (section 2.4).

The rest of this chapter formally defines the economic environment and describes goals for the auction design. It explains the determination of winners and several options for determining payments. Then it introduces sealed-bid and iterative combinatorial auction designs which have fostered the development of the Combinatorial Clock Auction, which was analyzed in the experimental study. Finally, performance measures used to assess final auction outcomes are defined.

The definitions and required concepts follow those used in the research field of combinatorial auctions, which can be found, e.g., in Cramton et al. (2006a).

2.1 Economic environment and notation

We assume an economic setting often encountered in spectrum sales. A set of buyers or bidders $\mathcal{I} = \{1, ..., n\}$ (e.g., the mobile operators) compete for a set of items $\mathcal{K} = \{1, ..., m\}$ (e.g., the licenses) sold by a single seller or auctioneer (e.g., the regulatory authority). Symbols $i, j \in \mathcal{I}$ denote specific bidders and $k, l \in \mathcal{K}$ specific items.

A ***package***, or ***bundle***, $S \subseteq \mathcal{K}$ is a subset of items which can also be empty. We assume each bidder i has an individual ***valuation*** $v_i(S)$ for all possible bundles S. Of course, in the case that the bidder is not interested in a bundle, the corresponding valuation can be *zero*. The valuation is a bidder's motivation to participate in the auction and to bid for the items or bundles. A bid of bidder i on a package S for a bid price $p_{bid,i}(S)$ is denoted with $b(S, p_{bid,i}(S))$.

If the auction assigns the bundle $S \subseteq \mathcal{K}$ to bidder i and requires him to ***pay a price*** of $p_{pay,i}(S) \in \mathcal{P}_{pay}$ then $\pi_i(S, \mathcal{P}_{pay})$ denotes his ***payoff***. We assume quasi-linear payoff functions for all bidders, i.e., $\pi_i(S, \mathcal{P}_{pay}) = v_i(S) - p_{pay,i}(S), \pi_i(\emptyset, \mathcal{P}_{pay}) = 0; \forall i$.

Thus, bidder i's valuation $v_i(S)$ represents the highest price $p_{pay,i}(S)$ the bidder is willing to pay for the bundle S in order to make a non-negative profit.

Let $\Pi = \sum_{i \in \mathcal{I}} p_{pay,i}(S_i)$ denote the ***auctioneer payoff*** where S_i is the bundle won by bidder i.

2.1.1 Complements and substitutes

As described in section 1.1, within spectrum sales there can be various valuation types: A mobile operator might assign a value to the combination of two licenses which is greater than the sum of the valuations of the individual licenses. In other cases, the combination might induce a lower valuation. The former effect characterizes a super-additive, the latter a sub-additive valuation function. Such effects can be found in many domains.

Formally, three valuation types can be distinguished in bidders' valuations of two disjoint bundles $S, T \subseteq \mathcal{K}$. The valuation function of bidder i is called locally

- ***additive***, if $v_i(S \cup T) = v_i(S) + v_i(T)$
- ***super-additive***, if $v_i(S \cup T) > v_i(S) + v_i(T)$
- ***sub-additive***, if $v_i(S \cup T) < v_i(S) + v_i(T)$.

If the relation holds for any two disjoint bundles $S, T \subseteq \mathcal{K}$, the bidder's valuation function is called additive, super-additive, or sub-additive respectively. Super-additive valuations describe ***complements***, i.e., items that create an additional value when combined (synergies). ***Substitutes***, on the other hand, create sub-additive valuations. Items are substitutes if the demand for one item does not change when the price of the other item is changed. A valuation function can comprehend all types of valuations for distinct bundle combinations.

2.1.2 Private, common, and affiliated values

Vickrey (1961) introduced the private values model, which assumes that each bidder can exactly determine the value of all possible bundles. ***Independent private valuations*** require that these valuations do not depend on other bidders' valuations and that all valuations are the private information of the bidders. Specifically, the valuations do not change when the bidder learns more about other bidders' valuations during the auction. This model serves as a benchmark model for the comparison of different auction designs, although this model implies that for larger settings, the bidders are required to know or determine the valuation of a large number of bundles. If externalities are excluded (the bidders are not interested in assignments to other bidders), each bidder can bid on $2^n - 1$ bundles with n bundles on sale. Practically, this entails a very large number of bundles for all but low numbers of items.

There are settings in which this assumption can be questioned because the exact value depends on future events or cannot be specified in detail for all possible bundles upfront. For example, drilling rights on an oil field may have the same value for all bidders, but the value depends on the actual amount of oil in the field, which is not known at the time of the auction. Wilson (1969) assumes that items have a specific value which is the same for all bidders, but that bidders do not know this value and have to rely on estimates of the true value and on signals of other bidders. Such values are called ***common valuations***. The bidder with the highest estimate of the true value is likely to win the auction. In cases where the average of all bidders' estimates equals the true value, the winner has estimated a too high value and might have to pay a price exceeding the true value. This phenomenon is called the ***winner's curse***, since winning is actually bad news about the winner's own value estimate. Wilson (1969) emphasizes the importance of conditioning the bidding strategy to the negative effect winning implies in common value settings.

Milgrom and Weber (1982) generalize the approaches of independent private values and common values in a model of ***affiliated valuations***, combining private information and signals from other bidders in a bidder's valuation. Here, bidders' estimates of the true value are affiliated random variables. If one bidder has a high value estimate, it is likely that the other bidders also have high estimates.

In spectrum sales in the field, bidders have to calculate the value of licenses by estimating future revenues of communication services offered to customers. The valuation of licenses also depends on the costs associated with rolling out the services, which might differ fundamentally between mobile operators. Thus, some authors argue that ***value uncertainty*** plays a role, and other constraints, such as strategic considerations or budget constraints, might apply (Bulow et al., 2009). Due to these complications, such calculations can become very intense and expensive for mobile operators. Ideally, the auction design guides bidders to the relevant bundles. Iterative combinatorial auctions can guide bidders and reduce value uncertainty through price feedbacks between rounds (section 2.6.2).

Due to the high importance of spectrum auctions for providers, there is a strong incentive to estimate valuations accurately prior to the auction. Valuations might differ significantly among providers due to different costs for building a network. Therefore, the valuations used in the experiments in section 5 stick to the common assumption of independent private valuations.

2.2 Auction design goals

Defining auction rules is a challenging task. The overarching goal is often high ***efficiency*** (section 2.7), i.e., to achieve an allocation of the items for sale that maximizes social welfare. That means that all items are assigned to the bidders that put them to the best use. Thus, a central concern in mechanism design is creating enough incentives for bidders to reveal their true valuations.

A bidder will only participate in an auction and tell the truth about his valuations of items and bundles if he can expect to be better off doing so than by not participating. Therefore, we claim that an auction should be individually rational.

Definition 2.1. *An auction is* ***individually rational*** *if bidders expect to gain higher payoff from participating in the auction than from avoiding it.*

The bidder will apply some type of strategy and hide his true preferences if he expects to be better off by doing so. But determining an efficient allocation requires the revelation of true valuations. Therefore, we claim that an auction should be incentive-compatible, i.e., that misreporting valuations for the items should never give an advantage to bidders.

Definition 2.2. *An auction is* ***incentive-compatible*** *if a bidder is better off when he truthfully reveals any private information the auction mechanism asks for.*

Ideally, bidders do not have any incentives to speculate, but can focus solely on reporting their true valuations. If there is no other strategy promising a better payoff independently of the other bidders' actions, then the bidder has a ***dominant strategy*** to report his true valuations (section 2.5).

An outcome should also prevent any coalition of bidders from renegotiating a better deal with the auctioneer after the auction has terminated. Such an outcome is said to be in the ***core*** (section 2.4.3).

Putting these aspects together, we can state that an auction design should satisfy the following properties or goals:

1. ***Efficiency***: Items are allocated in a way that maximizes the value generated.

2. ***Core property***: No coalition of bidders and the auctioneer can negotiate a mutually more beneficial deal among themselves.

3. ***Individual rationality***: Each bidder expects a non-negative payoff for participating.

4. ***Dominant strategy property***: The dominant strategy is for bidders to truthfully report their valuations.

Unfortunately, there is no auction design that satisfies all these goals. Market designers have to make trade-offs in the design of auction formats. For example, the Vickrey-Clarke-Groves auction (Vickrey (1961), section 2.6.1) collects all valuations from all bidders in one single round and efficiently assigns the items. It is the only direct mechanism that requires no payments from or to bidders and which gives bidders a dominant strategy of reporting true valuations (Green and Laffont, 1979). The Vickrey-Clarke-Groves (VCG) outcome satisfies properties one, three, and four, but fails to terminate in core outcomes in general settings. This leads to the problems of low or even zero revenue as well as incentives for bidders to collude or to use multiple fake identities to submit bids. Section 2.6.1.2 describes the weaknesses of the Vickrey-Clarke-Groves design. In large settings, the number of possible bundles can exceed the feasible number of bids. To guide bidders, iterative combinatorial auctions give price feedback to bidders in between rounds, helping them to focus on relevant bundles.

Prominent examples of iterative combinatorial auctions with attractive properties are the Ascending Proxy auction (Ausubel and Milgrom, 2006a) or the Clock-Proxy auction (section 3.2.6.1), which satisfy properties one, two, and three, but do not give bidders a dominant strategy to reveal their true valuations.

It appears that the goals of core outcomes (goal two) and dominant strategy property (goal four) cannot be achieved at the same time in general settings.

Section 2.6.3 discusses the *bidder submodularity* condition, which has to be satisfied for the Ascending Proxy auction to achieve VCG outcomes and, by this, to give bidders strong incentives to bid truthfully.

2.3 Determination of winners

The first question to be answered by a market mechanism is: Who will be assigned which items? In the context of an auction, an ***allocation*** $X = (S_i)_{i \in \mathcal{I}}$ describes an assignment of items or bundles to bidders as a result of the auction, based on the bids they have submitted within the auction (Cramton et al., 2006a).

Definition 2.3. *The set of feasible allocations $\mathcal{X}$ contains all allocations that assign items to bidders in such a way that each item is allocated to at most one single bidder, i.e., all bundles are disjoint. Thereby, items can also remain unsold, i.e., not assigned to a bidder.*

The allocation at the end of an auction is called ***final allocation***, while an allocation during the course of the auction (e.g., in between rounds of an iterative auction format) is called ***provisional allocation***.

Definition 2.4. *Among all allocations in $\mathcal{X}$, an allocation which maximizes social welfare is called the* ***efficient allocation*** *X^*. The efficient allocation does not have to be unique.*

The true valuations of all bidders for all bundles are hardly known by the auctioneer, since bidders may be hesitant to reveal their true preferences or it is impractical due to the sheer number of possible bundle valuations. Therefore, winners must be determined based on the elicited information available to the auctioneer. That is the set of submitted bids from the bidders. Thus, one essential issue in market design is to offer enough incentives to bidders to reveal their true valuations in order to identify an efficient allocation.

Determining the efficient allocation is comparably simple in a one-item setting. The efficient allocation assigns the item to the bidder with the highest bid for the item. If there are several bidders with the same highest bid, each of these bidders is assigned the item in one of the efficient allocations. In a combinatorial auction with multiple items, the determination of winners is more complex since the bundle bids from all bidders must be checked to find the best combination. Let $p_{bid,i}(S)$ denote the bid price of bidder i for bundle S. If bidder i did not submit a bid on S, $p_{bid,i}(S) = 0$. The determination of winners can be formulated as an integer linear program (ILP) which is called the ***winner determination problem*** (WDP):

$$\max \sum_{S \subseteq \mathcal{K}} \sum_{i \in \mathcal{I}} x_i(S) p_{bid,i}(S) \qquad (\textbf{\textit{WDP}})$$

s.t.

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

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

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

For each bidder i and each possible bundle S there is one binary variable $x_i(S) \in \{0; 1\}$ which equals 1 if bidder i finally wins the bundle S with the bid price $p_{bid,i}(S)$ and which is 0 if he has not. The objective function maximizes the aggregate bid prices of all bidders in $\mathcal{I}$ implied by the allocation. The first constraint of the ILP guarantees that each bidder can win at most one bundle. This implies a ***XOR bidding language***. Abandoning the first constraint would allow bidders to win multiple bundles (***OR bidding language***), but this would create a different kind of exposure problem for the bidders, who could win several bundles at the same time (Hoffman, 2011). The second constraint ensures that no item is allocated more than once and also allows for items that are not allocated and remain unsold. In case of multiple optimal solutions one is picked randomly.

A set of bidders $I \subseteq \mathcal{I}$ is called a ***coalition*** C_I. The set of all bidders $\mathcal{I}$ is called the ***grand coalition*** $C_{\mathcal{I}}$. Each bidder i receives a value of $v_i(S)$ if he is finally assigned the bundle S, that is if $x_i(S) = 1$. Assume that bidders can transfer individual value from the trade to one another without loss (concept of *transferable utility*). If bidders of the coalition C_I submit their true valuations, then the objective value of the WDP based on the efficient allocations represents the highest value that can be generated with this set of bidders. This corresponds to the coalitional value (or social welfare) of this set of bidders I:

Definition 2.5. *The* ***coalitional value*** *of a coalition C_I is defined as the maximum value created by the members of C_I working together:*

$$w(C_I) = \max_{X \in \mathcal{X}} \sum_{S \subseteq \mathcal{K}} \sum_{i \in I} x_i(S) v_i(S)$$

2.4 Determination of payments

Once the winners of an auction have been determined and the respective bundles have been allocated, the auction needs to determine the payments of winners, i.e., the ***pay prices*** $\mathcal{P}_{pay}$. In order to foster participation, bidders who have not been assigned a bundle are usually not required to make a payment.

2.4.1 First-price rule

The most direct way of determining pay prices is to use a ***first-price rule***. In this case, each winning bidder i pays the amount he has bid for the won bundle S: $p_{pay,i}(S) = p_{bid,i}(S)$. One prominent example of an auction format using the first-price rule is the Simultaneous Multi-Round Auction (section 3.1), which has been used in many spectrum auctions worldwide and which we used in our experimental study. One problem of the first-price rule is that a winning bidder pays considerably more than required when the second highest bid is far lower than his own bid. This gives bidders an incentive to shade their bids: In order to increase their payoff, bidders might bid less than their valuations. Thus, bidders speculate on the bid prices of other bidders and on the extent to which they can shade their own bids. This can result in inefficient allocations.

Consider the example in table 2.1: Three bidders 1, 2, and 3 compete for one item A. They have the valuations $v_1(A) = 20$, $v_2(A) = 30$, and $v_3(A) = 50$. The efficient allocation assigns A to bidder 3. In scenario a, all bidders bid truthfully and submit bids corresponding to their valuations. Bidder 3 wins the item and is required to pay his bid price of 50, giving him a payoff of 0. In scenario b, bidder 3 shades his bid and submits a bid of only 40. He still wins the item, but is required to pay 40, promising him a payoff of 10, which is higher than in scenario a. Therefore, he has an incentive to not reveal his true valuation and to speculate about how low he can bid and still win. Note that in this example any bid price by bidder 3 above 30 makes him the winner. But the lower his bid price, the higher his payoff.

In order to achieve an efficient allocation, the auctioneer is interested in eliciting the true valuations of all bidders. The example demonstrates that bidders have an incentive to speculate and shade their bids with the first-price rule. In the example, bidder 3 could bid less than 30 and lose the item to bidder 2 just because of speculation. So the true valuations may not be revealed, which can result in inefficient allocations. Vickrey (1961) suggested using a second-

Bidder	Valuation	Bid price	
		Scenario a	Scenario b
1	20	20	20
2	30	30	30
3	50	50	40
	Winner	Bidder 3	Bidder 3
	Payoff	0	10

Table 2.1: Example for first-price rule

price rule with the intention of giving bidders a strong incentive to bid their true valuations and to refrain from speculation. When the true valuations are elicited, items can be allocated efficiently.

2.4.2 Second-price rule

Vickrey (1961) proposed requiring a payment from winning bidders which is only as high as necessary. To illustrate the concept of second prices, we look at the one-item example from above (table 2.1).

To reduce bidder 1's incentive to speculate and shade his bid, the second-price rule requires him to pay only $30 + \epsilon$, i.e., the second-highest bid price. So his bid can be higher, but the payment remains at $30+\epsilon$. In order to maximize his chances of winning, each bidder has the incentive to bid as high as possible. The limit is set by his true valuation. If a bidder bids higher than that, he risks a negative payoff. Bidder 3 in the example wins with any bid price above 30. But with prices above 50 he would have a negative payoff. So he has an incentive to bid exactly 50 to maximize his chances of winning.

His strategy of truthfully reporting his valuation is independent of the bids of the other bidders. If the other bidders bluff and bid above their valuation, they might win the item, but would then be required to pay at least the bid price of bidder 3 or the second-highest bid price. This price would entail a negative payoff for bidder 3. If the other bidders bid less than their valuation, bidder 3 would still win with an even higher payoff. So independent of the other players' strategies, each bidder expects the highest payoff by revealing his true valuation. Such a strategy is called a ***dominant strategy*** (see also section 2.5).

The Vickrey-Clarke-Groves auction generalizes this idea for settings with many items. We introduce this auction design in section 2.6.1.

2.4.3 The core

An auction outcome (assignment of goods to bidders and payments) can be regarded as unstable if it leaves opportunities for a coalition of bidders to make a counteroffer to the auctioneer, putting themselves and the auctioneer at least as well off. Determining payments with the second-price rule can cause several problems, such as very low or even zero revenues. In fact, in section 2.6.1.2 we show that pay prices can be even lower than what losing bidders have bid. This can have the very unattractive consequence that these bidders can offer the auctioneer to pay more than the actual winners of the auction. A desirable auction outcome prevents such offers and ensures satisfactory payoffs for all market participants so they do not want to change the final allocation at given prices. Such payoffs are in the ***core*** of a coalitional game (Day and Raghavan, 2007).

The core concept ensures auction outcomes that are stable. The winning bidders collectively pay enough so that no subset of bidders $I \subseteq \mathcal{I}$ can separate from the set of all bidders $\mathcal{I}$ and collude to offer the auctioneer a more attractive deal. The grand coalition's valuation $w(C_{\mathcal{I}})$ corresponds to that of an efficient allocation which was given above in definition 2.5:

$$w(C_I) = \max_{X \in \mathcal{X}} \sum_{S \subseteq \mathcal{K}} \sum_{i \in I} x_i(S) v_i(S)$$

The payments of bidders transfer a share of their value to the auctioneer. Let $\pi = (\pi_i)_{i\in\mathcal{I}}$ denote the payoff vector of all bidders in the set $\mathcal{I}$ and $\Pi_{C_\mathcal{I}} = \sum_{i\in\mathcal{I}} p_{pay,i}(S_i)$ denote the auctioneer's payoff. We can also express the coalitional value as the sum of bidders' payoffs and auctioneer payoff:

$$w(C_\mathcal{I}) = \Pi_{C_\mathcal{I}} + \sum_{i\in\mathcal{I}} \pi_i$$

The formal definition of the core can now be formulated.

Definition 2.6. *The set of* ***core payoffs*** *is defined as*

$$Core\,(\mathcal{I}, w) :=$$

$$\left\{ (\Pi_{C_\mathcal{I}}, \pi) : \Pi_{C_\mathcal{I}} + \sum_{i\in\mathcal{I}} \pi_i = w(C_\mathcal{I}) \text{ and } \forall\, I \subset \mathcal{I} : w(C_I) \leq \Pi_{C_\mathcal{I}} + \sum_{i\in I} \pi_i \right\}$$

In order to get a stable outcome we claim that the coalitional value of any subset of bidders I must not exceed that of $\mathcal{I}$:

$$w(C_I) \leq w(C_\mathcal{I})$$

The auctioneer only accepts counteroffers that are at least as advantageous for him as the original outcome. Thus, we claim that the counteroffer from the coalition C_I gives an auctioneer payoff Π_{C_I} that is not higher than $\Pi_{C_\mathcal{I}}$:

$$\Pi_{C_I} \leq \Pi_{C_\mathcal{I}}$$

By combining the claims we can state the relationship of coalitional values that imply stable auction outcomes and define the core:

$$w(C_I) = \Pi_{C_I} + \sum_{i\in I} \pi_i \leq \Pi_{C_\mathcal{I}} + \sum_{i\in I} \pi_i = w(C_\mathcal{I}) - \sum_{i\in\mathcal{I}} \pi_i + \sum_{i\in I} \pi_i$$

In general, the core payoffs are not unique but all core payoffs protect against counteroffers. An auction design needs to specify which payoff vector of the set is to be chosen at the end of the auction. The Combinatorial Clock Auction uses a payment rule that chooses the payments which are closest to VCG payments from the set of all core payments (section 3.2.4). By selecting bidder-optimal core payments that maximize the bidders' payoffs, this rule guarantees that there is no coalition of losing bidders that can propose an attractive counteroffer. In addition, it minimizes the incentives for speculation by choosing payments as close as possible to the VCG payments as only with those bidders have a dominant strategy of reporting true valuations. In section 2.6.3 we discuss the conflict of the VCG outcomes with the dominant strategy property and core outcomes.

2.5 Relevant game-theoretical solution concepts

Before we look at the rules of combinatorial auction formats, we briefly introduce relevant solution concepts in game theory. We point the reader to two books that give a comprehensive overview of game theory: Vazirani et al. (2007) and Shoham and Leyton-Brown (2009).

Game theory is a counterpart of mechanism design which looks at the same setting from a different angle. While mechanism design is about the definition of the rules of the game, game theory analyzes outcomes of games given the rule set. The participants, or players, in the game have a set of strategies or actions to choose from. If there are many players, we expect each player's payoff to depend not only on his own strategy but also on the other players' strategies. In an auction, e.g., the price a bidder pays may depend not only on his own bids but also on what other bidders have bid in the auction. A **strategy profile** describes the interaction of all players' individual strategies.

It results in a payoff for each player. The payoff vector of all players is also called **outcome**. In game theory, we generally assume that

- all available strategies or actions of all players are known by all players,
- all players' payoffs as a result of all possible strategy profiles are also known by all players,
- all players know and fully understand the rules of the game, and
- all players behave in an individually rational way, i.e., each player selfishly maximizes his own payoff.

Although all of these assumptions can be challenged in realistic settings (Rothkopf, 2007a), game theory can contribute to the understanding of mechanisms and provide ideas for their design.

A strategy profile is called an ***equilibrium*** if no player could improve his payoff by unilaterally choosing another strategy. For auction designs, we require that final outcomes should be Pareto-optimal and in the core to prevent any coalitions from challenging the auction outcome. Only in such cases is the outcome stable. In the following, we describe relevant strategy profiles.

Suppose a player has a strategy that is the best available strategy for him regardless of the choices of the other players. Such a strategy is called a ***dominant strategy***. A game, which gives dominant strategies of telling the truth to players, is called ***strategy-proof***. It makes tactical analyses and speculation unnecessary for players and is therefore interesting for auction design. Green and Laffont (1979) have shown that the VCG mechanism (section 2.6.1) is the only mechanism that gives bidders a dominant strategy to report true valuations, which results in efficient outcomes, and which does not require any payments from or to losing bidders.

A less strong concept is the ***Nash equilibrium***. A Nash equilibrium is a set of strategies in which each player's strategy is a best response strategy to the other players' strategies. That means no player can achieve a better payoff by unilaterally deviating from this equilibrium. It assumes that each player will still try to maximize his own payoff based on the other players' choices. Since several Nash equilibria can exist in one game and none of the players knows which one is chosen by the other players, the concept of the Nash equilibrium is less strong than that of dominant strategies. It is still relevant for auction design because if one Nash equilibrium entails reporting true valuations for all bidders, then even if it is not a dominant strategy, bidders have a strong incentive to do so.

If information is incomplete and players do not know about the types (i.e., strategy options and associated payoffs) of other players and have to rely on probability distributions about the possible types of other players, the game is called a ***Bayesian game***. In such a game, players must consider all possible types of other players in the choice of their own strategy. If players do not want to change their strategy even when they learn about the strategies of other players after the game, the equilibrium is called an ***ex post equilibrium***.

2.6 Combinatorial auctions

In this section, we discuss combinatorial auction formats. We start with a direct mechanism called Vickrey-Clarke-Groves auction (VCG). It is a sealed-bid auction in which bidders submit all bids in one single round, and we highlight its unique dominant strategy property, which has high theoretical importance. We also address its weaknesses, which have prevented it from being implemented in many applications in the field.

Many of the VCG problems can be addressed with iterative combinatorial auctions (Porter et al., 2003). In such round-based auctions, bids are collected within each round, analyzed, and then bidders receive feedback (prices, provisional allocations, bid information, etc.). This helps guide bidders to the most relevant bundles aiming at efficient allocations and the reduction of value uncertainty. We briefly describe the Simultaneous Clock and the Ascending Proxy auction, which guarantees core outcomes. We conclude by discussing under which circumstances the design goals of core outcomes and dominant strategy property can both be satisfied.

2.6.1 Vickrey-Clarke-Groves auction

In order to avoid the unfavorable incentives for speculation inherent in the first-price rule, Vickrey (1961) suggested using pay prices that differ from the bid prices. His design is a sealed-bid second-price auction. There is only one round, in which bidders submit their bids. For a one-item setting, the winner is the highest bidder and is required to pay the price offered by the second-highest bidder. These prices are called ***second prices*** or ***Vickrey prices***. In the example from section 2.4.1, bidder 3 wins item A with the highest bid of 50 but has to pay only the price offered by the second-highest bidder, in this case bidder 2's bid of 30. The underlying idea is that bidder 3's bid only determines whether he wins, his own payment is not affected by the amount he has bid. Therefore, he has no incentive to shade his bid anymore.

Clarke (1971) and Groves (1973) have amended Vickrey's design for the multi-item case, now known as the ***Vickrey-Clarke-Groves auction*** (***VCG auction***).

A VCG auction also consists of only one round of sealed bids. Each bidder can bid on any bundle and can finally win at most one bundle (XOR bidding language). At the end of the auction, the auctioneer runs a winner determination, examining all bids to identify the revenue-maximizing combination. As in the single-item setting, winning bidders are not required to pay full bid prices but only second prices reflecting the opportunity costs of the items they have won. That means that each winning bidder receives a discount on his bid price which reflects the increase in auction revenue due to his participation.

To determine the pay price $p_{pay,i}(S)$ of winning bidder i, the auctioneer computes the coalitional value $w(C_{\mathcal{I}\setminus i})$ with all bids of i excluded, i.e., with the bids of the coalition $C_{\mathcal{I}\setminus i}$ only. The difference of the original coalitional value $w(C_{\mathcal{I}})$ and $w(C_{\mathcal{I}\setminus i})$ represents the discount bidder i gets on his bid price $p_{bid,i}(S)$.

Definition 2.7. *The pay prices of winning bidders in a VCG auction are defined as:*

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

The VCG auction has some desirable properties but also some deficiencies which are discussed in the following sections.

2.6.1.1 Strengths of the VCG auction

The VCG auction has some impressive properties: Truthfully reporting all valuations is a dominant strategy and if all bidders bid truthfully, the auction terminates in an efficient allocation (Ausubel and Milgrom, 2006b). An example illustrates this: Table 2.2 gives the valuations of the three bidders 1, 2, and 3 for the items A and B as well as for the bundle AB.

Bidder	A	B	AB
1			500*
2	200		
3		200	

Table 2.2: Example for VCG payments

If bidders truthfully submit their valuations, the VCG auction finds the efficient allocation (indicated by the star) and assigns the bundle of both items to bidder 1. For bidder 1's payment, we calculate the discount he gets on his bid price. His total payment is $p_{pay,1}(AB) = p_{bid,1}(AB) - (w(C_{\{1,2,3\}}) - w(C_{\{2,3\}}))$.

To calculate $w(C_{\{2,3\}})$ we remove the bids of bidder 1. Now, the efficient allocation assigns item A to bidder 2 and item B to bidder 3 with a total bid price of 400. Bidder 1's payment is therefore $p_{bid,1}(AB) = 500 - (500 - 400) = 400$.

In contrast to the setting with the first-price rule, bidders have no incentive to speculate about other bidders' bids anymore or to shade their bids. Their own bid price determines whether they win or not, but their own payment is not affected. So they have an incentive to bid as high as possible, which is their own true valuation.

From an economic point of view, speculation is a waste of effort, since it is not required to find the efficient allocation. In VCG, bidders can fearlessly report their true valuations for all available packages regardless of what competitors do. We called this a ***dominant strategy*** in section 2.5. One of the design goals for market mechanisms mentioned at the beginning of this chapter was to offer a dominant strategy to bidders. The second-price rule of the VCG auction makes truthfully reporting the valuations a dominant strategy, which facilitates an efficient allocation. In a VCG auction, bidders do not have to speculate, but rather can concentrate on their own valuations and simply bid them truthfully.

Green and Laffont (1979) and Holmstrom (1979) showed that VCG is the unique direct reporting mechanism with dominant strategies for bidders that results in efficient outcomes and does not require any payments from (or to) losing bidders. In other words, if we use payments that differ from the VCG payments, we lose the dominant strategy property for bidders to truthfully report their valuations.

Unfortunately, the VCG auction loses the dominant strategy property if valuations are not private and independent (Ausubel and Milgrom, 2006b). In spectrum auctions, binding budget constraints can apply which could challenge the assumption of independent private valuations.

2.6.1.2 Weaknesses of the VCG auction

The efficient outcomes and the dominant strategy property of the VCG mechanism come with detrimental weaknesses (Ausubel and Milgrom (2006b); Rothkopf (2007b)) which challenge the practical relevance of the design:

1. ***Low auctioneer revenue.*** Even if there is enough competition in the market and valuations are quite high, revenue can be very low or even zero. Consider the following example[1] in which valuations comprise complementarities: Two items A and B are auctioned to three bidders 1, 2, and 3. Bidder 1 is interested in the package of both items A and B and is willing to pay 2, bidders 2 and 3 are interested in single items for a maximum price of 2 each. Table 2.3 shows all valuations.

Bidder	A	B	AB
1			2
2	2^*	2	2
3	2	2^*	2

Table 2.3: Example for VCG weaknesses

VCG allocates the items efficiently, i.e., item A to bidder 2 and item B to bidder 3, since their combined bids maximize revenue. Bidder 2's payment is calculated as $p_{pay,2}(A) = p_{bid,2}(A) - (w(C_{\{1,2,3\}}) - w(C_{\{1,3\}})) = 2 - (4 - 2) = 0$. The pay price of bidder 3 is calculated the same way: $p_{pay,3}(B) = 0$. The total revenue of the VCG auction is therefore 0, even though there was competition and bidders had positive valuations greater than 0.

The problem with such an outcome is that it is unstable in the sense that bidder 1 might try to renegotiate privately with the auctioneer and

[1] The example was taken from Ausubel and Milgrom (2006b).

offer to pay up to 2 for the bundle. That would increase his own payoff, but the auctioneer would also be better off: Instead of selling both items to bidders 2 and 3 for zero revenue, he would get positive revenue from bidder 1. Therefore, stable outcomes require pay prices to be high enough to prevent such counteroffers. Such a stable outcome is said to be in the *core*. The concept of the core is discussed in sections 2.4.3 and 2.6.3.

Revenue is very often a concern in field applications, e.g., in industrial procurements, but also for governments, who can hardly justify comparably low revenues from public goods sales to taxpayers when other losing bidders were willing to pay more. The rather low revenue is one of the key reasons why the VCG has only rarely been applied in practice.

2. ***Non-monotonicity of the revenue in the number of bidders and in the bid amounts.*** The revenue of a VCG auction can actually decrease when additional bidders participate in the auction. Suppose bidder 3 did not participate in the example above. Then bidder 1 would win the bundle AB and $w(C_{\mathcal{I}})$ would be 2 which would increase the total revenue from 0 to 2. From a market design perspective, this is counterintuitive since adding bidders increases competition.

3. ***Collusion.*** The non-monotonicity opens up various loopholes for bidders. Losing bidders can collude to improve their outcomes. Consider the example from above with the valuations of bidders 2 and 3 changed to 0.5 for a single license. This makes them losers since bidder 1 offers 2 for the bundle of both items. If the two losing bidders collude and bid 2 for each single item, they will successfully outbid bidder 1 and win the items for a price of 0. The example shows that the VCG mechanism is prone to such deviations on the part of losing bidders.

4. ***Shill bidding.*** Shill bidding is closely related to the above vulnerability of the VCG design. Suppose in the example from above that only bidders

1 and 2 participate with bidder 1 being the winner of the package. By making up a third bidder and submitting bids under this fake identity, bidder 2 can turn himself into a winner with a pay price of zero. Therefore, if the auctioneer cannot verify and check bidder identities, bidders can try to manipulate the auction by using multiple identities.

5. ***Privacy concerns.*** Bidders might be reluctant to report all true valuations due to privacy concerns. Very often, the valuations reveal internal cost structures or expectations about future market developments. Such information is confidential, and bidders might not want to reveal it. These concerns can be addressed through encryption and independent auction platforms that ensure privacy.

6. ***Unfeasibility of reporting values for all possible bundles.*** In many field applications, the determination of valuations is costly, e.g., in the domain of spectrum sales, license valuations are based on comprehensive business cases which involve scenario analyses. It might just not be feasible for mobile operators to determine the valuation of all possible license combinations. In larger settings, the number of combinations can be too high to submit valuations for all bundles even if they are available. One way to address this disadvantage is to use an iterative design (section 2.6.2) which gives price feedback to bidders. This can help them to focus on the relevant bundles.

The decisive weaknesses one through four of the VCG mechanism arise only if bidder valuations include complementarities (Ausubel and Milgrom, 2006b; Rothkopf, 2007b). Since complementarities are present in many domains, the VCG design has hardly been applied in the field. Nevertheless, due to its dominant strategy property, it continues to serve as a reference point in auction theory.

The problems bidders have in reporting all possible valuations in one shot can seriously undermine efficiency. If all bidders concentrate on the most valuable bundles or the largest bundles, the auctioneer might not be able to assign smaller bundles, which would be necessary for an efficient assignment. This is what we found for the Combinatorial Clock Auction in our experiments. It is an inherent problem of sealed-bid auctions that bidders might not be able to report valuations for all available packages. This is because bidders do not get any price feedback to focus their attention (Parkes, 2006). In the next section, we introduce iterative combinatorial auctions that avoid many of the VCG problems by providing price feedback to bidders. This guides them to the relevant bundles and lets them revise their valuations as prices are discovered.

2.6.2 Iterative combinatorial auctions

Iterative combinatorial auctions are conducted in rounds, addressing the problem of preference elicitation often encountered in the field (Parkes, 2006). In contrast to sealed-bid auctions, the design space is a lot larger in iterative auction designs. Parkes (2006) discusses a number of options, such as timing issues (continuous versus discrete round-based designs), degree of information feedback (information provided to bidders after each round, e.g., ask prices, provisional allocation), termination conditions (fixed time versus rolling closure depending on a condition), bidding language (e.g., OR or XOR), use of automated bidding agents (proxies that enforce a predetermined bidding strategy), etc. Independent of the detailed rules, most iterative combinatorial auctions follow the same structure on a high level: At the beginning of each round, the auctioneer provides ask prices and the provisional allocation. Bidders can then submit new bids during the round, which are used by the auctioneer to determine the ask prices and the provisional allocation for the subsequent round. At the end of each round, the termination conditions are checked.

Many different designs have been suggested with different properties. Parkes (2006) provides a good overview. We describe the Simultaneous Clock, or Combinatorial Clock, (Porter et al., 2003) in section 2.6.2.1 and the Ascending Proxy auction (Ausubel et al., 2006) in section 2.6.2.2. The auction formats for our lab experiments are introduced in chapter 3.

The price feedback plays a pivotal role in the design of iterative combinatorial auctions since bidders submit new bids based on this feedback. Such prices represent the lower limit for bids in the subsequent round and are called ask prices. Ideally, these prices guide the auction towards an efficient outcome and provide enough incentives for bidders to reveal their true valuations (Parkes, 2006).

Ask prices can have different formats: Bundles can have a price representing the sum of ask prices of contained items or an individual bundle price, and prices can be identical for all bidders or personalized (Xia et al., 2004):

Definition 2.8. *A set of **ask prices** is called*

- ***linear**, if* $\forall\, i, S : p_{ask,i}(S) = \sum_{k \in S} p_{ask,i}(k)$, *and*
- ***anonymous**, if* $\forall\, i, j, S : p_{ask,i}(S) = p_{ask,j}(S)$

Since bidders generally do not know when the auction will terminate (the termination of an iterative auction can depend on various conditions, e.g., the combined demand of all bidders, the submission of new bids, etc.), a common assumption is that they will myopically maximize their payoff by ***bidding straightforwardly***. This means they bid their demand set, i.e., the bundles that maximize their payoff at current prices.

Definition 2.9. *A bidder's **demand set** includes all bundles which maximize the bidder's payoff at current prices:*

$$D_i(\mathcal{P}_{ask}) := \left\{ S \subseteq \mathcal{K} : \pi_i(S, \mathcal{P}_{ask}) \geq \max_{T \subseteq \mathcal{K}} \pi_i(T, \mathcal{P}_{ask}) \text{ and } \pi_i(S, \mathcal{P}_{ask}) \geq 0 \right\}$$

A bidder bids straightforwardly if he bids the lowest acceptable price on all packages within $D_i(\mathcal{P}_{ask})$ in every round.

After the auction has terminated, the auctioneer determines the final allocation of the items (section 2.3) and the required payments $\mathcal{P}_{pay}$ from winning bidders depending on a payment rule (section 2.4). The auctioneer revenue is then the sum of the pay prices of the winning bidders.

An auction outcome is attractive when all participants, i.e., all bidders and the auctioneer, are satisfied. That requires that no bidder wants to change the allocation by increasing prices further through the submission of new bids. The concept of competitive equilibrium describes such outcomes:

Definition 2.10. *The allocation X^* is supported by prices $\mathcal{P}_{pay}$ in **competitive equilibrium (CE)** if:*

$$
\begin{aligned}
\pi_i(S_i^*, \mathcal{P}_{pay}) &= \max_{S \subseteq \mathcal{K}} [\pi_i(S, \mathcal{P}_{pay}), 0] \quad \forall\, i \in \mathcal{I} \\
\Pi(X^*, \mathcal{P}_{pay}) &= \max_{X \in \mathcal{X}} \Pi(X, \mathcal{P}_{pay})
\end{aligned}
$$

This is referred to as: Prices $\mathcal{P}_{pay}$ and allocation $X^* = (S_1^*, \ldots, S_n^*)$ are in competitive equilibrium .

Thus, no bidder can expect a higher payoff by winning another bundle based on his reported preferences. All the losing bids are below the final prices. The auctioneer also needs to be satisfied, which requires that he cannot get higher revenue from another allocation based on the submitted bids.

Bikhchandani and Ostroy (2002) have shown that the core (section 2.4.3) is equivalent to the set of CE prices. All CE outcomes are in the core and all core outcomes can be priced. Further, they have shown that for an efficient allocation non-linear, personalized CE prices can always be found. A trivial example would be to require each bidder to pay his bid price (Parkes, 2006). But linear or anonymous CE prices can only be determined if specific conditions are satisfied (e.g., a sufficient and almost necessary condition for the existence of linear CE prices is that all goods are substitutes (Gul and Stacchetti, 1999; Kelso and Crawford, 1982)). That means that an iterative combinatorial auction design requires non-linear, personalized prices to terminate in CE outcomes in general settings (Ausubel and Milgrom, 2006a).

The following example shows that there can be a set of CE prices that satisfy the condition above.

Suppose two bidders are competing for one item A. Their valuations are $v_1(A) = 10$ and $v_2(A) = 5$. Bidder 1 would win the item since he has the higher valuation. But any price between 5 and 10 would satisfy the CE requirement. Assume that the auction chooses 10 to be the price for bidder 1. Bidder 2 does not want to change anything, but in that case, bidder 1 would have an incentive to shade his bid and submit a price less than 10 but greater than 5 to remain the winner and, at the same time, reduce his payment.

In order to encourage bidders to report their valuations, an auction design needs to ensure that the lowest prices are selected from the set of all possible CE prices, i.e., the minimal CE prices. In the example, this would require a price close to 5 for bidder 1.

Definition 2.11. ***Minimal CE prices*** *minimize auctioneer revenue for an efficient allocation X^* across all CE prices.*

Unfortunately, in general settings auction designs choosing outcomes with minimal CE prices lose the dominant strategy property of reporting true valuations. A bidder's payment in the VCG mechanism is always less than or equal to his payment at any CE price (Bikhchandani and Ostroy 2002). For the design of iterative combinatorial auction designs, the question of which prices to choose from the set of CE prices remains. If the CE prices are significantly higher than the VCG payments, bidders might have an incentive to speculate and shade their bids. Section 2.4.2 has shown that only VCG payments provide a dominant strategy to report truthfully. But such outcomes can be outside the core, which causes many problems, and results in unstable outcomes. So, there is a dilemma for the designers of auction rules: The payment rule of an auction can support either a dominant strategy or CE outcomes. Section 2.6.3 looks at this discrepancy.

In the following, we describe the Simultaneous Clock, which uses linear prices, and the Ascending Proxy auction, which uses non-linear personalized prices and implements minimal CE outcomes by using proxy bidding agents.

2.6.2.1 Simultaneous Clock

Porter et al. (2003) proposed the Simultaneous Clock, or Combinatorial Clock, which uses linear anonymous ask prices.

It supports multi-unit settings as encountered in spectrum sales, where several identical blocks are sold within one frequency band. In section 3.2, we formally define the multi-unit setting when the two-phase design Combinatorial Clock Auction (CCA) is introduced. It should not be confused with the Simultaneous Clock which has a much simpler pricing rule than the CCA.

The Simultaneous Clock is a round-based auction format providing one clock price for each item on sale. In the multi-unit case, there is one clock price for each category. Prices start at zero or a reservation price. Within each round, bidders state their demand by submitting as many bundle bids as they want, assuming a XOR bidding language. Thereby, bidders can only accept prices and are not allowed to use jump bids. The Simultaneous Clock uses linear prices, i.e., bundle prices are simply the sum of the clock prices of included items. After each round, the auctioneer aggregates the demand of all bidders per item. In the multi-unit case, this is achieved by including the bid with the most units from each bidder for each item. Clock prices of items for which the aggregate demand exceeds supply are increased by one tick, i.e., the increment, and a new round is started. All bids from all rounds remain active throughout the entire auction. Bids at current ask prices are called ***standing bids*** and bidders with at least one standing bid are called ***standing bidders***. Standing bids can be bids from the current round or bids from previous rounds on items for which the price has not ticked. If in one round the aggregate demand exactly equals supply for all items, the auction terminates and assigns the items according to the standing bids. If demand is less than supply, the WDP is run with all bids from the auction to determine the allocation. Only if this allocation includes all standing bidders is the allocation declared final. Otherwise, the losing but standing bidders are given the chance to submit higher prices. This means that the clock prices of items corresponding to the non-standing but winning bids are ticked and the auction continues.

Bidding activity is controlled through an activity rule: Porter et al. (2003) suggested a quantity-based rule. As prices tick upwards, a bidder cannot increase the total quantity of demanded items.

A variant of the Simultaneous Clock uses the OR bidding language, which requires some adjustments to the demand aggregation. The auctioneer has to aggregate all the bids of a bidder on the specific item, instead of including only the bid with the highest demand.

The auction rules are quite transparent, the linear anonymous prices are easy for bidders to understand, and guide them sufficiently well to high levels of efficiency (Scheffel et al., 2011). But especially towards the end of the auction, bidders have an incentive to artificially reduce their demand to terminate the auction at lower prices. This has a negative impact on efficiency. In addition, the activity rule requires some speculation or strategy from bidders since switching from a highly valued smaller bundle to a larger bundle with a lower value is prohibited. Thus, bidders might not bid straightforwardly and instead want to maximize their options in later rounds by bidding on the largest bundle with positive payoff. Ausubel et al. (2006) address this problem in their proposal of the Clock-Proxy auction (section 3.2.6.1), which combines a clock and a proxy phase. They suggest an activity rule based on the revealed preference of each bidder, which encourages straightforward bidding.

2.6.2.2 Ascending Proxy auction

The Ascending Proxy auction was suggested by Ausubel and Milgrom (2006a) to preserve some of the advantages of the VCG auction and at the same time avoid some of the disadvantages. When bidder valuations do not include complementarities, the design terminates in the VCG outcome and preserves the dominant strategy property. When this condition is not satisfied, it ensures core outcomes, preventing most of the VCG weaknesses described in section 2.6.1.2.

The Ascending Proxy auction is a direct revelation mechanism that makes the use of bidding proxies mandatory: Each bidder is required to report his valuations to a proxy bidder, a bidding agent that submits bids on the bidder's behalf. In this way, the Ascending Proxy auction ensures straightforward bidding. The Ascending Proxy auction implements non-linear, personalized prices throughout the auction. With the proxies' straightforward bidding, the auction terminates with minimal CE prices (Parkes, 2001). When the bidder submodularity condition (section 2.6.3) is satisfied, the payments support the VCG payments.

The auction has the following structure: Initially, all ask prices are set to zero. In every round, each proxy submits the demand set, i.e., all bundles maximizing his payoff at current prices. If there are no new bids in one round, the auction terminates. Otherwise, the auctioneer solves the WDP based on all bids from all bidders from all rounds. If all bidders receive a bundle in the current allocation, the auction terminates with this allocation. If there is at least one *unhappy* bidder who does not win a bundle in round t, the ask prices for the next round $t+1$ are updated: The bundle prices of all bids from unhappy bidders are increased by the minimum bid increment: $p^{t+1}_{ask,i}(S) = p^{t}_{ask,i}(S) + MinInc$. Then, the new round is started.

When the prices reach a bidder's valuation, he stops bidding. Then the proxy agent submits an empty bid, i.e., a bid on the empty bundle with a price of zero. This bidder now has at least this empty bid, which wins in each round to serve the termination condition. If one of his bids fits well with other bidders' bids, he wins with this bundle bid.

If a bidder wins the empty bundle, then he does not win any items and is not required to make a payment.

The Ascending Proxy auction avoids the weaknesses of the VCG auction and ensures core outcomes, making it an attractive design. As described above, bidders are required to provide all valuations at the beginning, which does not relieve the preference elicitation problem. But the Ascending Proxy auction can also be implemented in a multi-stage version in which bidders start by providing initial preferences and then get the opportunity to adjust and update their preferences at several stages (Ausubel and Milgrom, 2006a). That allows bidders to focus on the relevant packages, which in turn reduces costs for determining valuations as well.

2.6.3 VCG outcomes versus core outcomes

In order to find an efficient allocation, it is necessary to reveal the bidders' true valuations. As pointed out above, the auction design should ideally provide for a dominant bidding strategy to report true valuations. But the only direct mechanism that ensures such dominant strategies is the VCG auction (Ausubel and Milgrom, 2006b).

In general settings with complementarities, the VCG payments come with a series of problems caused by the fact that the outcome does not necessarily lie in the core. Therefore, revenue can be unattractively low, so that losing bidders can form coalitions and make counteroffers. In addition, they can collude or engage in shill bidding to improve their position. Such auction outcomes are unstable and therefore unfavorable. Thus, the VCG mechanism has hardly been implemented in the field.

The Ascending Proxy auction leads to CE or core outcomes which prevent low revenues and the forming of coalitions. But this comes at the price of losing the dominant strategy property.

From a mechanism design perspective, it is interesting to check the relationship of the dominant strategy property and the core property.

If there are no complementarities, VCG outcomes are in the core (Ausubel and Milgrom, 2006b). With complementarities, all the problems described in section 2.6.1.2 can arise. Bikhchandani and Ostroy (2002) show that in the presence of complementarities, the BAS condition is necessary and sufficient for the VCG outcome to be in the core.

Definition 2.12. *The* ***bidders are substitutes*** *condition (**BAS**) is fulfilled if* $\forall I \subseteq \mathcal{I}$ *and* $\forall\, i \in I$*:*

$$w(C_{\mathcal{I}}) - w(C_{\mathcal{I}\setminus I}) \geq \sum_{i \in I} \big(w(C_{\mathcal{I}}) - w(C_{\mathcal{I}\setminus i})\big)$$

The BAS definition requires the marginal value of a subset of bidders to the grand coalition to be at least as high as the sum of the marginal contributions of all bidders of the subset.

If the VCG outcome is achieved by the Ascending Proxy auction or an iterative auction format that converges to minimal CE prices, straightforward bidding is an ex post equilibrium strategy and both properties are fulfilled. But Ausubel and Milgrom (2006b) show that the BAS condition is not sufficient for the Ascending Proxy auction to terminate with VCG payments. Thus, there is no dominant strategy to report truthfully. They show further that an even stronger condition, the bidder submodularity condition (definition 2.13), is required to ensure that the set of minimal CE outcomes is equal to the set of VCG outcomes, so that VCG payments are achieved and truthfully reporting becomes a Nash equilibrium strategy profile (Ausubel and Milgrom, 2006b). In addition, minimal CE outcomes avoid the VCG weaknesses when VCG payments are not supported with minimal CE prices. This can happen when only BAS, but not BSM is satisfied.

Definition 2.13. *The* ***bidder submodularity*** *condition (**BSM**) is fulfilled if* $\forall I \subset I' \subseteq \mathcal{I}$ *and* $\forall i \in \mathcal{I}$*:*

$$w(C_{I \cup i}) - w(C_I) \geq w(C_{I' \cup i}) - w(C_{I'})$$

The BSM condition requires that the BAS condition is satisfied for every subset of the grand coalition. It is fulfilled if all bidders' individual contributions are higher when they join a smaller coalition I than a larger I'. If BSM is fulfilled, BAS is also satisfied.

If goods are substitutes, the BSM condition is satisfied. Unfortunately, it is almost necessary that valuations be substitutes (Parkes, 2001). So this condition is often not fulfilled in practical settings and, even worse, auctioneers typically do not know whether it is satisfied or not.

2.7 Performance measures

Several desirable properties of auction mechanisms have been suggested, such as high allocative efficiency, high revenue, low transaction costs for bidders, high auction speed, fairness (equal treatment of bidders), transparency, and scalability if used in a series of auctions (e.g., Pekec and Rothkopf (2003)).

From an economic point of view, the key criteria for the assessment of an auction outcome is efficiency, i.e., the distribution of items to bidders and the economic value generated. In the case of sales of public goods, efficiency maximizes the creation of income and wealth in an economy, which eventually leads to more tax revenue in the future. Besides this most common measure to assess auction performance, the literature uses other criteria to compare auction outcomes, such as robustness, price monotonicity, speed of convergence, etc. In the experimental study in section 5, we use *allocative efficiency* and *auctioneer revenue* as the main performance measures to compare the results. Here, we provide formal definitions of both.

Assume an auction terminates with allocation $X = (S_i)_{i \in \mathcal{I}}$ and price set $\mathcal{P}_{pay}$. Let $\pi_i(S_i, \mathcal{P}_{pay})$ denote the payoff for the bidder i for the bundle S_i he has won and $\pi_{all}(X, \mathcal{P}_{pay}) := \sum_{i \in \mathcal{I}} \pi_i(S_i, \mathcal{P}_{pay})$ denote the ***total payoff of all bidders*** for an allocation at the prices $\mathcal{P}_{pay}$. Further, let $\Pi(X, \mathcal{P}_{pay}) = \sum_{i \in \mathcal{I}} p_{pay,i}(S_i)$ denote the ***auctioneer revenue*** as defined in section 2.1.

Definition 2.14. ***Allocative efficiency*** *(or simply* **efficiency***) is defined as the ratio of the total valuation of the final allocation X to the total valuation of an efficient allocation X^* (Kwasnica et al., 2005):*

$$E(X) := \frac{\Pi(X, \mathcal{P}_{pay}) + \pi_{all}(X, \mathcal{P}_{pay})}{\Pi(X^*, \mathcal{P}_{pay}) + \pi_{all}(X^*, \mathcal{P}_{pay})} \in [0, 1]$$

The comparison of efficiency levels in different value models and settings is intricate. Depending on the setting, efficiency levels of allocations assigning all items can be rather high or rather low. Therefore, we introduce ***relative efficiency***, $E(X)^*$, which takes this phenomenon into account by introducing a baseline. For this, let P^{rand} denote the mean of social welfare over all possible feasible allocations, assuming all items are sold.

Definition 2.15. *The relative efficiency is defined as the ratio*

$$E(X)^* := \frac{\Pi(X, \mathcal{P}_{pay}) + \pi_{all}(X, \mathcal{P}_{pay}) - P^{rand}}{\Pi(X^*, \mathcal{P}_{pay}) + \pi_{all}(X^*, \mathcal{P}_{pay}) - P^{rand}}$$

This calculation follows the one used in Kagel et al. (2010). For this definition, the relative efficiency of an efficient allocation is still 100%, while the mean efficiency of random allocations of all items is the baseline 0. In contrast to the first efficiency measure, allocations below this mean have negative relative efficiency.

Another measure looks at the distribution of the overall economic value among the auctioneer and bidders, i.e., the revenue distribution.

Definition 2.16. *The* ***auctioneer revenue share*** *or* ***auctioneer payoff share*** *is defined as the ratio of the auctioneer's revenue to the total sum of valuations of an efficient allocation X^*:*

$$R(X) := \frac{\Pi(X, \mathcal{P}_{pay})}{\Pi(X^*, \mathcal{P}_{pay}) + \pi_{all}(X^*, \mathcal{P}_{pay})} \in [0, E(X)] \subset [0, 1]$$

We use the term revenue interchangeably with auctioneer revenue share depending on the context.

Definition 2.17. *The* ***bidder revenue*** *or* ***bidder payoff*** *is defined as the ratio of the bidders' revenues to the total sum of valuations of an efficient allocation X^*:*

$$U(X) := \frac{\pi_{all}(X, \mathcal{P}_{pay})}{\Pi(X^*, \mathcal{P}_{pay}) + \pi_{all}(X^*, \mathcal{P}_{pay})} \in [0, E(X)] \subset [0, 1]$$

The sum of $R(X)$ and $U(X)$ equals $E(X)$ of an auction outcome. The delta of $E(X)$ and 100% corresponds to the loss in the auction, i.e., the value that cannot be distributed among the auctioneer and the bidders.

Chapter 3

Auction formats

You have to learn the rules of the game.
And then you have to play better than anyone else.
Albert Einstein

This section introduces the two auction formats which are used in the experimental study in section 5: Simultaneous Multi-Round Auction (SMRA) and Combinatorial Clock Auction (CCA). Both auction designs have been applied in the field to sell spectrum in multi-unit settings: The SMRA was introduced by the FCC in 1994 to sell spectrum licenses in the US and since then has been used in numerous spectrum sales worldwide with only minor rule adjustments. The Combinatorial Clock Auction (CCA) was recently proposed as an alternative to SMRA (Ausubel et al., 2006; Cramton, 2009b), promising strong incentives for truthful bidding and highly efficient results. Different versions of the CCA have been suggested which are addressed at the end of this section. For the experiments, we used the rules which were applied in the Austrian 2.6 GHz auction in 2010.

3.1 Simultaneous Multi-Round Auction

The ***Simultaneous Multi-Round Auction (SMRA)*** is a generalization of the English auction for more than one item. All items and units have individual prices. In fact, SMRA treats multiple units of the same item as individual items. For brevity, we use the term *item* for all units of all items and state explicitly the difference to *units* where required.

All items are auctioned simultaneously in rounds, and bidders can bid on any items but are not allowed to submit bundle bids. New bids must increase the current item price by at least a predefined ***minimum increment***. The possibility of further increasing the bid price depends on the specific implementation of SMRA. Some countries allow arbitrary increases, others limit further increases to predefined increments to prevent signaling by using the trailing digits of the bid price to transmit information (Niemeier, 2002; Weber, 1997). These predefined increments are referred to as ***click-box***. The maximum number of bids a bidder can place in one round is governed by an ***activity rule***. Each item requires a certain number of bid rights depending on the properties of the item (e.g., this can be the number of MHz of a spectrum block in the domain of spectrum sales). The number of a bidder's bid rights cannot increase during the course of the auction. In order to keep a bid right, a bidder is required to use it. Bid rights that are not exerted in a round are lost for the remaining rounds of the auction. Depending on the implementation, several activity levels are possible. A ***stacked activity rule*** defines different phases of required activity from the bidders. E.g., in a 50% activity phase a bidder is required to use only half of his bid rights in order to keep the current number of bid rights. After each round, the ***provisional winner*** of each item is determined by the highest bid price. Ties are broken randomly.

Depending on the chosen ***information policy***, the bids from the previous rounds are revealed at the beginning of each round, including the bidder identity, item, bid price, and whether it was declared to be provisionally winning. Information provided to bidders can be used by them for tactics and speculation. Some versions of SMRA include ***withdrawals*** which allow a bidder to withdraw a provisionally winning bid with the condition that he must pay the bid price if no other bidder bids on the withdrawn item. Other versions give each bidder a number of ***waivers***. When a bidder uses a waiver, he does not lose any bid rights even if he uses fewer than required. Of course, these instruments can be included in a bidding tactic by bidders. In section 5.4.2 we analyze bidding tactics used by subjects in the lab experiments.

The auction terminates for all items at the same time if in a round no bidder places a single bid, i.e., raises the price for any bid. The bidder holding the highest bid for each item is assigned the item. SMRA uses the first-price rule as described in section 2.4.1, so each winning bidder is required to pay the bid price for the won item. If items are substitutes and bidders are price takers, the auction terminates in competitive equilibrium (Milgrom, 2000).

3.1.1 Exposure risk

Cramton (2009a) discusses a number of problems in spectrum auctions with the SMRA, most notably the exposure problem and limited substitution (section 3.1.2). While SMRA is compelling due to its simple auction rules, there is one major problem for bidders with complementary valuations. This is called the ***exposure risk***. It describes a bidder's problem of winning only a fraction of the intended bundle and paying a price exceeding the valuation of the smaller subset of items. An example illustrates the point. Assume a bidder with valuations of 10 for each of the items A and B, and a valuation of 30 for the bundle of A and B. If this bidder wants to bid the synergistic valuation of the bundle, he might bid more than 10 for each item. If prices rise further, he might not be able to win both items and end up winning only one item at a price higher than his valuation of 10.

3.1.2 Limited substitution

The problem of limited substitution is caused by the activity rules employed by regulators. The monotonicity requirement does not allow bidders to submit bids on more items than in the previous round (with the exception of activity levels lower than 100%). Sometimes, a less preferred alternative can have more items, which can lead to inefficiencies in cases where a bidder is outbid on the preferred allocation. These activity rules lead to ***eligibility management*** and the parking of eligibility points in less desirable items (Salant, 1997), which have been observed in the context of FCC spectrum auctions (Porter and Smith, 2006). Sometimes a bidder might also prefer to bid on a package with a higher number of eligibility points rather than the preferred package of items in order to have the option of returning to it later.

In contrast to clock auctions, SMRA also allows various forms of signaling and tacit collusion. Jump bidding is usually seen as a strategy to signal strength and preferences and post threats. Sometimes, even the standing bidder increases his winning bid for the same purpose. However, there are more reasons for jump bids, for instance avoiding ties (Boergers and Dustmann, 2003).

3.1.3 Equilibrium strategies

If bidders have substitute preferences and bid straightforwardly, the SMRA terminates in a Walrasian equilibrium (Milgrom, 2000), i.e., an equilibrium with linear prices (Gul and Stacchetti, 1999; Kelso and Crawford, 1982). Straightforward bidding means that a bidder bids on the bundle of items which maximizes his payoff at the current ask prices (section 2.6.2). However, Milgrom (2000) has shown that with more than three bidders and at least one non-substitutes valuation, no Walrasian equilibrium exists. Bidder valuations in spectrum auctions typically include complementarities. Brusco and Lopomo (2002) demonstrate the possibility of collusive demand reduction equilibria in the SMRA. In an environment with substitutes and complements, SMRA results in an exposure problem (section 3.1.1). A number of lab experiments document 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). Therefore, the exposure problem has become of central concern. Goeree and Lien (2010a) provided a Bayes-Nash equilibrium analysis of SMRA, considering complementary valuations and the exposure problem. They show that due to the exposure problem, the SMRA may result in non-core outcomes, where small bidders obtain items at very low prices and seller revenue can decrease with the number of bidders just as in the VCG auction (Ausubel and Milgrom, 2006b). Regulators have tried to mitigate this problem via additional rules, such as the possibility to withdraw bids, provided that the bidders make corresponding new bids on equivalent spectrum. However, as mentioned above such rules can also provide incentives for gaming behavior.

3.2 Combinatorial Clock Auction

There have been similar suggestions for this auction format by Cramton (2009b) or Ausubel et al. (2006) who call this design *Package Clock* or *Clock-Proxy auction*. Work on these mechanism rules was nourished by the attempt to address the major limitations of SMRA and to avoid the drawbacks of the VCG auction. SMRA is quite simple in its rules and effectively guides bidders in discovering the necessary valuations. At the same time, it makes bidding very complicated because in settings with complementarities, bidders have to handle the exposure problem. Further, the first-price rule gives incentives for demand reduction, and the transparent information feedback opens up possibilities for collusion and signaling tactics, etc. Altogether, there is ample space for tactics in SMRA. In an attempt to reduce the incentives for complex bidding tactics and to foster price discovery (which is especially relevant

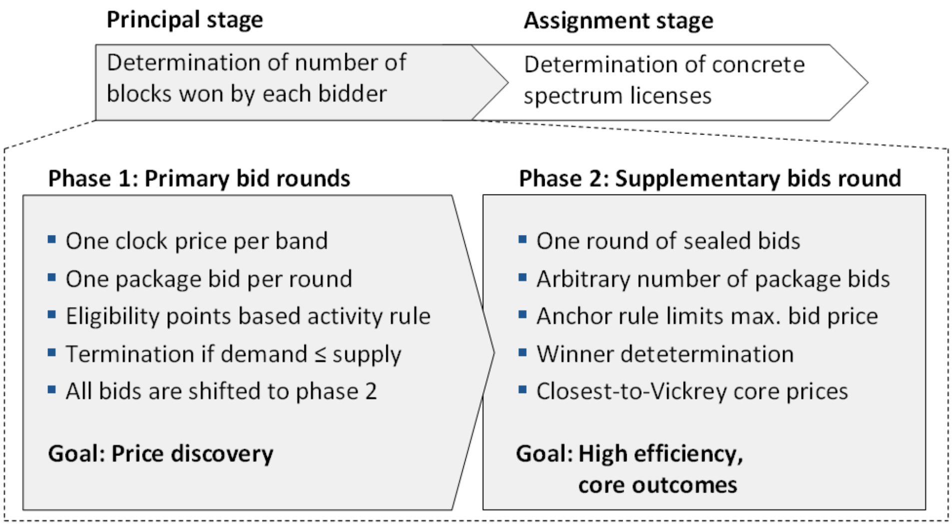

Figure 3.1: CCA as a two-stage auction design

in domains with expensive value determination such as the sale of spectrum licenses), the idea of the CCA is to use a clock phase followed by a phase of supplementary bids to enhance efficiency.

In our experiments, we used the rules of implementation as applied in the 2.6 GHz auction in Austria and refer to it as the Combinatorial Clock Auction (CCA). We address differences to the Clock-Proxy auction and the Package Clock in section 3.2.6.

3.2.1 CCA as a two-stage design

The ***Combinatorial Clock Auction*** (CCA) makes explicit use of the multi-unit setting often encountered in spectrum sales. CCA is a two-stage combinatorial auction design with a ***principal stage*** to determine the number of units each bidder wins in each band, and an ***assignment stage*** to determine the specific blocks of each band (figure 3.1).

We focus on the principal stage from now on and leave the assignment stage aside since in the field the principal stage is most important and receives all the attention. We use the terminology of the spectrum domain for which the CCA has been suggested and refer to *blocks* and *bands* instead of *units* and *items*.

The principle stage has two phases: Bids for packages of blocks are made through a number of sequential rounds (the ***primary bid rounds*** or clock phase) followed by a final sealed-bid round (the ***supplementary bids round***). In the primary bid rounds the auctioneer announces prices from a combinatorial clock with one clock price for each spectrum band (i.e., category of items) $k \in \mathcal{K}$. The bidders state their demand at the current price levels, i.e., the number of blocks within each band. Prices of items (i.e., spectrum bands in the context of spectrum auctions) with excess demand are increased by a fixed increment and a new round is started until there is no longer any excess demand. Since there are no provisional winners, bidders have to resubmit their bids in every round if they want to remain active. Jump bidding is not possible. In the primary bid rounds, bidders can submit a bid on only one package per round. This rule is different to the proposal by Ausubel et al. (2006) (section 3.2.6.1).

An activity rule based on eligibility points is applied. This means a bidder cannot bid on combinations requiring higher eligibility than in the previous round. The primary bid rounds allow for price discovery, while the payment rule is intended to induce truthful bidding. In the supplementary bids round, bidders can submit multiple bids on arbitrary bundles, whereby the bid price is limited by the ***anchor activity rule*** (3.2.2). The winner determination after the supplementary bids round (section 3.2.3) involves consideration of all bids, which have been submitted in the primary bid rounds and the supplementary bids round and selects the revenue-maximizing allocation. The bids by a single bidder are mutually exclusive, i.e., the CCA uses an XOR bidding language.

The CCA uses a ***core-selecting payment rule*** to guarantee stable auction outcomes. Section 2.4.2 shows that VCG outcomes are efficient and give bidders the dominant bidding strategy of reporting true valuations. In order to minimize incentives for bid shading, the CCA payment rule selects ***closest-to-Vickrey core prices***, i.e., the distance of these core prices to the VCG prices is minimized by minimizing the Euclidean distance. Day and Milgrom (2007) and Day and Raghavan (2007) discuss an algorithm to determine such bidder-Pareto-optimal core payments, which guarantees a unique outcome. We implemented an iterative approach to calculate such prices, as suggested by Maldoom (2007) (section 3.2.4.2).

While the VCG payment rule leads to a dominant strategy equilibrium, a core-selecting payment rule does not, and a bidder might be able to reduce his payments by bidding less, even if the incentives are lower than in a pay-what-you-bid sealed-bid combinatorial auction. 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 show that there is no Bayesian incentive-compatible core-selecting auction when the VCG outcome is not in the core. The core-selecting payment rule used in the CCA also shares another unattractive feature with the VCG payment rule introduced by Day and Milgrom (2007), namely revenue non-monotonicity (Lamy, 2009). This means, auctioneer revenue can decrease with additional bids in the auction.

3.2.2 Anchor activity rule

Successful price discovery depends on the incentives for bidders to reveal their preferences truthfully. Prices after the primary bid rounds are meant to reduce value uncertainty in the market. Bidders can then pay attention to the most promising bundles and put effort into determining these valuations. An activity rule needs to be employed to prevent bidders from holding back their true valuations until late in the auction (bid sniping) and to encourage them to report the payoff-maximizing bid in each round of the auction. Bidders should not be able to shade their bids and then provide huge jump bids in the supplementary bids round.

An ***eligibility points activity rule*** is used to enforce activity in the primary bid rounds. The number of a bidder's eligibility points is non-increasing between rounds, and it limits the number of items the bidder can bid on in subsequent rounds.

In the supplementary bids round, the ***anchor activity rule*** applies as follows:

- There is no limit on the supplementary bid that can be made for the package bid in the final primary bid round.
- The supplementary bid for any other package S is subject to a cap determined in the following way:
  1. First, we determine the last primary bid round in which the bidder was eligible to bid for package S. Call this round the ***anchor round*** n. This will either be the final round or some round in which the bidder dropped his eligibility to bid and gave up the opportunity to bid for packages the size of S in later primary bid rounds.
  2. Suppose bidder i bid for package T in the anchor round n. Call this package the ***anchor combination*** T. Let $p^{max}_{bid,i}(T)$ denote the highest bid of bidder i for package T which is the supplementary bid for this package, if he has made one, or otherwise the highest primary rounds bid. The supplementary bid for package S cannot exceed the highest bid $p^{max}_{bid,i}(T)$ plus the price difference between packages S and T that applied in round n (i.e., the differing items are priced at the ask prices in round n): $p^{supp}_{bid,i}(S) \leq p^{max}_{bid,i}(T) + p^{n}_{ask}(S) - p^{n}_{ask}(T)$

Note that after bidding on package T in the final primary bid round, a bidder can still submit a bid on a larger bundle S in the supplementary bids round.

However, the bid is limited by the price difference between packages S and T of round n. Since he had the opportunity to choose between S and T back in round n, and opted for T, the bidder revealed the relative value of S and T. In the supplementary phase, the bidder cannot reverse this reported preference.

This is also true for packages S' that are smaller than the package T of the final primary bid round. The maximal bid price for S' is limited by the same idea: Since the bidder chose the larger package T instead of the smaller package S', he revealed the premium that he is willing to pay for the larger package T relative to S'. The anchor activity rule precludes him from increasing his bid for S' relative to T in the supplementary bids round.

Cramton (2009b) describes this as the simplified revealed preference activity rule in his definition of the Package Clock (section 3.2.6.2). If a bidder is able to follow a straightforward bidding strategy, this activity rule does not restrict him in revealing his true valuations. But if the payoff-maximizing bundle requires more than available eligibility points, he cannot bid straightforwardly. Thus, Cramton (2009b) or Marsden et al. (2010) argue that the eligibility point activity rule may encourage bidders to bid on the largest bundle with positive payoff to maximize eiligibility points in later rounds instead of bidding straightforwardly.

3.2.3 Winner determination

The result of the principal stage is the determination of winners and the respective number of blocks each winner receives within each band. The CCA makes use of the multi-unit character of spectrum auctions. Within one band of spectrum, all blocks can be considered identical. Thus, bidders can state their demand by simply announcing the number of blocks they are willing to buy within each band. We amend the definition of the economic setting of section 2.1 by introducing quantities of each item. For each band (or item)

$k \in \mathcal{K} = \{1, ..., m\}$ let Q_k denote the number of identical blocks (or units) available of item k. The vector $Q = (Q_1, ..., Q_m) \in Z_+^m$ describes the available number of blocks in each band. As defined in section 2.1, the bidders $\mathcal{I} = \{1, ..., n\}$ compete for the spectrum blocks on sale. In the CCA a package bid in round t contains the bid price $p_{bid,i}^t(a)$ and the bundle $a = (a_1, ..., a_m)$ specifying the number of lots within each band. Denote the set of all possible bundles as $\mathcal{A} = \{(0, ..., 0), ..., (Q_1, ..., Q_m)\}$. The bid price of bundles the bidder has not bid on throughout the primary bid rounds and the supplementary bids round are set to zero. If a bidder has bid multiple times on the same package a, the revenue-maximizing combination only includes the highest bid on a package. Therefore, we can exclude all lower bids and define $p_{bid,i}(a)$ as the highest bid on a of all rounds: $p_{bid,i}(a) := \max_t\{0, p_{bid,i}^t(a)\}$. The winner determination can now be stated for the multi-unit case:

$$\max \sum_{a \in \mathcal{A}} \sum_{i \in \mathcal{I}} x_i(a) p_{bid,i}(a) \qquad (\textbf{\textit{Multi-unit WDP}}) \qquad (1)$$

s.t.

$$\sum_{a \in \mathcal{A}} x_i(a) \leq 1 \qquad \forall\, i \in \mathcal{I}$$

$$\sum_{a \in \mathcal{A}} \sum_{i \in \mathcal{I}} x_i(a) a \leq Q$$

$$x_i(a) \in \{0, 1\} \qquad \forall\, i \in \mathcal{I}, a \in \mathcal{A}$$

As in the WDP, the solution to the Multi-unit WDP is the revenue-maximizing allocation of blocks to bidders. It does not have to be unique. If there is a set of optimal combinations, one is determined randomly to be the final allocation of the CCA. The first constraint implements the XOR bidding language, i.e., each bidder can win at most one package bid. The second constraint ensures that the allocation does not assign more blocks to bidders than there is supply. It also allows for blocks to remain unassigned.

3.2.4 Closest-to-Vickrey core payments

The payment rule plays a decisive part in creating incentives for truthful bidding. First-prices as in SMRA or clock auctions create incentives for demand reduction, especially for big bidders who recognize the negative impact of their demand on price levels (Ausubel and Milgrom, 2002). The consequences are complex bidding tactics. With VCG payments, on the other hand, there is a dominant strategy to reveal the true valuations because each winner pays only the opportunity costs of his winnings (section 2.4.2). Section 2.6.1.2 discussed several serious deficiencies of the VCG auction which can occur if the VCG outcomes is outside the core. One major problem is that the payments of winners can be so low that a coalition of losers has actually bid more than what winners are required to pay. Such a coalition could try to negotiate with the auctioneer after the auction has terminated.

The solution is to raise payments of winners to ensure that they are in the core (section 2.4.3). If the VCG payoffs are already within the core, then they can be used as final payoffs to determine the final prices. If they are not in the core, then there is at least one coalition of bidders which could make a more attractive counteroffer to the auctioneer. In that case, the prices need to be increased to prevent such coalitions and to guarantee a core outcome. In order to accomodate the combined interest of bidders (as opposed to the auctioneer), the bidder-optimal payments (i.e., the lowest possible combined payments) are chosen from the core. We call such prices ***minimal core prices***, and the implied bidder-Pareto-optimal payoffs ***maximal core payoffs***.

Since those are not necessarily unique, Day and Milgrom (2007) suggested using the closest-to-Vickrey core prices. In order to give bidders the least possible incentive to deviate from reporting true valuations, the required payments are split so that the Euclidean distance to the VCG payments is minimized. So prices are as high as necessary to prevent any coalitions of losing bidders from offering a more attractive deal to the auctioneer and they are as low as possible

Bidder	A	B	AB
1	28*		
2		20*	
3			32
4	14		
5		12	

Table 3.1: Example of core payments (Day and Cramton, 2008)

to foster truthful bidding.

An example illustrates the point (Day and Cramton, 2008). Assume two items A and B and five bidders 1 to 5 with valuations as given in table 3.1. The winning allocation is marked with a star. Figure 3.2 shows each bid represented with a separate line (B1 through B5) constraining the payments of the winning bidders 1 and 2. The VCG payments would be 14 for bidder 1 and 12 for bidder 2 in this example which are given by the losing bids of bidders 4 and 5. Clearly, bidder 3's bid price of 32 for the package AB is higher than the combined VCG payments 14+12=26 of the winning bidders. Thus, the VCG outcome is outside the core. To prevent counteroffers from bidder 3 the combined core payments need to be at least 32. The bidder-optimal core payments are given by this minimum of 32 (the bold line in figure 3.2). The CCA chooses the payments which are closest to the VCG payments leading to payments of 17 and 15 for bidders 1 and 2 respectively.

Day and Raghavan (2007) proposed a constraint-generating method to determine these bidder-optimal core prices. It is based on the following idea. The algorithm starts by determining the set of winners $\mathcal{W}$ by solving the original WDP and to determine VCG payoffs for the bidders. The goal is to raise payments of winners to ensure a core outcome. In the core the combined payments exceed the counteroffers of all possible coalitions. So each such coalition defines a constraint on the core payments. The number of possible coalitions that must be considered grows exponentially with the number of bidders. The

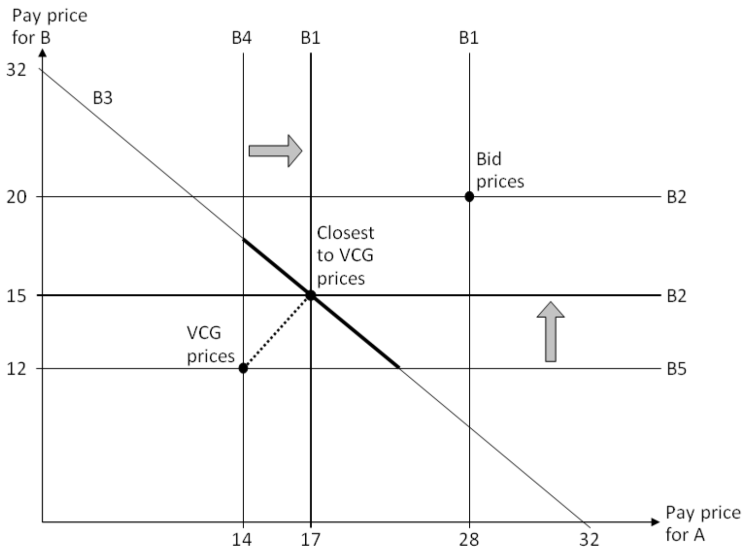

Figure 3.2: Example for closest-to-VCG prices

method proposed by Day and Raghavan (2007) uses another optimization to find the core constraint which is violated the most by the current solution. This constraint is added to the original optimization to increase pay prices and by this prevent the coalition of bidders from making a counteroffer. This is repeated until there is no coalition left that could suggest a better deal to the auctioneer. Cramton (2009b) argues that this approach is highly efficient because in practical applications there are usually only a handful of violated constraints which let the procedure terminate after a few iterations.

Besides creating incentives to truthfully report valuations, bidder-optimal core pricing has some attractive properties: When the VCG outcome is in the core, the closest-to-Vickrey core price rule finds the VCG prices. So bidders have an incentive to bid truthfully. Whenever the VCG outcome is not in the core, the closest-to-Vickrey core prices ensure that payments are high enough to prevent the typical VCG problems of low revenue (Day and Milgrom, 2007).

For the lab experiments, we amended the MarketDesigner platform and implemented an iterative approach proposed by Maldoom (2007) to compute the closest-to-Vickrey core prices. The rest of this section provides an overview of this approach.

3.2.4.1 Inputs for the iterative approach

Maldoom (2007) suggests an approach that first determines the total revenue winners are required to pay and then minimizes the distance from VCG prices. This section gives some notation and definitions required for the description of the approach which is based on payoffs instead of prices directly.

Since valuations are not known and only bid prices $p_{bid,i}(a)$ can be observed, let $\pi_{bid,i}$ denote a bidder i's payoff relative to his bid price, i.e., $\pi_{bid,i} := p_{bid,i}(a) - p_{pay,i}(a)$. Further, let $\pi_{bid} = (\pi_{bid,i})_{i \in \mathcal{I}}$ denote the vector of relative payoffs of all bidders in $\mathcal{I}$.

We first determine the VCG payoffs $\pi^{VCG}_{bid,i}$ based on the revealed information: The solution of the multi-unit WDP gives the coalitional value $w(C_{\mathcal{I}})$ of the set of all bidders $\mathcal{I}$. The calculation of the VCG payment for each winning bidder i requires computing the coalitional valuation $w(C_{\mathcal{I}\setminus i})$ for the set of bidders with the winning bidder i taken out. This means solving the WDP for each winner based on the set of bids with those of bidder i removed. As described in definition 2.7, each winning bidder i is given a discount on his bid price $p_{bid,i}(a)$ for the bundle a, determined by the delta in coalitional values:

$$p^{VCG}_{pay,i}(a) = p_{bid,i}(a) - (w(C_{\mathcal{I}}) - w(C_{\mathcal{I}\setminus i})) \tag{2}$$

The corresponding payoff is therefore:

$$\pi^{VCG}_{bid,i} = p_{bid,i}(a) - p^{VCG}_{pay,i}(a) = w(C_{\mathcal{I}}) - w(C_{\mathcal{I}\setminus i}) \tag{3}$$

Core outcomes guarantee that the total of the winners' payments is enough to prevent any coalition C_I of bidders from offering a more attractive solution to the auctioneer. These payments constrain the combined payoff of winners. Each possible coalition of a subset of bidders I defines a cap $\alpha(C_I)$, which has to be satisfied by a payoff vector in the core. With this, it is possible to restate the definition of the core (Maldoom, 2007):

$$\begin{aligned} Core\,(\mathcal{I}, w) \quad &= \quad \{(\Pi_{C_{\mathcal{I}}}, \pi_{bid}) : \pi_{bid,i} \geq 0, \forall I \subseteq \mathcal{I} : \sum_{i \in I} \pi_{bid,i} \leq \alpha(C_I)\} \\ with \quad & \quad\ \alpha(C_I) = w(C_{\mathcal{I}}) - w(C_{\mathcal{I} \setminus I}) \end{aligned} \tag{4}$$

As pointed out, the number of possible coalitions, and therefore of constraints, grows exponentially with the number of bidders. So even for settings of modest size, there can be a large number of constraints, and enumerating all of them might not be feasible. But checking a given payoff vector for its core membership is comparably easy. Winning bids of the original WDP must still be optimal if all bids of bidder i are reduced by an amount $\pi_{bid,i}$ reflecting the new pay prices (Maldoom, 2007). This corresponds to implicit bid shading where each bidder reduces the bid prices by his target payoff. Thus, if winning bids are reduced to the core prices with a floor at zero and all other bids are reduced by the same amount to ensure the original preferences of the bidder, then the originally winning bids would still win. Maldoom (2007) uses a π-WDP reflecting this idea:

$$\max \sum_{a \in \mathcal{A}} \sum_{i \in \mathcal{I}} x_i(a) \max(p_{bid,i}(a) - \pi_{bid,i}, 0) \qquad (\pi\text{-}\boldsymbol{WDP}) \tag{5}$$

s.t.

$$\sum_{a \in \mathcal{A}} x_i(a) \leq 1 \qquad \forall\, i \in \mathcal{I}$$

$$\sum_{a \in \mathcal{A}} \sum_{i \in \mathcal{I}} x_i(a) a \leq Q$$

$$x_i(a) \in \{0, 1\} \qquad \forall\, i \in \mathcal{I}, a \in \mathcal{A}$$

This corresponds to the original WDP, where the bid prices of bidder i are adjusted with $\pi_{bid,i}$.

A test on the core membership of a payoff can easily be performed now. A payoff vector $\pi_{bid} \in R_+^I$ lies in the core if and only if the solution of the WDP is also a solution to the π-WDP (Maldoom, 2007). In that case payoffs are low enough and payments high enough to prevent any counteroffers from losing bidders.

3.2.4.2 Iterative approach

With the definitions from above, Maldoom (2007) describes an algorithm to determine the closest-to-Vickrey core payments $p_{pay,i}^{ctV}$. We used it for the implementation of the CCA in our lab experiments. The following description follows that of Maldoom (2007) and has only been amended in some comments and transferred to the notation used in this thesis.

1. Initialize the set of constraints to be $R = \{\mathcal{W}\}$ with the set of all winners of the original WDP, i.e., a single constraint on the sum of all winners' payoffs. Together with the non-negativity constraints, this ensures that the set of feasible $\pi_{bid,i}$ is bounded.

2. Solve the linear program

$$\max \sum_{i \in \mathcal{W}} \pi_{bid,i} \tag{6}$$

$$\text{s.t.}$$

$$\sum_{i \in C_I} \pi_{bid,i} \leq \alpha(C_I) \qquad \forall\, I \in R$$

$$\pi_{bid,i} \geq 0 \qquad \forall\, i \in \mathcal{I}$$

   If there is not a unique solution, pick one randomly.

3. Compute the corresponding π-WDP and check whether the solution of the original WDP is still optimal. If so, the winners' combined payments are sufficiently high. In this case go to step 7.

4. When the set of winners of the π-WDP is not the same as the original set of winners, there is a coalition of bidders I that can offer a deal to the auctioneer which puts themselves and the auctioneer in a better position. Therefore, we need to add the coalition C_I to the set of constraints, i.e., we add a new subset I to R, consisting of those original winners who are no longer winners in the π-WDP.

5. Compute the corresponding $\alpha(C_I)$ for the subset I added to R in step 4 representing the new core constraint implied by the new subset of bidders.

6. Return to step 2 to compute the new (lower) optimal payoff vector.

7. Let $T = \sum_{i \in \mathcal{I}} \pi_{bid,i}$ be the total payoff of the current intermediate solution. This is the maximal combined core payoff of all winners.

8. Determine the payoffs closest to the VCG payoffs $\pi^{bid}_{VCG,i}$ by solving the quadratic program

$$\min \sum_{i \in \mathcal{W}} (\pi_{bid,i} - \pi^{VCG}_{bid,i})^2 \tag{7}$$

$$\text{s.t.}$$

$$\sum_{i \in C_I} \pi_{bid,i} \leq \alpha(C_I) \qquad \forall\, I \in R$$

$$\pi_{bid,i} \geq 0 \qquad \forall\, i \in \mathcal{I}$$

$$\sum_{i \in \mathcal{W}} \pi_{bid,i} = T \tag{8}$$

9. Compute the corresponding π-WDP and check whether the solution of the original WDP is still optimal. If so, terminate.

10. Where the set of winners of the π-WDP is not the same as the original set of winners, the outcome is outside the core. To prevent any coalitions of losing bidders that could offer more attractive deals add a new subset I to R consisting of those original winners who are no longer winners in the π-WDP.

11. Compute the corresponding $\alpha(C_I)$ for the subset I added to R in step 10.

12. Return to step 8 and iterate to exclude any coalitions of that kind.

When the algorithm terminates, the value of $\pi_{bid,i}$ represents the closest-to-Vickrey core payoffs of a winning bidder i, which directly implies the closest-to-Vickrey core price $p^{ctV}_{pay,i} = p_{bid,i} - \pi^{VCG}_{bid,i}$.

3.2.5 Bidding strategies

While SMRA provides a number of opportunities for auction tactics such as signaling or budget bluffing, the opportunities for the respective tactics are much reduced in the CCA. The possibility to submit bundle bids avoids the exposure problem and reduces problems of eligibility management. Since bidders are only allowed to accept prices in the primary bid rounds, signaling is prevented to a great extent. We showed above that bidders can bid their full valuation in the supplementary bids round if they were able to bid straightforwardly in the primary bid rounds. The core-selecting payment rule mitigates demand reduction (Ausubel et al., 2006), which may be a problem in a Simultaneous Clock with first-price payments (section 2.6.2.1). Since there is no dominant strategy equilibrium, the strategic thinking of bidders in the supplementary bids round boils down to the questions of (i) which bundles to bid on, and (ii) how much to bid for these bundles? We show that bidders have incentives to bid on a large set of different bundles and also to shade their bids to some extent.

3.2.5.1 Bundle selection

Bidders need to decide which bundles they want to bid on in the supplementary bids round: All possible bundles, a selected set, or none. A bidder with a high valuation for a package A might not want to submit bids on other packages in order to increase the likelihood of winning package A. With a VCG payment rule, such speculation does not make sense, and bidders have a dominant strategy of revealing the valuations for all their bundles. This means that even if the bidder wins a smaller bundle, his payoff cannot decrease compared to the larger bundle.

We want to illustrate this point with a simple example, which played a role in our experiments, where bidders actually did not bid on all possible bundles but only on a subset and the bundle selection was guided by the valuation of the bundle. Assume there are only two items A and B and two bidders 1 and 2. Both bidders have valuations for individual items but, for the sake of simplicity, none of the bidders has a value for the bundle. If $v_1(A)+v_2(B) < v_2(A)+v_1(B)$ holds true, the efficient solution is to sell A to bidder 2 and B to bidder 1. Assume further that A is the higher valued item for both bidders and bidder 1 speculates that he should not bid on B in order to win the higher valued item A. His VCG payoff is $v_1(A) + v_2(B) - v_2(A)$ if he reports a value $v_1(B) = 0$. In contrast, his VCG payoff is $v_2(A) + v_1(B) - v_2(A) = v_1(B)$ if he reports truthfully. It would only be profitable for bidder 1 to report a zero bid on B if $v_1(B) < v_1(A) + v_2(B) - v_2(A)$, but this is not possible, because $v_1(A) + v_2(B) < v_2(A) + v_1(B)$. Assuming a traditional VCG auction, this rationale extends to one of the value models we used in the lab experiments, where all bidders are interested in four items, but at least one of the four bidders cannot obtain these four items since there are only fourteen items on sale: If a bidder does not bid on a smaller bundle which has a positive value to him, he cannot increase his own VCG payoff, but risks not even winning the smaller bundle.

Strategies in core-selecting auctions are no longer dominant (Goeree and Lien, 2010b), but there is also no rationale for bidders to submit only a subset of the available bundles.

3.2.5.2 Bid shading

In CCA, there is no dominant strategy of truthfully reporting all valuations as is the case in VCG. Bidders can try to shade their bids because, in contrast to the VCG auction, a bidder's payment is influenced by his own bid price. That implies that a lower bid price for a package could actually lead to a lower payment by the bidder in the CCA. Given the fact that the CCA has been used in high-stakes spectrum auctions, such speculation is not unlikely. Recall the example of table 3.1 (Day and Cramton, 2008).

There, five bidders 1 to 5 had valuations for two items A and B. As described in section 3.2.4, the winning allocation was to give A to bidder 1 and B to bidder 2. The sum of the VCG payments was 26, which was outside the core due to the price of 32 bid by bidder 3 for AB. Thus, the CCA chose closest-to-Vickrey core payments of 17 and 15 for bidders 1 and 2 respectively.

Now, if bidder 1 shaded his bid to 15 in this example, the coalition of bidders 1 and 2 would still win with the same VCG payment, but the minimal core prices of both bidders would be different. Bidder 1 would only pay 15, while bidder 2 would have to pay 17 totaling 32, i.e., the bid price of bidder 3. So, by shading his bid, bidder 1 would manage to successfully reduce his payment.

If such auctions are modeled as a complete information game, bidder-optimal core prices yield the VCG outcome when it is in the core and result in higher auctioneer revenue when the VCG outcome is outside the core, avoiding the VCG drawback (Day and Milgrom, 2007). Here, bidders follow a truncation strategy, where all reported values of non-null goods assignments are reduced by a non-negative constant. If modeled as an incomplete-information game, Goeree and Lien (2010b) showed for a simple setting that risk-neutral bidders have an incentive to shade their bids and that the resulting outcome yields revenues that are lower than with VCG and inefficient outcomes that are on average further from the core than VCG outcomes.

In the CCA, bidders who remain active until the end of the primary bid rounds face the question of whether they are required to bid on the bundle of the last primary bid round if they want to ensure that they win it. In light of the anchor activity rule, which limits other bidders in the supplementary bids round, and the fact that increasing the bid can result in higher pay prices, the question is how much to raise the last bid in the supplementary bids round in order to win the bundle. For risk-averse bidders in particular, this might serve as a guideline in the lab as well.

Theorem 3.1. *If demand equals supply in the last primary bid round, a bidder's standing bid from the last primary bid round cannot become losing after the supplementary bids round if he increases it by a small amount ϵ.*

This implies that, with the CCA activity rule, a bid from the last primary bid round can only become losing if in the last primary bid round demand is strictly below supply. In the following corollary, $\mathcal{P}_{ask}^{prim}$ describes the ask prices in the last primary bid round, and $p_{bid,i}^{prim}(a)$ is the bid price of bidder i on a bundle a, submitted in the last primary bid round.

Corollary 3.1. *If in the last primary bid round supply exceeds demand by a package M, a supplementary bid $p_{bid,i}^{supp} > p_{bid,i}^{prim}(a) + M * \mathcal{P}_{ask}^{prim}$ cannot become losing.*

We provide proofs in Bichler et al. (2011). If the auctioneer does not reveal by how many items supply exceeds demand after the primary bid rounds, a standing bidder i after the primary bid rounds needs to take into account the possibility that all other bidders $\mathcal{I} \setminus i$ might reduce their demand to zero in the last round. Since M is the complement of his own bid, this leads to a very high safe supplementary bid. However, the actual amount required might be much lower.

3.2.6 Relation to the Clock-Proxy auction and the Package Clock

At the beginning of this chapter, we pointed out that the above introduced CCA rules are close to those of similar proposals, namely the Clock-Proxy auction (Ausubel et al., 2006) and the Package Clock (Cramton, 2009b). In an attempt to reduce the incentives for complex bidding tactics and to foster price discovery, Ausubel et al. (2006) suggested the Clock-Proxy auction. It takes a simple Simultaneous Clock and runs a proxy phase after the clock phase has terminated. The Clock-Proxy design was the main basis for the Package Clock and the CCA as used in our experiments.

The following sections briefly describe the rules of the Clock-Proxy auction and the Package Clock and highlight the differences to the CCA as used in our experiments.

3.2.6.1 Clock-Proxy auction

Ausubel et al. (2006) suggested the Clock-Proxy auction to capture the attractive properties of two formats: It starts with a Simultaneous Clock and closes with an Ascending Proxy auction.

In the ***clock phase***, there is one clock with an individual price for each item category (spectrum band). In each round, bidders state their demand as package bids by reporting the intended quantities they are willing to buy at current prices. In contrast to the CCA, bidders in the Clock-Proxy auction can submit multiple bids per round. At the end of each round the auctioneer increases the clock price of items for which demand exceeds supply by a fixed increment and announces a new round. Information feedback for bidders is reduced to the new clock prices and the excess demand in order to reduce options for signaling and speculation. The clock phase terminates when there is no excess demand on any item.

The intention of the clock phase is to rule out the exposure problem by allowing for package bids and to allow for price discovery through the iterative approach. In many settings of spectrum sales, the number of possible packages is very high, and determining bundle valuations can be rather expensive. Some guidance is then necessary for bidders to help them identify the most promising bundles. The clock phase provides for this with a simple structure and linear anonymous prices, i.e., item-based prices which are the same for all bidders. Price discovery is threatened when bidders do not report their true demands. Therefore, an activity rule needs to be specified accordingly. Ausubel et al. (2006) suggested using an activity rule that ensures consistency in the bids submitted by each bidder, i.e., the revealed preferences. We explain this rule in detail at the end of this section. With the clock phase alone, many bidders cannot submit bids on all bundles that they want, since only one price path is covered. If the required bids cannot be submitted, efficiency can also be negatively impacted.

Thus, after the clock phase comes a ***proxy phase***, with the intention of terminating the auction with a core outcome. Bidders report their bundle valuations to proxies. This can be seen as a last-and-final opportunity to submit bids, because in the proxy phase the proxy agent bids on each bidder's behalf. So, it is strategically equivalent to a sealed-bid auction (Day and Raghavan, 2007). The use of a proxy ensures a straightforward bidding strategy, i.e., in each round the proxy submits the bundles that maximize the bidder's payoff based on the reported valuations. At the end of each round, the auctioneer determines the provisionally winning bids by running a WDP including all bids from the bidders from the clock and the proxy phases. In contrast to the clock phase, the auctioneer determines bidder-specific bundle prices in the proxy phase. Although this limits price discovery, it is necessary to provide the required incentives to arrive at an efficient allocation. For the next round, prices are increased with a predetermined increment. The auction ends when there is no new bid submitted within one round.

Due to the straightforward bidding of the proxies, the auction ends with a bidder-Pareto-optimal core outcome (Day and Milgrom, 2007), which is an efficient allocation with competitive payoffs for the bidders and competitive revenue for the seller (Ausubel et al., 2006). There are no incentives for demand reduction. Also, the Clock-Proxy auction is comparably fast because the proxy phase is performed automatically by the proxies only. The interface for the proxy can be customized to fit the requirements of the respective domain (Hoffman, 2011). This can enhance the expressiveness of the valuations, which finally supports efficiency (Ausubel et al., 2006).

Crucial for the Clock-Proxy auction's support of price discovery is an appropriately designed activity rule. Only if bidders have the incentive to report true preferences in the early clock rounds is price discovery supported. Therefore, the proxy bids need to be constrained by the bidder's clock bids in some way. Ausubel et al. (2006) suggested a ***revealed preference activity rule*** which ensures consistent bids throughout both phases of the auction. Consider a bidder i who has valuations $v_i(S^s)$ for bundle S^s and $v_i(S^t)$ for bundle $S^t, S^s \neq S^t$. Bidder i accepts a price of $p^s_{ask}(S^s)$ for the package S^s in round s and a price of $p^t_{ask}(S^t)$ for the package S^t in round $t > s$. By doing so, he reveals the following preferences:

- in round s he prefers bundle S^s to bundle S^t, i.e., $v_i(S^s) - p^s_{ask}(S^s) \geq v_i(S^t) - p^s_{ask}(S^t)$, and
- in round t he prefers bundle S^t to bundle S^s, i.e., $v_i(S^t) - p^t_{ask}(S^t) \geq v_i(S^s) - p^t_{ask}(S^s)$.

Together, these conditions yield the revealed preference rule, which implies that in later rounds bidder i can switch from S^s to S^t only when the bundle price of S^s has increased more than that of S^t. Formally, this is: $p^t_{ask}(S^s) - p^s_{ask}(S^s) \geq p^t_{ask}(S^t) - p^s_{ask}(S^t)$

Within the proxy phase, this rule is always satisfied by the straightforward bidding of the proxies. But in the clock phase, bidders might reduce demand at the end to stop prices from rising higher. To prevent any inefficiencies stemming from this demand reduction, the activity rule is amended to allow bidders to slightly expand their demand from the end of the clock phase. Ausubel et al. (2006) introduce a factor $\alpha \geq 1$ allowing for this. The ***relaxed revealed-preference activity rule*** requires a bid on a bundle S^t to satisfy the following condition for all bundles S^s the bidder has previously bid on: $\alpha(p^t_{ask}(S^s) - p^s_{ask}(S^s)) \geq p^t_{ask}(S^t) - p^s_{ask}(S^t)$

Even in complex settings including complementary valuations, the Clock-Proxy auction performs well due to the combination of both phases (Ausubel et al., 2006). The clock phase is simple to understand and provides good price discovery. The final allocation after the proxy phase is efficient, revenue is competitive, and the outcome is in the core with respect to reported valuations. If items are substitutes, the Clock-Proxy auction implements the VCG outcome, since the unique bidder optimal point in the core is the VCG point. If items are not substitutes, the VCG outcome may be outside the core and the Clock-Proxy auction revenue may exceed the VCG revenue. Prices and revenue in the Clock-Proxy auction are monotonic with the number of bidders. If the BSM condition holds true (section 2.6.3), truthful reporting is a Nash equilibrium strategy and the Clock-Proxy auction implements the VCG outcome.

Apart from its favorable properties, the Clock-Proxy design has some implementation issues (Ausubel et al., 2006):

- *Expression of proxy values.* Bidders are often unable to specify enough and the right valuations for the proxy agents. A clever tool support could help determine the structure of valuations and create various valuations based on input parameters. Bidders can be supported with a flexible interface which is customized to the domain to fit individual needs.

- *Calculation of final prices.* VCG payments are the only payments for which bidders have the dominant strategy of truthfully reporting the valuations. But the VCG outcomes may be outside the core when there are complementary valuations. In that case, there is a set of bidder-optimal core points and the pricing rule must choose one of them as the final prices. The closest-to-Vickrey core prices of the CCA (3.2.4) and the Package Clock (3.2.6.2) address this problem.

- *Confidentiality of private valuations.* Bidders may be reluctant to reveal private valuations to proxy agents. This can be addressed in a multi-round implementation of the proxy phase, in which bidders can increase their valuations in several steps in the phase depending on consistency with prior reports.

- *Clock price increments.* Choosing the right increments is crucial to allow all items to clear in the clock phase at approximately the same time. This is necessary to avoid a decrease in demand quantities of pre-cleared items when a bidder stops bidding on a bundle with complementarities.

3.2.6.2 Package Clock

Cramton (2009b) has built on the Clock-Proxy design and defined the Package Clock as a clock phase followed by a single round of sealed bids. The revealed preference activity rule of the Clock-Proxy auction is quite complex, since checking correctness of a new bid does not involve only a single constraint. Instead, there is one constraint for each of the clock bids, so some sort of support is necessary for bidders to find feasible bids. In addition, in practice some common value aspects might influence the valuation of bidders. Cramton (2009b) argues that in such cases the revealed preference rule is quite strong and might limit bidders too much. He suggests a ***simplified revealed-preference activity rule***, which is easier but still promises enough incentives for bidders to report valuations truthfully. Here, one constraint at most is applicable to each new bid.

During the clock phase, demand can increase only if the larger bundle S^{t+1} in round $t+1$ has become relatively cheaper than the package S^t of the prior round t, i.e., $p_{ask}^{t+1}(S^{t+1}) - p_{ask}^{t}(S^{t+1}) \leq p_{ask}^{t+1}(S^t) - p_{ask}^{t}(S^t)$. In the supplementary phase, bids are limited by a single constraint of revealed preference. This rule has been explained in section 3.2.2 as the anchor activity rule of the CCA. In the notation of this section it follows: Packages S^s smaller than or equal to the package S^f of the final clock round f are constrained by the final clock package S^f. With $p_{bid,i}^{max}(S^f)$ denoting the highest bid on bundle S^f by the bidder i from the clock rounds and the supplementary round so far, the bid on S^s is constrained by $p_{bid,i}(S^s) \leq p_{bid,i}^{max}(S^f) + p_{ask}^{f}(S^s) - p_{ask}^{f}(S^f)$. Packages S^l larger than the final clock package S^f must satisfy the revealed preference constraint with regard to the smaller package S^m, where m is the first round the bidder has bid on a package smaller than S^l. Let $p_{bid,i}^{max}(S^m)$ denote the highest bid on bundle S^m by the bidder i from the clock rounds and the supplementary round so far. Then the constraint is: $p_{bid,i}(S^l) \leq p_{bid,i}^{max}(S^m) + p_{ask}^{m}(S^l) - p_{ask}^{m}(S^m)$.

Together with the closest-to-Vickrey core payments (section 3.2.4), this ensures that bidders have a strong incentive to bid truthfully in both auction phases. Especially if bidders bid straightforwardly in the clock phase, they can bid up to their valuations in the supplementary phase. The bundle of the last clock round is especially important for the constraints of maximum bundle prices. Cramton (2009b) argues that bidders do not know in advance which round is the final clock round and thus have a strong incentive to bid straightforwardly throughout the clock phase.

In fact, apart from differences in the activity rule of the primary bid rounds the Package Clock design is very similar to the CCA implementation of the Austrian 2.6 GHz auction that we used in the lab experiments. Our implementation used a simple eligibility points activity rule in the primary bid rounds.

Chapter 4

Laboratory experiments

Learning to run experiments
is like learning to play the piano
- at some point you have to start practicing.
Vernon Smith

This chapter introduces laboratory experiments (or lab experiments) as a complementary research approach to game theory and computational experiments. We highlight the required assumptions and prerequisites a lab experiment has to fulfill in order to receive transferable and reproducible results, and characterize typical environments of spectrum sales focusing on bidder capabilities. Addressing the external validity of experiments in the field of spectrum sales, we introduce competitions in which subjects participate in teams and have more time to prepare. The chapter closes with a pre-study comparing competitions and traditional lab experiments with unprepared subjects to test for the effect of the level of bidder preparation on bidding behavior and auction outcome.

4.1 Methodological approach of lab experiments

Experimental economics are now complementing the more traditional approaches of game theory, computational simulations, and field studies in investigating market mechanisms. Lab experiments have become more and more important in examining competitive markets, especially environments with multiple items and many participating sellers or buyers. The principle objective of a ***lab experiment*** (or laboratory experiment) is to create a manageable microeconomic environment where adequate control can be exerted and accurate measurement of relevant variables is guaranteed (Smith, 1982). For that purpose, unprepared participants are invited to the lab and put in an artificially created economic environment. The description of the environment and all required information on the experimental setup, the rules, and the reward structure are given to them at the beginning. In order to create a controllable environment and to receive reproducible results, the subjects' motivation is controlled through financial incentives. Each participant's financial reward depends on his choices during the experiment and the final outcome. The preferences and the rules of the market mechanism are determined by the experimentator, making it possible to analyze the results as well as the participants' behavior.

Game theory examines strategies in well-defined economic environments and studies the existence and uniqueness of strategy equilibria in competitive markets. This is done by making assumptions, e.g., about bidders' valuations (section 2.5). Literature provides results of equilibrium strategies in small settings and single-item auctions such as the English auction or the Vickrey auction, which can well describe bidder behavior observed in lab experiments (e.g., Krishna (2002); Vickrey (1961)). For more complex environments with many items, multiple units per item, and side constraints such as budget limits, game-theoretical analysis is comparably harder since the design space is larger. Analyzing equilibrium strategies in such settings often requires applying very restrictive assumptions of available probabilistic information on bidder types or valuations, which are often not met in realistic environments (Pekec and Rothkopf, 2003). For example, Brusco and Lopomo (2009) analyze an environment with only a few items and assume budget constraints which are known to all bidders. Other studies derive equilibrium strategies for specific value models, either including or excluding complementarities (Brusco and Lopomo, 2002). Analyses within more complex markets often focus on a specific strategic situation observed in the field. Ewerhart and Moldovanu (2003) described the strategic situation of a strong bidder in the German UMTS auction in 2000 who is trying to push out a weaker new entrant by disregarding any other effects. Analyzing the complete auction, including all other bidders' actions, would require a model which could hardly be handled.

New auction formats can be analyzed strategically by applying game-theoretical models and past experiences, but cognitive limits and specific behavior of bidders might significantly influence the course and final outcome of an auction (Scheffel, 2011; Ziegler et al., 2010). Theory helps to understand the strategic situations in an environment, which then can be analyzed in lab experiments that include the effects of bidding behavior. Connolly and Kwerel (2007) argue that testing an auction design in a lab experiment is like testing a new aircraft model in a wind tunnel: "Both wind tunnel tests and economic experiments can provide information about the performance of new designs beyond what experience with old designs or theory can predict".[1] A purely game-theoretical approach will likely lead to unrealistic results for which the transfer to the field is quite hard (Rothkopf, 2007a). Behavior observed in the lab itself can initiate considerations of new theoretical models.

[1] A prominent example of experimental results actually leading to the use of a new format is the 700 MHz auction in the US, in which Hierarchical Package Bidding (HPB) was used after successful experiments at the California Institute of Technology.

4.2 Classification of lab experiments

Experiments can serve various purposes depending on the desired goals, e.g., comparing auction formats by average efficiency in a distinctive environment, testing whether subjects bid in order to maximize their personal utility, or advising policy makers and governments in choosing an appropriate mechanism for selling public goods. Based on these, Douglas and Holt (1992) and Roth (1995) among others, proposed classifications of lab experiments. The one by Douglas and Holt (1992) has gained high popularity. They distinguish *market experiments*, *experiments on individual behavior*, and *experiments to test game theoretical-models*. They can be described as follows (Guala and Salanti, 2001).

Market experiments analyze trading institutions and market mechanisms in various environments with regard to final outcomes and equilibrium properties. Results of such experiments have furthered the design of market mechanisms and auction formats. *Experiments on individual behavior* investigate implications of structural determinants on the behavior and the decision-making of subjects in the lab. Such experiments (e.g., Mosteller and Nogee (1951)) have added a number of contributions to the theory of individual choice behavior, which has affected, e.g., expected utility theory. *Experiments testing game-theoretical models* provide the opportunity to test theory under the strong assumptions that theory is built on (e.g., complete information, no uncertainty in valuations, no side constraints). For example, in a setting with multiple Nash equilibria, such an experiment can investigate which of them is chosen by the subjects. The sensitivity of such results with respect to these assumptions can also be analyzed.

Our experiments to compare the performance of the CCA and the SMRA in the domain of spectrum sales (section 5) can be categorized as *market experiments*. We also analyzed the bidding behavior in detail which puts the experiments into the category of *experiments on individual behavior* as well.

4.3 Internal and external validity

The literature distinguishes between internal and external validity of lab experiments. ***Internal validity*** is given if the setting of a lab experiment generates robust and replicable results. Only then can reliable conclusions be drawn from the experiment. ***External validity*** describes the ability to transfer learnings from the lab environment to other environments of interest, e.g., the field (Loewenstein, 1999).

Smith (1982) describes the fundamental objective of lab experiments as the creation of a manageable environment, "where adequate control can be maintained and accurate measurement of relevant variables [is] guaranteed". In an attempt to define a methodological framework for lab experiments to achieve these objectives and foster valid and reproducible results in experimental economics, Smith (1982) defines sufficient conditions for a microeconomic experiment. Lab experiments differ from field experiments (e.g., Harrison and List (2004)) in that for the latter only a few aspects of the environment can be controlled and that access to the economic agents is limited (Roth, 1988). In some of these experiments, the subjects' preferences are elicited upfront in order to determine the efficiency of auctions after the experiment (Ostertag et al., 2002). Since this is not always feasible, field experiments cannot be conducted on a large scale. In the lab, the economic environment and especially the preferences can be fully controlled by the experimenter by using an appropriate reward structure and property right system. Smith (1982) postulates five precepts that provide such a controlled environment:

1. ***Nonsatiation.*** The reward scheme needs to be designed in a way that subjects are not saturated by the financial reward, i.e., utility $U(\pi_i)$ is a monotone increasing function of the monetary reward, $U'(\pi_i) > 0$, with π_i being the payoff in Euro won by the subject i in the experiment.

2. ***Saliency.*** Subjects must fully understand the reward scheme, the mar-

ket mechanism, and consequences of their actions in the experiment on their financial reward. They must be able to rely on having a property right to the reward.

3. ***Dominance.*** Costs of participation in the experiment are dominated by the reward scheme to render non-monetary utilities non relevant.

4. ***Privacy.*** All subjects learn only about their individual payoff alternatives (and valuations), a situation resembling the field, where competitors' preferences cannot be observed either.

5. ***Parallelism.*** The lab setting sufficiently fulfills the same ceteris paribus conditions as the target environment, i.e., propositions about the market mechanism and the behavior of subjects in the target environment also apply in the lab.

Nonsatiation and *saliency* create an experimental microeconomy in which motivated individuals (through financial incentives) act within an institution defined by the market mechanism. When *dominance* and *privacy* are also fulfilled, any individual costs of participation and "individious, egalitarian, or altruistic cannons of taste" (Smith, 1982) are addressed and a controlled experimental microeconomy is created. In such a setting, experiments can be conducted to test hypotheses. One can expect reliable and replicable results in such an experimental setup, which means that the internal validity is given.

Transferring results from the lab experiment to other environments, such as the field, is only valid if the parallelism precept holds true. If the market mechanism and incentives in the lab differ considerably from those in the environment to which the results should be transferred, the subjects' behavior may differ significantly and external validity may not be given. In such a case, implications of lab results must be interpreted with care.

Defining an experimental setup always requires dealing with the tension of external and internal validity and should be guided by the main goals pursued with the experiment. The confirmation or falsification of a game-theoretic model often imposes strict assumptions on the setting. By oversimplification, abstraction, reduction of complexity, and smaller numbers of items or market participants within the lab environment, single effects can be isolated and experimental results are more tractable and reproducible, i.e., internal validity is high. Experimental results from more realistic settings with high external validity can differ fundamentally from the predicted results (Smith, 1985). But findings of experiments of that kind can more easily be transferred back to complex environments in the field.

4.4 Competitions

The domain of spectrum auctions is characterized by a number of specific properties, most notably complex settings and, consequently, high levels of preparation for such auctions by bidders in the field. These need to be considered with regard to the external validity of lab experiments in this domain. Competitions address bidder preparation by allowing subjects to prepare prior to the experiment and participate as teams. In this way, competitions can complement traditional lab experiments with unprepared subjects. In this section, we describe the complexity of spectrum auctions, define competitions, and report on a pre-study comparing the results of lab experiments and competitions in an environment resembling the German Super Auction of 2010.

4.4.1 Spectrum auctions as complex markets

The basic characteristics of the domain of spectrum sales have been described in section 1.1. In spectrum sales, the government, i.e., the regulatory authority, offers usage rights for bandwidth to mobile operators, who build networks to provide telecommunication and data services to end customers. Since bandwidth is limited but essential for the operations of mobile providers, they have paid high prices for spectrum in the past. For example, the revenue of the German 3G auction in 2000 totaled more than 50 billion Euro (Niemeier, 2002). One difficulty is the value uncertainty faced by bidders. The valuation attached to a spectrum block is based on projections of future revenues and anticipated costs, which are uncertain by definition.

The setting of spectrum auctions can be quite complex. For example, in the Advanced Wireless Service auction in 2006, no fewer than 1,122 different licenses were on sale to 168 bidders (Bulow et al., 2009). The licenses differed in their geographic spread from nationwide to local licenses. Bidders could either buy a nationwide license or aggregate regional licenses to achieve nationwide coverage. Switching was difficult and risky due to the activity rules employed. In the German 4G auction in 2010, the licenses on sale were located among licenses that had already been sold in prior auctions. Thus, the bidders' valuations were rather complex, and individual valuations of specific spectrum blocks differed fundamentally among bidders (Niemeier, 2002). Such characteristics provide space for a range of bidding tactics during the auctions.

The sheer amount of money at stake makes mobile operators invest in the preparation of such spectrum auctions. The literature reports on teams of experts and consultants who spend months or even years preparing strategies for such spectrum sales and also have considerable decision support during the auctions (e.g., Bulow et al. (2009); Niemeier (2002)).

4.4.2 Characteristics of competitions

The traditional approach of experimental economics is to invite unprepared subjects to the lab, provide all relevant information about an adapted, simplified economic environment and the reward structure, and conduct the experiment. Through this procedure, reproducible and robust results, e.g. on the performance of different auction formats such as the CCA and the SMRA in this specific environment, are generated (high internal validity). As pointed out in section 4.3, valid transfers of lab findings to other environments require similar ceteris paribus conditions with respect to the auction mechanism and the behavior of participants. In the domain of spectrum sales, auction rules can be implemented in the lab that are in accordance with the format used in the field, but it is questionable whether this is also true for bidder behavior.

Since the preparation for spectrum auctions in the field reaches such high levels, unprepared subjects in the lab might exhibit bidding behavior that is not sufficiently similar to that of teams of experts and consultants that have prepared for months or even years and have sophisticated decision support tools at their disposal. The external validity of lab experiments with such unprepared subjects, especially in a complex setting, might then not be sufficient to transfer findings to the field without adjustments.

Only a small number of empirical studies have looked at the effects of bidder preparation, learning, or experience levels of lab subjects. For example, Abbink et al. (2005) compared different auction formats in the context of the British 3G auction in 2000. They allowed subjects to participate multiple times in the experiment to gain experience and found a significant difference between experienced and inexperienced subjects in their bidding activities in the lab. In their experiments, differences with regard to revenue between the analyzed auction formats diminished with higher levels of bidder experience. Sutter et al. (2007) conducted experiments with individuals and with teams in UMTS auction settings. They found that auctions with teams had more rounds and that teams paid significantly higher prices. Teams made smaller profits than individuals, but the efficiency was higher.

We propose ***competitions*** as a method to analyze bidder behavior in environments where the strategic complexity for subjects is such that bidders in the field typically have substantial training and preparation. In such situations, the parallelism precept does not hold true for experiments with unprepared subjects, and bidder behavior as well as outcomes may differ significantly. To improve external validity, competitions differ from experiments in several ways:

1. Subjects get detailed, objective, and neutral information about different strategies and their risks.
2. Subjects have sufficient time before the competition to become familiar with the auction rules, strategies, and risks, and to obtain information about other players (e.g., estimates about their preferences and side constraints, such as budget limits).
3. Subjects work in small teams. They prepare a written document about their strategy before the competition and a summary of their actions and the rationale for their behavior after the competition.

In contrast, in lab experiments, bidders only learn about the rules of the market mechanism and are not exposed to strategies or previous experiences in order to avoid influencing their actions. Also, they typically have a limited amount of time to prepare for an auction, which becomes an issue when subjects face complex decision situations.

4.4.3 Pre-study with competitions

In order to analyze the effect of the level of preparation on bidder behavior and consequently on auction performance in rather complex environments, we ran a pre-study with competitions and traditional lab experiments in a setting very close to a field auction. The German 4G auction of 2010 served as an example of a rather complex setting in which bidders in the field spent a great amount of time and money to prepare for the auction. In an attempt to recreate these field conditions, we did not reduce the complexity of the experimental setup and deliberately put aside common assumptions about independent private valuations and simplified settings. Instead, we drew the full complexity of the field setting into the lab. As described in section 4.4.2, we also allowed subjects in the competitions to have more preparation time and access to literature, and to participate in teams as bidders did in the field. We found that bidders in competitions revealed a bidding behavior which was much closer to the field than that of unprepared subjects in the lab. This resulted in significantly different auction outcomes. Therefore, we argue that the use of competitions serves well to enhance the external validity of experiments in complex environments.

4.4.3.1 The German 4G auction of 2010

We based our experimental design on the German 4G auction of 2010, since bid data is publicly available[2] which allows for comparisons with bidder behavior in the lab and in competitions. The German 4G auction is a good example of a complex market: The economic environment as well as the auction rules[3] had specific properties creating a rather complex setup for bidders.

The economic environment. Several spectrum bands (0.8 GHz, 1.8 GHz, 2.1 GHz, and 2.6 GHz) were allocated simultaneously, each band divided into blocks of paired (10 MHz) or unpaired spectrum (5 MHz), 41 blocks in total. Of special interest was the paired spectrum. The complexity for the four bidders Deutsche Telekom (DT), Vodafone (VF), Telefonica O2 (O2), and Eplus (E+) was based on the fact that all of them already owned licenses in the 1.8 GHz and 2.1 GHz bands prior to the auction. This made the acquisition of additional adjacent spectrum blocks in the same band attractive to them. Thus, preferences could become very complicated, and differ significantly between

[2] *www2.bundesnetzagentur.de/frequenzversteigerung2010/rundenergebnisse.html*
[3] *www2.bundesnetzagentur.de/frequenzversteigerung2010/images/Praesidenten–kammerentscheidung.pdf*

bidders depending on their individual goals. Figure 4.1 gives an overview of the paired spectrum sold in the auction. The white color indicates blocks to be auctioned while the shades indicate spectrum already owned by the mobile operators.

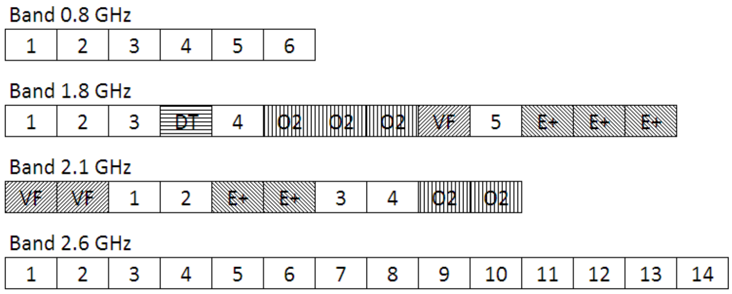

Figure 4.1: Bandplan including pre-allocated spectrum

Due to the technical properties of the spectrum, blocks in specific bands are more suitable for various technologies that implement voice or data services (e.g., GSM, UMTS, LTE, WiMAX, etc.) and can have super-additive valuations. In addition, the valuations can differ between bands. The 0.8 GHz band represented the most valuable part of the spectrum due to its technical properties. Its final price in the German 4G auction made up 81% of the auction revenue, although it comprised only 17% of the overall volume of spectrum sold (including paired and unpaired spectrum).

The auction format. The spectrum was auctioned through an SMRA implementation (section 3.1) with the following specific amendments which further contributed to the complexity of the setup.

To prevent monopolization of the 0.8 GHz band, ***spectrum caps*** were introduced, which limited winners to at most two or three out of six blocks in the 0.8 GHz band depending on the number of blocks already owned by the bidder. In an attempt to reduce complexity and the exposure to win fragmented spectrum, blocks of equal quality within one spectrum band were sold as ***abstract*** blocks. This means a bidder was only required to win a sufficient number of blocks within a band, since the regulator arranged that each winner received adjacent blocks at the end. However, some blocks were still sold as ***concrete*** blocks in cases where pre-owned spectrum was of importance, or relevant technical or legal issues existed.

The German regulatory authority chose an ***open information policy***. At the beginning of each round the bidders were informed about all prior (winning and losing) bids in the auction, including the identities of the corresponding bidders. To prevent signaling by using digits of the bid price (Niemeier, 2002; Weber, 1997), ***click-box*** bidding was introduced: Jump bids were limited to a fixed set of values which the bidder could add to the minimum bid price. The auction was conducted in rounds with a default round duration of 90 minutes. To ensure active participation from the beginning, a ***stacked activity rule*** was used (Banks et al., 2003). In order to maintain the eligibility for a certain number of bid rights, each bidder was required to bid according to the current level of activity. The auction started with 50% required activity and moved to 65%, 80%, and finally 100%. The ***minimum increment*** for new bids was set to 15% above the provisionally winning bid and was lowered to 10%, 5%, and 2% by the regulator during the course of the auction. Ties were broken randomly. The auction ended when no bidder submitted a bid within one round in the 100% activity phase. Bidders had the possibility to ***withdraw*** bids, but they had to bear the risk of paying their bid price if no other bidder bid on the withdrawn block. The price of the withdrawn block did not decrease to the second highest bid, but remained at the previous level.

The auction lasted for 27 days with 224 rounds. The total revenue was 4.4 billion Euro.[4]

[4] *www.bundesnetzagentur.de*

4.4.3.2 Experimental setup

The goal of the pre-study was to analyze the effects of bidder preparation within a complex environment. For this, we implemented all major characteristics of the environment as described in section 4.4.3.1 above without deliberate simplification. Especially the complex valuation structure, differences among bidders, mixture of blocks on sale with pre-owned spectrum, and the specific auction rules of the field implementation made up the complexity. We decided to model rank based utility with superimposed budget constraints, which do not simplify the complex valuation structure of the field. All details can be found in appendix A.

We ran lab experiments with unprepared subjects and competitions within the exact same setting to allow for direct comparison. The only differences were the levels of bidder preparation and the team structure. While subjects in the lab (***treatment Lab***) learned about the auction rules and the valuations on the day of the experiment, subjects in competitions (***treatment Comp***) received the introduction two weeks in advance. Also, they participated in teams of two people and were recruited from a class on auction theory and market design. They were asked to prepare a strategy paper outlining the basic ideas of their intended bidding strategy.

Details on the valuations, budget constraints, the treatment structure, recruiting of subjects, and the organization of lab experiments and competitions can be found in appendices A.1 and A.2.

4.4.3.3 Results and conclusion

For the sake of brevity, only the main results are presented here and the details are provided in appendix A.3.

We found that bidders in competitions paid significantly lower final prices ($p = 0.0575$) for allocations with significantly higher utility ($p = 0.0249$). In competitions, the price levels of different bands more closely resembled the differences in valuations of the spectrum indicating a better understanding of the value model. Comparing the bidding behavior in the two treatments, we found that Comp bidders used various strategies similar to those observed in the field. They placed more bids on their own blocks ($p > 0.1$), they placed significantly less bids on blocks which were not the cheapest ($p = 0.0068$), and used jump bids significantly more often ($p = 0.0638$) and more effectively than Lab bidders.

In addition, Comp bidders managed to end the auction within the given budget limits and exceeded their budgets only temporarily during the auction. Lab bidders did not estimate competitors' budgets or final price levels correctly and violated their budget limits more often. The lack of preparation led Lab bidders to bid in a way that maximized their flexibility in later rounds. Comp bidders, on the other hand, managed eligibility more actively to reach their target allocations.

This raises the question about the transferability of existing experimental results to complex spectrum auctions in the field. Recently, there have been a number of comparisons of SMRA and various combinatorial auction formats. Those comparisons are typically based on small value models with only a few items. The results of our initial study suggest that competitions can add to the external validity of lab experiments. The main experiments for this thesis (section 5) were conducted to compare the SMRA with the Combinatorial Clock Auction. The latter format provides fewer opportunities for the application of tactical instruments (Cramton, 2009b). To improve the external validity of these experiments, we used the results of this pre-study and conducted competitions in addition to lab experiments with unprepared subjects.

Chapter 5

Analysis of CCA and SMRA

The only relevant test of the validity of a hypothesis
is comparison of prediction with experience.
Milton Friedman

This section starts by introducing the experimental design of our experiments. We report on the economic setting, the value models, the implementation of auction formats, the specifics of competitions, and the organization of the experiments. We then present aggregate results on the performance of CCA and SMRA and analyze in detail the observed bidding behavior in both formats.

5.1 Experimental design

In the following, we explain the characteristics of the economic setting and the three value models used in our experiments. We provide further details on the implementation of the auction rules of CCA and SMRA as used in the experiments, as well as the treatment structure and the organization of our experiments.

5.1.1 Economic setting and value models

We used an economic setting which closely resembles the settings of the European 2.6 GHz band spectrum auctions. The frequencies of this band are available for mobile services in all regions of Europe, which is probably unique. It includes 190 MHz divided into blocks of 5 MHz, which can be used to deliver wireless broadband services or mobile TV. There are two standards in particular which will likely be used in the 2.6 GHz band, LTE and WiMAX (section 1.1). LTE uses paired spectrum, i.e., units of two blocks, while WiMAX uses unpaired spectrum, i.e., units of one block (section 1.1). While some European countries have auctioned only the 2.6 GHz band, others have combined several spectrum bands in a single multiband auction.

We adapted a setting mirroring the situation of many European spectrum auctions where four large incumbents dominate the market. Therefore, four bidders participated in each of our experiments. We used value models reflecting the characteristics of bidder valuations in the field. The structure of the value model was known by all bidders. Although the value models resembled the characteristics of spectrum sales in Europe, this was not known to the subjects in the lab (neutral framing). Bidders in the lab used an artificial currency called Franc.

In an attempt to investigate auction performance and bidding behavior in environments of different complexity, we used three value models, allowing for different market characteristics and alternative decision spaces for bidders.

5.1.1.1 The base value model

In the base value model, we used a band plan with two bands of items, as has been used in several European countries. There are fourteen paired blocks (or items) in band A and ten unpaired blocks in band B (figure 5.1). A blocks required two eligibility points, B blocks only one. In this multi-unit setting,

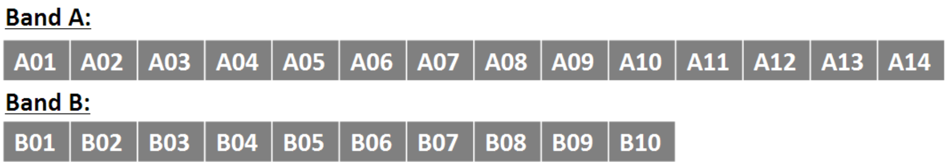

Figure 5.1: Bandplan of the base value model

a bundle is defined by the number of blocks in band A and by the number of blocks in band B. A specific block is assigned to a bidder after the auction. During the auction, blocks within a single band can be considered identical. Bidders had a positive valuation for up to six items in each band. Additional blocks did not give extra value.

Each bidder received ***base valuations*** v_A and v_B for each of the bands. The base valuations represented the valuations of a single item within each band and were drawn randomly from a uniform distribution, v_A in the range of $[120, 200]$ and v_B in the range of $[90, 160]$. Reflecting the technical properties of LTE, we modeled ascending complementarities in the valuation of bundles of several A items. In the A band, a bundle of two items received a complementary value of $1.2 * 2 * v_A$, i.e., a complementarity bonus of 20% on top of the base valuations. In reality, four 5-MHz blocks allow for peak performance rates with LTE. Thus, the complementarity in the value model rose with the number of items in the bundle. A bundle of three items had a complementarity of 40% and a bundle of four items of 80%. There was no additional bonus for the fifth and sixth items.

In total, each bidder was interested in up to $7 * 7 - 1 = 48$ different bundles. Four items in band A had the highest valuation per item for all bidders due to the bonuses. If all bidders aim for four items with fourteen items for sale in the A band, it is possible that either two or three bidders will obtain this bundle, while the other bidders will win only two or three items in band A.

Bidders had purely additive valuations in band B for up to six items. The total valuation of items from both bands was the sum of valuations within the bands. We assumed item valuations to be bidder-specific, but the synergy structure of bundles to be the same for all bidders. This can be motivated by the fact that synergies often arise from a mobile operator's ability to achieve peak performance with a technological standard after winning a certain amount of bandwidth, and these synergies are the same for all operators. It also limits the complexity for bidders in the lab, because the valuation model is simpler.

5.1.1.2 The multiband value model

The multiband value model was inspired by recent discussions suggesting that the CCA should be used for the sale of multiple bands in several countries. The multiband value model also had twenty-four items, four bands with six items each (figure 5.2).

Band A was of high value to all bidders, whereas bands B, C, and D were of lower value. As in the base value model, each bidder received a base valuation for an item in each band. Base valuations were uniformly distributed: v_A was in the range of $[100, 300]$ while v_B, v_C, and v_D were in the range of $[50, 200]$.

Again, bidders had complementary valuations for bundles of items. The complementarities in the multiband value model were descending. In all bands, bundles of two items resulted in a bonus of 60% on top of the base valuations, bundles of three items in a bonus of 50%. As with the base value model, more items did not add any extra bonus on top of the base valuation for this band. Overall, bidders in the multiband setting could bid on $7 * 7 * 7 * 7 - 1 = 2,400$ different bundles, which is significantly more than the 48 bundles in the base value model.

5.1.1.3 The multiband$_{\text{small}}$ value model

We also configured a variant of the multiband value model to create an environment with a number of possible bundles between that of the base value model

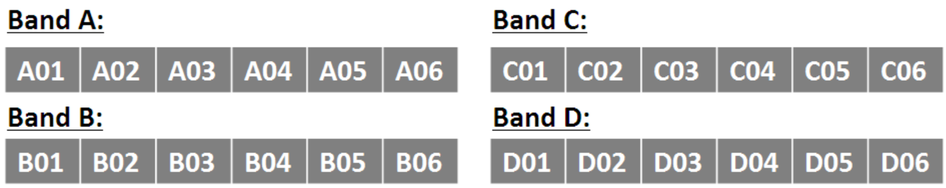

Figure 5.2: Bandplan of the multiband value model

(48) and that of the multiband value model (2, 400). This variant used the same band plan as the multiband value model. But bidders in the multiband$_{\text{small}}$ value model were restricted to at most four items per band. Thus, each bidder could bid on $5 * 5 * 5 * 5 - 1 = 624$ different bundles.

In the multiband$_{\text{small}}$ value model, we allowed for ***arbitrary complementarities*** for bundle sizes of two, three, and four items per band. The complementarity factors were drawn randomly from a uniform distribution in the range of $[0, 120\%]$ and applied only to the item it was drawn for. In contrast to the multiband setting, we modeled bidder-specific complementarities. We drew one set of complementarities for the A band and another set for the B, C, and D bands. Thus, each bidder had an individual preference for a specific bundle size per band defined by the highest complementarity. The individual draws of complementarities for each bidder created various competitive environments across the bands.

5.1.1.4 Overview of value models

Table 5.1 gives an overview of the key characteristics of our value models.

All settings included four bidders, which resembles the competitive situation of European spectrum sales. We analyzed the performance of CCA and SMRA in these settings and compared the bidding behavior depending on the complexity of the value model. Our value models ranged from a rather simple setting with 48 possible bundles to choose from to a large multiband setting with

Value model / setting	Base	Multiband	Multiband$_{small}$
No. of bidders	4	4	4
No. of lots	24	24	24
No. of bands (lots)	2 (14,10)	4 (6,6,6,6)	4 (6,6,6,6)
Max no. of items/band	6	6	4
Range base valuations	A: [120,200] B: [90,160]	A: [100,300] B,C,D: [50,200]	A: [100,300] B,C,D: [50,200]
Comp. type	Fixed, ascending	Fixed, descending	Variable
Bundles with comp.	2,3,4	2,3	2,3,4
Range comp.	20-80%	50-60%	0-120%
No. of possible bundles	48	$2,400$	624

Table 5.1: Overview of value models

several thousand bundles. Also, several types of complementarity structures were used: We implemented fixed and variable complementarities, ascending and descending complementarity levels, super-additivities for different sizes of bundles, and values were drawn from various ranges, the largest being [0, 120%].

5.1.2 Auction formats

Our experiments were based on the MarketDesigner software framework,[1] which we expanded, using implementations of the SMRA and the CCA as described in section 3. Our implementations followed those of recent spectrum auctions in the field: The SMRA implementation was similar to the German Super Auction in 2010,[2] the implementation of the CCA followed the rules specified in the guidelines for the Austrian spectrum auction in 2010.[3]

[1] *www.marketdesigner.org*

[2] *www2.bundesnetzagentur.de/frequenzversteigerung2010/images/Praesidenten−kammerentscheidung.pdf*

[3] *www.rtr.at*

5.1.2.1 Simultaneous Multi-Round Auction

In SMRA all items were sold at the same time with an individual price for each item. Start prices were set to 100 Franc for each A item and 50 Franc for each B, C, and D item. Bidders could not bid on bundles. After each round, the provisional winner of each item was determined by the highest bid. Ties were broken randomly. A bid on an item had to exceed the standing high bid by at least the minimum increment. The minimum increment for items in band A was 20 Franc and in bands B, C, and D 10 Franc. In many implementations of SMRA in the field, further increases are restricted to predefined levels (click-box) to prevent signaling by using the last digits of rather high bid prices. We defined six steps from 1 up to 50 Franc to cover the range of small to high increases. The exact steps were 1, 2, 5, 10, 20, and 50 Franc above the minimum increment.

An activity rule restricted the number of items a bidder could bid on across all bands. Following the German SMRA design, we implemented a stacked activity rule with different levels: At the beginning, each bidder was assigned eligibility to bid on all items on 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, 100% was required. The first level gave bidders a chance to reduce demand in order to split the items at low prices, which can be an attractive option for bidders in the field. At the beginning of each round, all bids from the previous round (winning and losing) were revealed to all bidders. Finally, the auction terminated if no bidder submitted a bid within one round. Bidders won the items for which they held the highest bid and were required to pay the bid price.

Appendix B.2 provides a screenshot of the bidding interface.

5.1.2.2 Combinatorial Clock Auction

As introduced in Section 3.2, the CCA was composed of two phases, the primary bid rounds (or clock rounds) and the supplementary bids round. All items within one band had the same price. In the base value model, there was one price for the A band and one for the B band; in both multiband value models, there were separate prices for all four bands.

The auctioneer announced the new ask price for each band in each round of the clock phase, and bidders decided on the quantities of items they wanted to bid on within each band. The quantities specified in all bands formed one package bid. Each bidder could submit a maximum of one bid in each clock round. If there was excess demand in at least one band (i.e., if the combined demand of all bidders within one band exceeded the number of items), a new round was started with higher prices for the bands with excess demand. Start prices in the first round were set at 100 Franc for items in the A band and 50 Franc in the B, C, and D bands. In cases of excess demand, prices were increased by increments of 20 Franc in band A and 10 Franc in the other bands.

Bidders did not learn about other bidders' bids; the only information they received was whether there was excess demand in the previous round for each band. An activity rule ensured that the bundle size remained constant or decreased from round to round. In our experiments, each bidder started with eligibility for all items in the first round. The primary bids phase ended when there was no longer any excess demand in any bands.

The supplementary bids round consisted of only one round with as many sealed bids as desired by the bidders. They were able to bid on any combination of items regardless of the bids of the first phase. Only the maximum bid price was limited by the anchor activity rule (section 3.2.2). At the end of the round, the optimal allocation was calculated using all bids from both phases, with the condition that at most one bid from each bidder could win. Then the bidder-optimal core-selecting payments were calculated following the algorithm described in section 3.2.4.2.[4]

Appendix B.2 provides a screenshot of the bidding interface.

5.1.3 Competitions

In spectrum auctions in the field, bidders typically work in teams of experts and they spend significant amounts of time preparing for the auction. Section 4.4.3 described a pre-study which showed that a higher level of preparation of subjects in the lab can lead to different results than those obtained with unprepared lab subjects. Addressing the external validity of the experiment, we conducted competitions, as introduced in section 4.4.2, in addition to the lab experiments with unprepared subjects.

The subjects in these competitions were recruited from a class on auction theory and market design and were grouped into teams of two participants. The subjects were invited to the lab two weeks prior to the experiment and received the same introduction as lab subjects. In addition, we provided them with literature on previous spectrum auctions, which described known strategies and tactics of bidders in the field. For two weeks, they prepared their strategy on the basis of the material provided and any other resources they found useful.

We intentionally deviated from traditional experimental procedures in the aspects of individual participation and level of preparation, in order to understand how these impact the bidding behavior of subjects and how robust experiments in the lab are in a more complex environment such as spectrum auctions. With cognitively complex environments and with complex auction rules as in the CCA, this setting might be closer to the environment in the field.

[4]All optimizations were performed using the IBM/CPLEX optimizer version 11.

5.2 Treatment structure

We considered two major treatment factors, ***auction format*** and ***value model***. Auction format has two levels (SMRA and CCA), value model has three levels (base, multiband, and multiband$_{\text{small}}$). In addition, we analyzed the base value model treatments with bidders in the lab (Lab) and in the competition (Comp), which yields another treatment factor ***bidder***. Overall, we had eight treatments in total (table 5.2).

Treatment	Value model	Auction format	Bidder	Auctions
1	Base	SMRA	Lab	20
2	Base	CCA	Lab	20
3	Multiband	SMRA	Lab	16
4	Multiband	CCA	Lab	16
5	Multiband$_{\text{small}}$	SMRA	Lab	8
6	Multiband$_{\text{small}}$	CCA	Lab	8
7	Base	SMRA	Comp	9
8	Base	CCA	Comp	9

Table 5.2: Treatment structure

For the base value model, we drew valuations for five waves (A through F) randomly. Each wave consisted of four different auctions, which were conducted in the lab within one session. Thus, we determined a total of twenty auctions with different valuation draws. For each treatment combination, we conducted a run with CCA and a run with SMRA in the lab. All auctions of waves A, B, and the first auction of wave C were also used in the competition with both auction formats to enable a direct comparison with the lab. In the multiband value model, we defined four waves with four different auctions each. For the multiband$_{\text{small}}$ value model, only two waves were drawn and used in the lab. This was sufficient to check the consistency and plausibility of the results of the base and multiband value models which we focused on.

5.3 Organization

We conducted the experiments at the TU München in 2010 and 2011. Subjects were recruited from the departments of mathematics and computer sciences. In total, 106 students participated in the experiments, including the students in competitions and backups. Each lab subject participated either in one CCA or in one SMRA session but never in both. One session comprised all four auctions of one wave[5] and lasted on average five hours.

All the information and training required were given to the participants at the beginning of each session. To reduce differences between lab sessions, the introduction was delivered in the form of a video, which was shown to the subjects. Each participant was invited to offer comments on a handout and was able to pause the video whenever required. In addition, at least one staff member was present to answer questions while the participants were watching the introduction video. Subjects were familiarized with the auction software through a demo auction. An additional tool to analyze bundle valuations and payoffs was introduced to all subjects. This tool showed a simple list of all available bundles which could be sorted by bundle size, bidder individual valuation, or the payoff based on current prices. In order to ensure a full understanding of the economic environment, value model, auction rules, and the financial reward scheme, all subjects had to pass a web-based test (ability checker). Any questions that arose were answered for the benefit of all participants.

At the beginning of each auction, all subjects received their individual draw of valuations, the distribution of valuations, and information about the complementarity structure. Examples of valuation sheets for all three value models are provided in appendix B.1. With this information, subjects were asked to consider the implications of the draw on their bidding in the upcoming auction. Each round was scheduled for three minutes. The supplementary phase of the

[5] One session in the competition consisted of five auctions.

CCA lasted about ten minutes to provide enough time for bid submission. The subjects could also ask for more time if required.

After each session, subjects were compensated financially. The total compensation consisted of a ten Euro show-up reward and the auction reward. The show-up reward covered costs for participation, e.g., the ticket price for public transportation. The auction reward consisted of a three Euro participation reward plus the payoff of all auction payoffs converted from Franc into Euro at a 12:1 ratio. Negative payoffs were deducted from the participation reward. Negative payoffs higher than the participation reward were capped, i.e., there was no negative auction reward. Due to the different payment rules in the two auction formats, payoffs in CCAs were higher than in SMRAs. We therefore leveled the expected payoff per participant by financially compensating three out of the four auctions of the SMRA sessions, while only two out of the four auctions were compensated in CCA sessions. We randomly determined the auctions which were rewarded by rolling a dice at the end of each session. On average, each subject received 93.52 Euro.

5.4 Results

We begin by presenting efficiency and revenue of both auction formats on an aggregate level, comparing the outcomes of the experiments with each other and with the results from computational simulations. We then move on to discuss individual bidder behavior in SMRA and CCA including differences between the lab and competitions.

Taking into account the fact that each subject participated in four auctions, we compare the performance metrics with the ***rank-sum test for clustered data*** (Datta and Satten, 2005): $\sim$ describes an insignificant order, $\succ^{*}$ indicates significance at the 5% level, and $\succ^{**}$ significance at the 1% level.

5.4.1 Aggregate measures

On the aggregate level, we compared CCA and SMRA based on the definitions of efficiency and revenue in section 2.7. Table 5.3 presents the results of our experiments.

Value model	Auction format	Bidder	$E(X)$ in (%)	$E(X)^*$ in (%)	$R(X)$ in (%)
Base	SMRA	Lab	96.16	63.27	83.74
Base	CCA	Lab	96.04	63.96	64.82
Multiband	SMRA	Lab	98.46	93.85	80.71
Multiband	CCA	Lab	89.28	56.71	33.83
$\text{Multiband}_{\text{small}}$	SMRA	Lab	97.82	90.69	84.51
$\text{Multiband}_{\text{small}}$	CCA	Lab	90.77	62.77	49.51
Base	SMRA	Comp	98.57	87.28	75.06
Base	CCA	Comp	94.15	47.17	55.38

Table 5.3: Aggregate measures of auction performance

Result 1: *The efficiency of SMRA was not significantly different to that of CCA in the base value model in both the lab (SMRA $\sim$ CCA) and the competition (SMRA $\sim$ CCA). In contrast, the efficiency of CCA was significantly lower than that of SMRA in the multiband value model (SMRA $\succ^*$ CCA, $p = 0.0123$) and in the multiband$_{small}$ value model (SMRA $\succ^*$ CCA, $p = 0.0140$).*

Support for result 1 is presented in table 5.3 and figure 5.3. In summary, the SMRA led to higher efficiency than the CCA in two out of three runs in the base and both multiband value models. In the multiband value model, CCA terminated with very low efficiency. Table 5.4 shows that the CCA led to a number of unsold items in the multiband value model (5.2%, or 1.25 items, CCA $\succ^{**}$ 0, $p = 0.0002$), in the $\text{multiband}_{\text{small}}$ value model (5.7%, or 1.38 items, CCA $\succ^{**}$ 0, $p = 0.0079$), and in the competition (1.9%, or 0.44 items, CCA $\sim$ 0), which had a detrimental effect on efficiency.

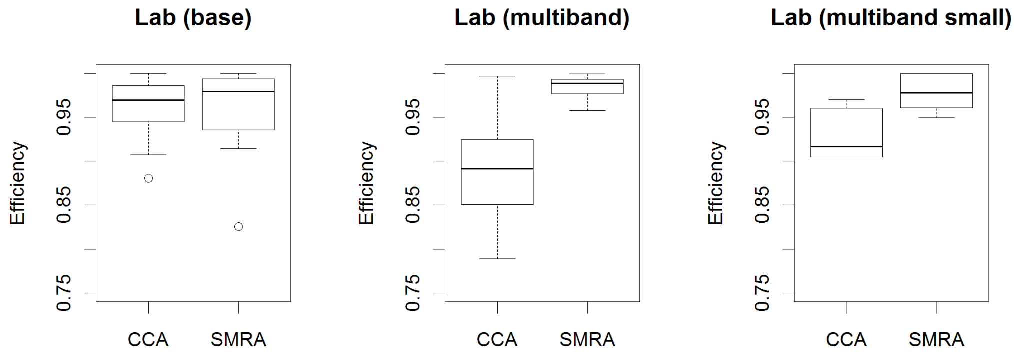

Figure 5.3: Efficiency

Value model	Auction format	Bidder	Unsold items
Base	SMRA	Lab	0
Base	CCA	Lab	0
Multiband	SMRA	Lab	0
Multiband	CCA	Lab	1.25 (5.2%)
$\text{Multiband}_{\text{small}}$	SMRA	Lab	0
$\text{Multiband}_{\text{small}}$	CCA	Lab	1.38 (5.7%)
Base	SMRA	Comp	0
Base	CCA	Comp	0.44 (1.9%)

Table 5.4: Number of unsold items

But even in the cases where all items were sold, the CCA's efficiency was still considerably lower than that of SMRA. In the multiband value model it was only 93.61% which compares to 98.46% for SMRA, and in the $\text{multiband}_{\text{small}}$ value model it was 93.29% while SMRA reached 97.82%. In SMRA, bidders in competitions achieved higher efficiency than lab bidders while in the CCA lab bidders achieved higher efficiency. Both differences were not significant.

The concept of relative efficiency helps to compare performance across value models.[6] SMRA led to significantly higher relative efficiency in both multiband

[6]Relative efficiency emphasizes results below the mean disproportionately. In one SMRA,

value models than in the base value model (multiband $\succ^*$ base, $p = 0.0309$; multiband$_{\text{small}}$ $\succ^*$ base, $p = 0.0498$). With more bands of items, bidders tended to focus on the bands for which they had high valuations, and they were willing to take an exposure risk in these bands, which supported efficiency.

In contrast, the CCA performed best in the base value model, even though the differences were not significant. This lack of significance is due to the large variance of relative efficiency values. While the base value model offered 48 different bundles, the number of choices in the multiband value model (2,400 different bundles) and the multiband$_{\text{small}}$ value model (624 different bundles) were considerably higher. The CCA uses the XOR bidding language, which requires bidders to combine the number of items across all bands in each bundle bid. Thus, it was more difficult for bidders to coordinate and find allocations with high efficiency in the multiband and the multiband$_{\text{small}}$ value models. Boxplots of all treatments can be found in appendix B.3.

Next, we analyzed auctioneer revenue. The core-selecting payment rule of the CCA impedes a direct comparison of its auction revenue with SMRA results. We, therefore, conducted additional simulations for the CCA which serve as a baseline for its performance in the lab. This enabled a comparison of CCA results in the lab to its performance with bidders in the simulation. These artificial bidders bid straightforwardly on their payoff-maximizing bundle in the primary bid rounds and revealed all their valuations truthfully in the supplementary bids round. The results helped us quantify the differences in efficiency and revenue which arise from the fact that bidders deviated from these strategies in the lab (section 5.4.3).

Table 5.5 presents aggregate results of the computational simulations. Efficiency and relative efficiency of CCA were obviously 100% with truth revealing bidders. Based on the payment rule of CCA, an auctioneer can expect revenue

the efficiency and the relative efficiency were low (82.6% and −85.7%) causing the mean relative efficiency of SMRA in the base value model to fall even below the mean of CCA.

of 86.16% in the base setting, 75.72% in the multiband setting, and 78.07% in the multiband$_{\text{small}}$ setting.

Value Model	Auction Format	Bidder	$E(X)$ (in %)	$E(X)^*$ (in %)	$R(X)$ (in %)
Base	CCA	Simulation	100.00	100.00	86.16
Multiband	CCA	Simulation	100.00	100.00	75.72
Multiband$_{\text{small}}$	CCA	Simulation	100.00	100.00	78.07

Table 5.5: Aggregate simulation results

Result 2: *The auctioneer revenue in SMRA was significantly higher than that in CCA in all three value models in the lab (base: SMRA $\succ^*$ CCA, $p = 0.0339$; multiband: SMRA $\succ^{**}$ CCA, $p = 0.0072$; multiband$_{small}$: SMRA $\succ^{**}$ CCA, $p = 0.0094$). The differences between lab and competitions were not significant for either auction format. In the multiband setting, the revenue in the CCA in a simulation with truth revealing bidders was on average more than twice as high as the revenue in the lab. In the multiband$_{small}$ setting it was still approximately 60% higher. While the SMRA revenue did not differ on a large scale between the value models, CCA earned significantly higher revenue in the base value model.*

Support for result 2 can be found in figure 5.4, table 5.3, and table 5.5. The payment rule of the CCA had a significant impact and led to low revenue given the discounts and the low number of bids and bidders. Another reason for the differences was the number of unsold items in CCA runs. Unsold items translated into missed revenue opportunities for the auctioneer. Both reasons explain the difference in auctioneer revenue between the SMRA and the CCA, which was highly significant in the lab. There was also a difference between the auction formats in the competition, but it was insignificant (SMRA $\sim$ CCA). But apart from the payment rule, the low number of bids in the lab had a decisive impact on the poor revenue in CCA, especially in both multiband settings. The simulation of CCA with truth revealing bidders led to a revenue

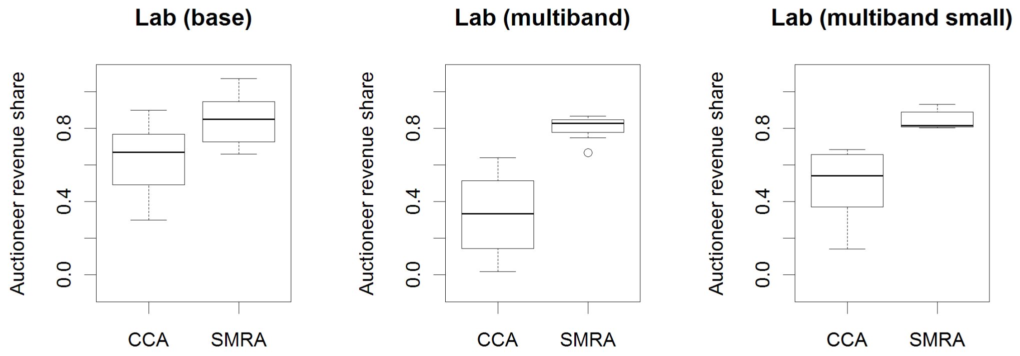

Figure 5.4: Auctioneer revenue share

share of 75.72% in the multiband setting and 78.07% in the multiband$_{\text{small}}$ setting, which compares to only 33.83% and 49.51% in the lab. Thus, if bidders revealed more of their bundle bids truthfully, the CCA could gain considerably more revenue and reach the levels of the SMRA in the lab (80.71% for the multiband setting and 84.51% for the multiband$_{\text{small}}$ setting).

The exposure problem puts bidders in SMRA at risk of winning only a fraction of their intended bundle at a price exceeding their valuation. In a number of cases in the lab, this caused bidders to pay considerably more than their valuation and to end up with a negative payoff. In one SMRA run, the total revenue was even higher than the total valuation of the efficient allocation, leading to auctioneer revenue of more than 100%.

The auctioneer revenue in CCAs was higher in the base value model than in both multiband value models. Again, the number of possible bundles may serve as an explanation, since it causes difficulties when bidders try to coordinate and find the efficient solution. Given the low number of bundle bids, the second best allocation was much lower and resulted in high discounts and low payments. Five of sixteen CCAs in the multiband value model and two of eight CCAs in the multiband$_{\text{small}}$ value model terminated with an auctioneer revenue share of 30% or less. One auction in the multiband value model yielded as little as 2% auctioneer revenue share.

One question is whether bidders would bid differently in the primary bid rounds if there was no supplementary bids round and what the consequences would be. Some researchers argue, that bidders would not change their behavior in the primary bid rounds (Jewitt and Li, 2008). We evaluated the results of the auctions, ignoring the bids in the supplementary bids round and assuming a pay-what-you-bid payment rule.

Result 3: *In all three value models, auctioneer revenue in the CCA after the primary bid rounds (Primary) would be significantly higher than with the supplementary bids round and the bidder-optimal core-selecting payment rule (CCA), if bidders submitted the exact same bids as in the CCA (base: Primary* $\succ^{*}$ *CCA,* $p = 0.0112$*; multiband: Primary* $\succ^{**}$ *CCA,* $p < 0.0001$*; multiband*$_{small}$*: Primary* $\succ^{**}$ *CCA,* $p < 0.0001$*).*

Value model	Bidder	$E(X)$ (in %)	$E(X)^*$ (in %)	$R(X)$ (in %)
Base	Lab	91.71	25.37	78.36
Multiband	Lab	86.28	44.38	67.47
Multiband$_{\text{small}}$	Lab	78.96	13.77	62.58
Base	Comp	90.19	10.54	74.30

Table 5.6: Aggregate measures of CCA after primary bid rounds

Support for result 3 is presented in table 5.6. With the pay-what-you-bid payment rule, bidders do not get a discount on their bid price and the revenue is higher than with the CCA payment rule.

Table 5.7 shows that the average sum of bid prices of winning bids in the supplementary bids round is 12 to 32% above the average of winning bids in the primary bid rounds. The analysis of bidding behavior in CCA in section 5.4.3 shows that bidders bid close to their valuations in the supplementary bids round. This implies that the prices in the primary rounds already rose to quite high levels and bidders were able to bid 68 to 88% of their final bid prices. Since bidders are only allowed to submit a single bid in each round, the relative price levels between bands may prevent bids including bundles with items from several bands. This can result in lower total bid prices. This problem is most pronounced in the multiband$_{small}$ value model.

Value model	Bidder	Total bid price of winning bids in primary bid rounds (Franc)	Total bid price of winning bids in supplementary bids round (Franc)	Increase (%)
Base	Lab	4,084	4,594	12
Multiband	Lab	4,302	5,269	22
Multiband$_{small}$	Lab	5,886	7,764	32
Base	Comp	3,904	4,611	18

Table 5.7: Average sum of bid prices with and without supplementary bids

5.4.2 Bidder behavior in the SMRA

Exposure risk is a central strategic challenge of the SMRA in the presence of complementary valuations. It describes the bidder's risk of ending up with a subset of the intended bundle at a price exceeding his valuation for the subset. Strong bidders with a high valuation might want to take this risk, while weak bidders would decide to reduce demand in order to keep prices low. Alternatively, weak bidders could try to pretend to be strong and bid aggressively, hoping others would believe them and reduce their demand.

The base and multiband value models included fixed complementarities while the multiband$_{small}$ value model assumed a variable complementarity structure (table 5.1). Bidders in the settings with fixed complementarities, i.e., with identical complementarities for all bidders, can be grouped in strong and weak bidders by their base valuation. Weak bidders have a base valuation lower than the mean of possible draws and strong bidders greater than the mean. For the A band in the base value model in particular, we derive in Bichler et al. (2011) the minimum base valuation for which a risk-neutral bidder would be willing to take exposure risk. The value is 158 Franc which is close to the mean of 160 Franc. Here, we report the results with the derived value. There are no complementarities in band B and we take the mean of the base valuations, i.e., 125 Franc. For the multiband setting we used the following values to separate strong and weak bidders: 200 Franc for band A and 125 Franc for bands B, C, and D. Due to the variable complementarity structure in the multiband$_{\text{small}}$ value model, there are no generally strong or generally weak bidders and we do not make such a distinction in this setting.

The fixed complementarity structure of the base setting and the multiband setting allow for the definition of different but fixed levels of exposure risk which let us analyze how bidders have managed the exposure risk in settings using these two value models. Complementarities in band A in the ***base value model*** are identical among bidders and rise with the bundle size (for up to four items): The per item valuation in a bundle of two items is higher than the base valuation, the per item valuation in a bundle of three items is higher than in a bundle of two items, and the per item valuation in a bundle of four items is higher than in a bundle of three items.

Thus, bidders have to decide whether to bid above their base valuation for an A item (they take on ***Exposure1***), above the per item valuation in a bundle of two items (they take on ***Exposure2***), or even above the per item valuation in a bundle of three items (they take on ***Exposure3***). Suppose a bidder keeps bidding on four items until prices exceed the per item valuation in a bundle of four items, i.e., he takes on Exposure3. At this point, demand reduction is impossible without losses because the per item valuation in bundles smaller than four items is lower than the price he has already bid.

In the ***multiband value model*** with decreasing complementarities for bundles of size two and three, the decision within each band is whether to bid above the base valuation (***Exposure1***) or above the per item valuation in a bundle of two items (***Exposure2***). Due to the higher synergy of two items, bidders can bid on three items and then reduce from three to two items without experiencing losses when prices rise too high. Only a reduction from two items to one item will result in a loss if prices have risen above the base valuation.

Different degrees of exposure risk in the value models and the decreasing versus increasing complementarity structures give various options to the bidders. In the following, we analyze whether bidders took exposure risk and the subsequent implications on payoffs.

Result 4: *In the base value model, strong bidders took an exposure risk less often than weak bidders in the lab and the competition. In contrast, strong bidders took a moderate exposure risk (Exposure1) more often than weak bidders in all four bands of the multiband value model. In addition, strong bidders took higher levels of exposure risk more often than weak bidders in the more valuable band A while weak bidders took it more often in the other bands. Bidders in competitions took exposure risk less often than lab bidders. This holds true for strong and weak bidders and all levels of exposure risk. Bidders in both the lab and the competition bid up to their valuations instead of reducing demand and terminating the auction at low prices.*

Tables 5.8 and 5.9 show the share of bidders who took the different levels of exposure risk in both value models. In the base value model, the competitive situation made it comparably easy for strong bidders: With fourteen items on sale in band A, strong bidders expected to win four items each while the two weaker bidders had to split the remaining six items. Therefore, weaker bidders faced the threat of not winning four items without taking exposure risk. This explains why weak bidders took exposure risk more often than strong bidders in the base value model.

Bidder	Strength	No. of bidders (=100%)	Exposure1 $bid > v_A$ (%)	Exposure2 $bid > 1.2 * v_A$ (%)	Exposure3 $bid > 1.4 * v_A$ (%)
Lab	All	80	88.75	72.50	56.25
Lab	Strong	39	87.18	64.10	53.85
Lab	Weak	41	90.24	80.49	58.54
Comp	All	36	86.11	55.56	36.11
Comp	Strong	18	83.33	55.56	22.22
Comp	Weak	18	88.89	55.56	50.00

Table 5.8: Share of bidders taking different levels of exposure risk in band A, base value model

Band	Strength	No. of bidders (=100%)	Exposure1 $bid > v_A$ (%)	Exposure2 $bid > 1.5 * v_A$ (%)
A	All	64	79.69	21.88
A	Strong	24	91.67	25.00
A	Weak	40	72.50	20.00
B	All	64	81.25	17.19
B	Strong	33	90.91	12.12
B	Weak	31	70.97	22.58
C	All	64	84.38	25.00
C	Strong	36	86.11	11.11
C	Weak	28	82.14	42.86
D	All	64	81.25	20.31
D	Strong	34	91.18	14.71
D	Weak	30	70.00	26.67

Table 5.9: Share of bidders taking different levels of exposure risk, multiband value model

Value model	Bidder	Bidders with negative payoff	Total bidders (=100%)	Share (%)
Base	Lab	19	80	23.75
Multiband	Lab	5	64	7.81
Multiband$_{small}$	Lab	4	32	12.50
Base	Comp	5	36	13.89

Table 5.10: Bidders with negative payoff

Bidders in the multiband setting faced a different strategic situation. With only six items per band, it was very likely that either two bidders would win three items each, or three bidders would win two items each. Weak bidders were less willing to take exposure risk and to risk ending up with only one item. Thus, the strong bidders faced strong competitors within the band, forcing them to take exposure risk themselves. Within all four bands, strong bidders took exposure risk more often than weak bidders.

In competitions, strong as well as weak bidders took exposure risk less often than bidders in the lab. This difference grows for higher levels of exposure, i.e., the risk of ending up with negative payoff.

Table 5.10 shows that bidders in competitions successfully avoided negative payoffs by taking exposure risk at higher levels more prudently. While 23.75% of the bidders in the lab received negative payoff, only 13.89% of the bidders in the competition had a loss due to taking an exposure risk. Since bidders had four bands with complementarities to coordinate in the multiband value model, the risk was smaller and only 7.81% of bidders in the multiband and 12.50% in the multiband$_{small}$ value model made negative payoff.

We did not find evidence of successful tacit collusion in SMRA, neither in the lab nor in the competition, although the first activity level gave bidders the option to bid on smaller bundles without losing the chance of bidding on larger bundles in the second activity phase. Bidders signaled their preferences, but none of the auctions resulted in agreements at low revenue. Even though bidders who rate their valuations as weak have an incentive to reduce the number of items they bid on in order to keep prices low and win a small bundle with higher payoff, we could observe this behavior neither in the lab nor in the competition. Final allocations of all auctions only emerged after the weakest bidder was overbid. Nevertheless, it is interesting to observe signaling behavior in the lab. We focus our analysis on jump bids and bids on own items.

By using a jump bid and bidding more for an item than required by the auction rules (i.e., price of standing bid plus minimum increment), a bidder can demonstrate a strong will to win the item and try to discourage other bidders from bidding on the same item. The same signal can be given by raising the bid on an item for which the bidder already holds the standing high bid.

Result 5: *Jump bids were used by all bidders in all treatments: 41.05% to 61.42% of all bids were jump bids. Bidders in the lab used jump bids more often than bidders in the competition (Lab $\succ^*$ Comp, $p = 0.0103$). Bidders in the competition focused on lower jump bids.*

Table 5.11 shows that jump bids were heavily used across all bands. The number of jump bids varied slightly between 41.05% for band B without complementarities in the competition (base value model) to 61.42% for band A with complementarities in the lab (multiband$_{\text{small}}$ value model).

Bidders in competitions used jump bids less frequently than bidders in the lab in all three value models. This is in line with the result that bidders in competitions reached efficiencies similar to those of bidders in the lab, while the total revenue of competitions was lower. One reason might be that more bidders in competitions considered the risk of paying more than necessary by using jump bids.

Table 5.12 shows the number of jump bids of different sizes as share of the

Value model	Bidder	Band	No. of jump bids	No. of bids	Share (%)
Base	Lab	All	22.45	40.39	55.59
Base	Lab	A	12.91	23.23	55.60
Base	Lab	B	9.54	17.16	55.57
Multiband	Lab	All	31.50	59.52	52.93
Multiband	Lab	A	8.09	15.33	52.80
Multiband	Lab	B	6.88	14.72	46.71
Multiband	Lab	C	9.22	15.72	58.65
Multiband	Lab	D	7.31	13.75	53.18
$\text{Multiband}_{\text{small}}$	Lab	All	32.31	59.75	54.08
$\text{Multiband}_{\text{small}}$	Lab	A	13.28	21.63	61.42
$\text{Multiband}_{\text{small}}$	Lab	B	5.88	12.53	46.88
$\text{Multiband}_{\text{small}}$	Lab	C	6.44	13.50	47.69
$\text{Multiband}_{\text{small}}$	Lab	D	6.72	12.09	55.56
Base	Comp	All	16.42	36.22	45.32
Base	Comp	A	8.58	17.14	50.08
Base	Comp	B	7.83	19.08	41.05

Table 5.11: Jump bids per bidder by band

total number of bids. Low jump bids are those bids which exceed the ask price by 1 or 2 Franc (two lowest steps of the click-box), medium jump bids exceed the ask price by 5 or 10 Franc (two steps in the middle) and high jump bids by 20 or 50 Franc (two top steps). Low jump bids can be used to avoid ties. Bidders in both the lab and the competition used low jumps quite often (Lab $\sim$ Comp). Medium and high jump bids are used to demonstrate strength and discourage other bidders from bidding on this very block. We found that bidders in competitions used medium and high jump bids significantly less often than lab bidders (medium: Lab $\succ^{**}$ Comp, $p = 0.0004$; high: Lab $\succ^{**}$ Comp, $p = 0.0032$). In the multiband value model, high jump bids made up the biggest bulk of jumps altogether, while in the $\text{multiband}_{\text{small}}$ value model low jumps were used more often. This might be explained by the lower competition within each band induced by the flexible complementarity structure of the multiband$_{\text{small}}$ value model.

Value model	Bidder	No. of bids (=100%)	All jumps (%)	Low jumps (%)	Medium jumps (%)	High jumps (%)
Base	Lab	40.39	55.59	21.11	21.02	13.46
Multiband	Lab	59.52	52.93	18.09	14.12	20.71
Multiband$_{\text{small}}$	Lab	32.31	54.08	23.27	12.61	18.20
Base	Comp	36.22	45.32	24.77	12.81	7.75

Table 5.12: Jump bids per bidder by step size (all bands)

Result 6: *Bidders of all treatments placed bids on items that they had provisionally won in the previous round (bids on own items). In bands of higher valuation (band A), bidders used a higher number of bids on own items than in other bands across all three value models.*

Support for result 6 is presented in Table 5.13. Remarkably, bidders in competitions placed an almost five times higher share of bids on their own items in the more valuable A band (9.40%) than in band B (1.89%). Bidders in the lab spread bids more equally on their own items in bands A (6.73%) and B (4.01%). In the multiband$_{\text{small}}$ value model, bidders used twice as many bids on their own items (4.34 or 7.27%) as in the multiband value model (2.11 or 3.54%). They focused these bids on the A band, which was most valuable, while in the multiband value model, bidders spread their bids more equally among bands. One reason might be that bidders expected higher chances of winning valuable A blocks, since it was not clear upfront how the band would be split. Due to the flexible structure of complementarities, bidders with high base valuations as well as bidders with high complementarities for small bundle sizes could try to succeed in the A band.

Value model	Bidder	Band	No. of bids on own items	No. of bids	Share (%)
Base	Lab	All	2.25	40.39	5.57
Base	Lab	A	1.56	23.23	6.73
Base	Lab	B	0.69	17.16	4.01
Multiband	Lab	All	2.11	59.52	3.54
Multiband	Lab	A	0.68	15.33	4.44
Multiband	Lab	B	0.48	14.72	3.29
Multiband	Lab	C	0.59	15.72	3.75
Multiband	Lab	D	0.36	13.75	2.61
Multiband$_{\text{small}}$	Lab	All	4.34	59.75	7.27
Multiband$_{\text{small}}$	Lab	A	2.22	21.63	10.26
Multiband$_{\text{small}}$	Lab	B	0.88	12.53	6.99
Multiband$_{\text{small}}$	Lab	C	0.75	13.50	5.56
Multiband$_{\text{small}}$	Lab	D	0.50	12.09	4.13
Base	Comp	All	1.97	36.22	5.44
Base	Comp	A	1.61	17.14	9.40
Base	Comp	B	0.36	19.08	1.89

Table 5.13: Bids on own items per bidder

5.4.3 Bidder behavior in the CCA

The two phases of the CCA design put bidders in different strategic situations. In the primary bid rounds, bidders can only accept prices and state their demand by submitting a single bundle bid per round. The strategic decisions are limited mainly to the question of whether a bidder wants to bid straightforwardly or not. In the supplementary bids round, bidders can choose the number of package bids, the packages, and the bid price. We start by analyzing the considerably more complex supplementary bids round.

Result 7: *Bidders in all treatments bid close to their valuation in the supplementary bids round. Several bidders bid below their valuation and the slope of the regression is less than one in all three value models in the lab and in the competition.*

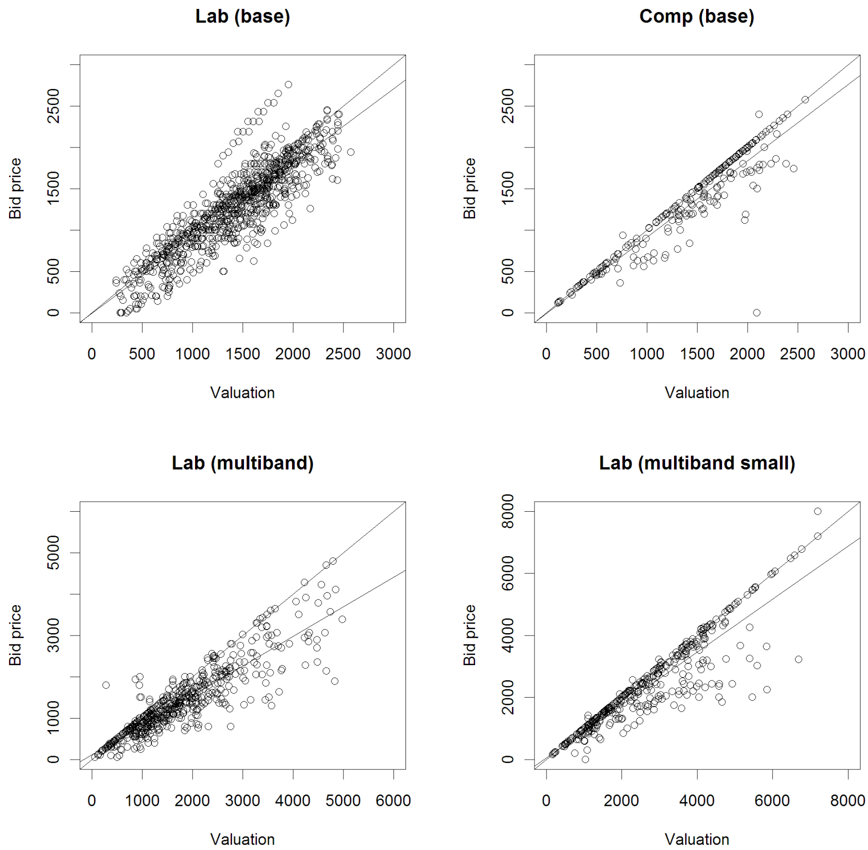

Figure 5.5: Bid prices in the supplementary bids round

Figure 5.5 shows whether bidders bid below, at, or above their valuation on a bundle in the supplementary bids round. Interestingly, most supplementary bids are at or below their valuation. In the base value model in the lab, some bids were above the valuation. The figure also plots a regression line in addition to the diagonal with a slope of one. The slope of this regression can serve as a benchmark. For the base value model, the slope is 0.90 (adjusted $R^2 = 0.77$) for data from the lab and 0.92 (adjusted $R^2 = 0.87$) for the bid data from the competition. In the multiband value model, the slope of the regression is 0.72 (adjusted $R^2 = 0.79$) and in the multiband$_{\text{small}}$ value model it is 0.85 (adjusted $R^2 = 0.83$).

Note that bidders in the competition knew about the possibility of speculation and they bid either at their valuation or below; almost nobody bid above their valuation in competitions. In the base value model in the competition, only 3.24% of the bids were above their valuation, while in the lab 22.66% of the bids were above the valuation. In the multiband value model, only 8.26% of the bids were above the valuation and in the multiband$_{\text{small}}$ value model only 4.34%. A single lab bidder in the base value model bid consistently above his valuations. Three out of four of his bids were above his valuation, which accounted for almost half of all the bids above the valuation. Without this bidder, only 12.81% of the bids were above valuations of lab bidders in the base value model.

Next, we wanted to understand the selection of bundles in the supplementary bids round. With a VCG auction rule and independent private values, bidders have a dominant strategy to bid on all bundles with a positive payoff at the prices of the last primary bid round (section 2.6.1.1). The CCA does not have a VCG payment rule and thus no dominant strategy either. It is not obvious how bidders might strategically select their bundles in such a setting.

Result 8: *In the supplementary bids round, bidders in the lab bid only on 23.67% or 11.36 bundles out of 48 potential bundles they could bid on in the base value model, on 8.33 of the 2,400 possible bundles (0.35%) in the multiband value model, and on 11.50 of 624 possible bundles (1.84%) in the multiband$_{small}$ value model. In the competition, bidders submitted an average of 6.08 bids (12.67%) in the base value model.*

Lab bidders in both multiband value models actually submitted fewer bundle bids in absolute numbers than in the smaller base value model. Some bidders in the small value model tried to bid on almost all bids in the supplementary bids round, while we conjecture that in the multiband value models this was perceived as impossible. We had bidders who submitted 36 out of 48 possible bundle bids in the base value model. In contrast, in the multiband

and multiband$_{\text{small}}$ value models, bidders submitted at most 22 bids in the supplementary bids round.

We made similar observations in the field. In the L-band auction in the UK in 2008, for instance, 17 specific lots were sold, resulting in 131,071 possible bundles, but the 8 bidders only submitted up to 15 bids in the supplementary bids round (Cramton, 2008). Similarly, in the 10-40 GHz auction in the UK in 2008, bidders could bid on 12,935 distinct bundles. 8 bidders only submitted up to 22 bundles, while one submitted 106 and another 544 bundle bids (Jewitt and Li, 2008).

There are several conjectures to explain this phenomenon. One explanation is that bidders only value a small number of bundles in the field. Bidders may also be simply unprepared and may not have fully understood the consequences of particular strategies in the CCA (Jewitt and Li, 2008). This might hold true for the lab, the competition, and the field to some extent. Another explanation is that bidders in the field do not have a pure private values model. In particular, strong bidders might try to maximize their chance of winning their preferred allocation, which is a strategic goal of the company, and minimize the possibility of winning a less attractive combination. In many cases, it is also difficult to trade off various possible smaller allocations for money, which is assumed in a pure private values model with quasi-linear utilities.

Bidders in the lab or in the competition might have been guided by similar considerations, although this is risky, as bidders might end up winning nothing. In the competition, bidders submitted even fewer bids in the supplementary bids round than in the lab. On the basis of reports given by participants after the competition, we saw that bidders with a high base valuation particularly wanted to maximize their chances of winning bundles with the highest valuation, assuming this would also yield the highest payoff. To illustrate this point, let us assume a setting similar to our situation in band A of the base value model with fourteen items and four bidders, each interested in four items. If

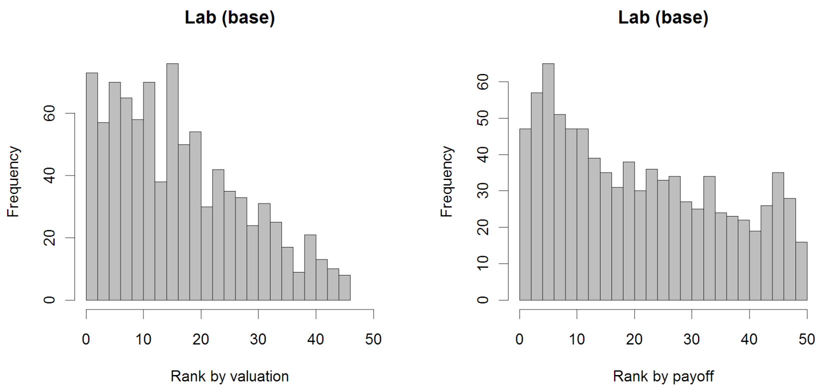

Figure 5.6: Rank of supplementary bids by valuation and payoff at final clock prices, base value model, lab

three strong bidders submitted a bid of 40 for four items and the weak bidder submits a bid of only 30 for four items, the three strong bidders will win. If, however, one of the strong bidders submitted a bid for two items at 15 in addition, the large coalition would win, but the strong bidder would win only the small package of two items.

Result 9: *Bidders in the lab and in the competition used simple heuristics to select bundles in the supplementary bids phase. In band A of the base value model, they experienced the highest synergies with four items. As a consequence, they submitted many bids with four items in the A band. Strong bidders in the base value model submitted significantly fewer bids on bundles with less than four items than weak bidders did. Similarly, in the multiband value model bidders had the highest synergies for two items and, actually, most of their bundles were packages with two items in a band. In the* $multiband_{small}$ *value model, bidders had flexible complementarities, so we restricted the analyses to the valuation rank and the payoff rank. Bidders submitted a larger number of bids on bundles with a high payoff at final clock prices in all three value models, especially in both of the multiband value models.*

We began with the base value model. We calculated ranks of each bid sub-

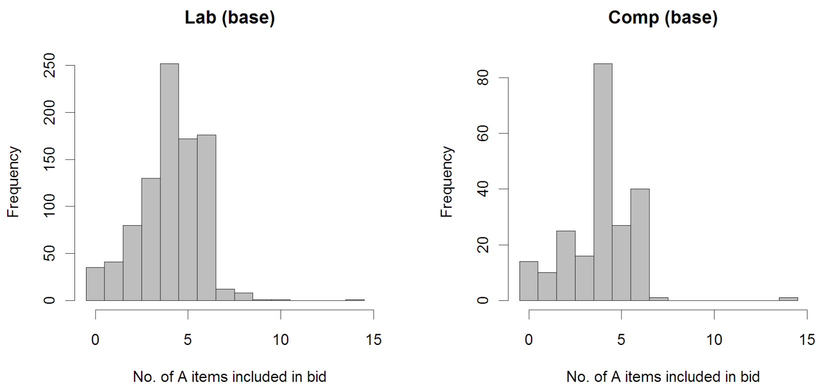

Figure 5.7: Number of A items in supplementary bids, base value model, lab and competition

mitted in the supplementary bids phase, one rank based on the valuation of the bundle for a bidder, another rank based on the payoff the bidder had for the bundle at the end of the primary bid rounds using the ask prices in the final round. Figures 5.6 (lab) and B.11 in the appendix (competition) show that bidders exhibited a slight tendency to select bundles with a better rank based on payoff in both the lab and the competition. However, bidders also submitted a considerable number of bids for which their payoff at final clock prices was low or negative in the base value model.

Then, figures 5.7 and 5.8 reveal that most bids in band A were on four items, where the complementarity was highest, whereas bidders bid on up to six items in band B. There was also a significant difference between weak and strong bidders (figure B.7 in the appendix). While only a few strong bidders submitted bids on less than four items in band A, weak bidders typically submitted such bids. This was even more pronounced in the competition (figure B.12 in the appendix).

The results indicate that bidders in the lab and in the competition did not rely on the ranking of bundles by valuation and payoff, but used information about the synergies in the value models and tried to win the bundles with

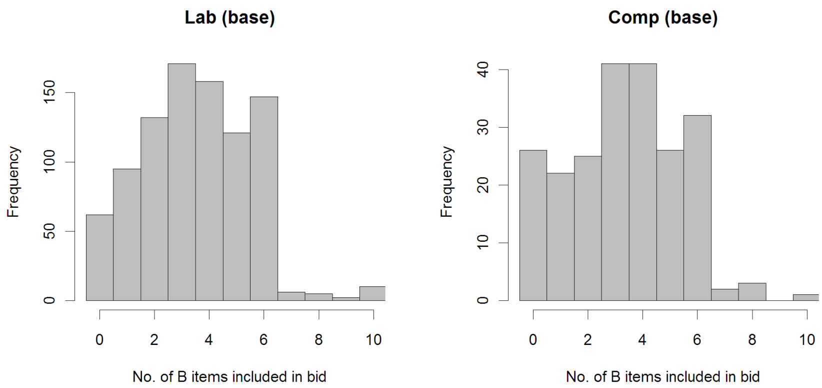

Figure 5.8: Number of B items in supplementary bids, base value model, lab and competition

the highest synergies. Remember that bidders had a spreadsheet to rank-order their bundles by payoff at the prices of the final clock round and based on valuation. Bounded rationality and satisficing behavior, as introduced by Simon (1991), can serve as explanations for such behavior.

We proceeded with the multiband value models. Figures 5.9 and 5.10 show the frequency of bids ranked by valuation or by payoff at final clock prices for both value models. It seems that bidders picked those bundles with the highest payoff after the primary bid rounds, but that those bundles were often worst in terms of their valuation. Bidders often bid on small bundles which were ranked very low compared to large bundles with many items from each band. For the multiband value model, figure B.8 in the appendix shows that most bundles included only two or three items from a band, which was motivated by complementarities for bundles of these sizes in the value model. Since the highest frequencies of all bands are at zero, it also demonstrates that many bundle bids did not include items from all bands.

Finally, we also examined whether bidders bid straightforwardly in the primary bid rounds. In other words, did they select the bundle with the highest payoff in each round? This is the intention of the activity rules.

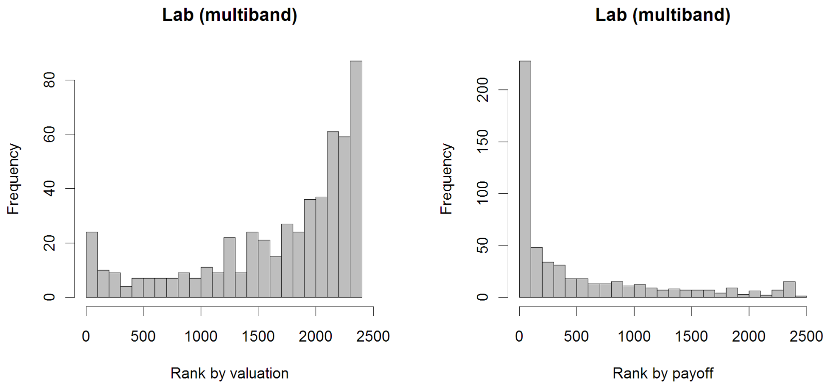

Figure 5.9: Rank of supplementary bids by valuation and payoff at final clock prices, multiband value model

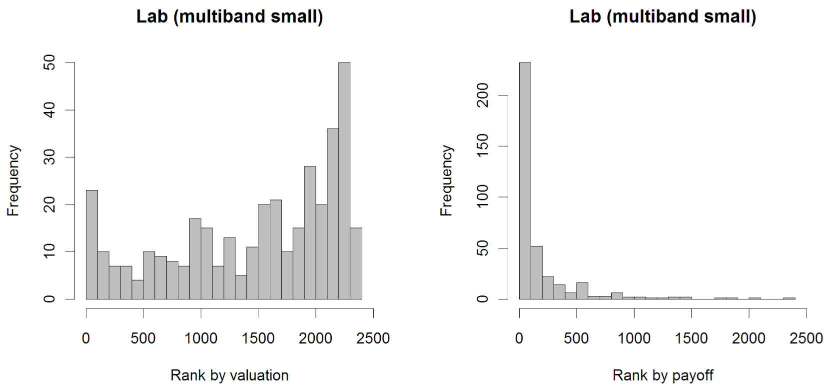

Figure 5.10: Rank of supplementary bids by valuation and payoff at final clock prices, $\text{multiband}_{\text{small}}$ value model

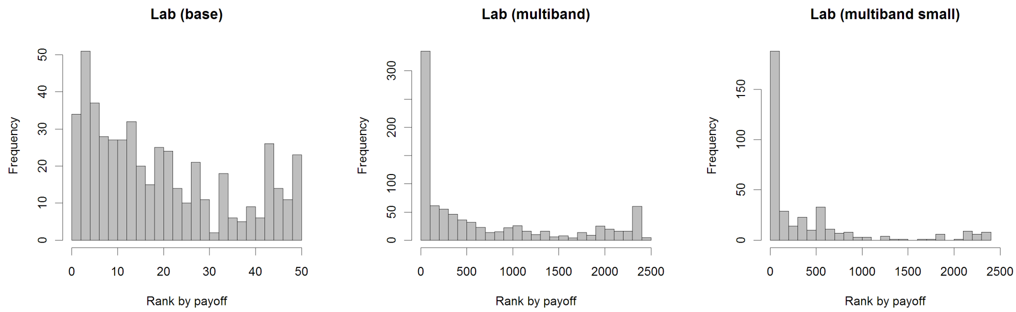

Figure 5.11: Rank of primary bids

Result 10: *In the primary bid rounds bidders did not follow a straightforward bidding strategy in all three value models. Bundle selection followed the same pattern as in the supplementary bids round, guided by synergies in the value model. In contrast to the supplementary bids round, the activity rule also led to a larger number of bundles which were not ranked top in terms of payoff in the primary bid rounds.*

Figures 5.11 (lab) and B.13 in the appendix (competition) show that the ranking by payoff had less of an impact in the base value model and was outweighed by the activity rule, which led bidders to submit large bundles, particularly in the early rounds. Bidders did not bid straightforwardly but focused on the synergies and eligibility in subsequent rounds. Again, figure 5.12 suggests that bidders selected bundles with four to six items in band A.

In the multiband value model, bidders most frequently selected bundles with two or three items in a band, because they exhibited synergies (see figure B.9 in the appendix). Here again, many bundles did not include blocks of all bands. Figure 5.11 shows the rank of bundle bids based on payoff at final clock prices for the multiband and multiband$_{\text{small}}$ value models, exhibiting a strong spike to the left. It can be explained by a number of large bundles with up to six items per band in the multiband setting and up to four items in the multiband$_{\text{small}}$ setting, which yield both a high valuation rank and a high payoff rank at final

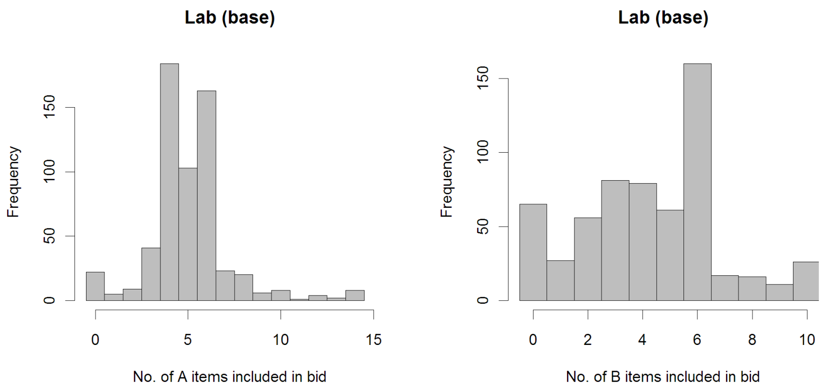

Figure 5.12: Number of items in primary bids, base value model, lab

clock prices. Particularly in the first few rounds, bidders often selected very large bundles which were high in value and payoff at initial prices to preserve a high eligibility.

5.4.4 Summary

One of the main results of our experiments is that the CCA did not yield higher efficiency in the small base value model and was significantly worse in both multiband value models. Revenue was significantly lower in all treatments and sometimes items remained unsold despite sufficient demand. This was due to the low number of bundle bids, the low number of bidders in the setting, and the CCA payment rule. It is interesting to note that if bidders had submitted bids on all possible bundles truthfully, as we did in our simulations, the revenue would have been competitive with the revenue of SMRA in the lab.

In the CCA, bidders submitted only a small subset of all possible bundle bids. In the base value model 11.36 out of 48 possible bundles, in the multiband value model only 8.33 bids out of 2,400 possible bids, and in the multiband$_{\text{small}}$ value model only 11.50 of the 624 possible bundles were submitted by bidders in the supplementary bids round, which was a major reason for inefficiency and unsold items. Bidders used heuristics to select bundles, mainly based on their strengths and the synergies in the value model. In the base value model, strong bidders avoided bids on small bundles in the most valuable A band, while weak bidders bid on smaller combinations as well. The bundle bids submitted in the supplementary bids round were either at the valuation or slightly below in all treatment combinations, which is in line with theoretical predictions.

The observed bundle selection is more difficult to explain theoretically. The bidders had sufficient time to submit as many bundle bids as they wanted, but chose to submit only a few bids. One explanation is that neither bidders in the lab nor those in the competition fully understood the dominant strategy in a VCG mechanism and the theory of core-selecting payment rules. It is also likely that bidders felt unable to submit 624 or 2,400 bundle bids in the multiband settings, and they bid on those that either had the highest payoff after the primary bid rounds (suggesting they had the highest chance of winning), or that had the highest synergies. Such behavior could be explained as satisficing, since bidding optimally did not seem practical.

It might be thought that bidders in high-stakes spectrum auctions behave differently. Interestingly, observations from the field show that bidders also submit only a small number of bundle bids in the supplementary bids round (Hoffman, 2011). An additional reason for strong bidders in the field not to bid on small bundles is that they sometimes have the strategic goal of winning large bundles of licenses on top of budgets earmarked for specific allocations. That alone cannot explain the observations from the field, however. In any case, it seems very likely that bidders in the field, facing several hundred or thousand possible bids, as is typically the case in multiband auctions, also do not bid on a sufficiently large number of bids to guarantee high efficiency in the CCA. In our experiments, this led to the effect that efficiency was very low, items remained unsold, and revenue was much lower than expected.

For bidders in SMRA, exposure risk was a central strategic challenge. In the competition, bidders were more cautious about taking this risk. Jump bids and bids on own items, where the bidder holds the high bid, were used for signaling in both the lab and the competition. Again, bidders in the competition used these tactics more carefully, thus better avoiding the associated risks and achieving higher payoffs. While bidders faced strategic difficulties due to the exposure risk, the SMRA elicited the valuations of bidders on individual items sufficiently well to allow for high efficiency even in the multiband value models. Although bidders with low valuations did have an incentive to reduce demand early in the auction in order to win a small bundle with a high payoff, bidders were not able to terminate auctions at low prices.

Still, our results cannot necessarily be generalized to very different value models. We modeled different types of complementary valuations, but one could also argue for even other types in some settings, such as sub-additivities or inter-band complementarities. Also, we analyzed a pure private values model, while values might be affiliated or budget constraints might apply in some applications.

Chapter 6

Conclusions

It doesn't matter how beautiful your theory is,
it doesn't matter how smart you are.
If it doesn't agree with experiment,
it's wrong.
Richard P. Feynman

Spectrum and the licenses to use it are regarded as a national resource. The sale of spectrum usage licenses to telecommunication service providers should thus ensure that the spectrum is assigned to those who can put it to the best use. Bidders with the highest valuations should get the licenses. The auction should also create an acceptable level of revenue to justify the allocation to losing bidders and to the taxpayers. The Simultaneous Multi-Round Auction (SMRA) has been the de facto standard for selling licenses due to its simplicity and its excellent price discovery. But it imposes serious problems for the bidders, foremost the exposure risk. This has led to a lot of bidding strategies and speculation among bidders. Mobile operators have hired experts and sought advice from consultants to define a bidding strategy for SMRAs. From a market design perspective, no strategies are required to find an efficient allocation, only the knowledge about the valuations is necessary. Bidding strategies are therefore counterproductive and eventually lead to lower efficiency.

Cramton (2009b) suggested a two-phase design called Package Clock or the Combinatorial Clock Auction (CCA), which gives bidders a strong incentive to report their true valuations and promises high efficiency. The first phase, a clock phase, collects one bid per round from each bidder. It reduces value uncertainty and provides some guidance for bidders to focus on the relevant bundles. The second phase is a sealed-bid round in which bidders can bid on any bundle they like. The activity rule gives bidders the incentive to bid truthfully during the first phase, a bidder-optimal core-selecting payment rule protects auctioneers against low revenues and outcomes outside the core. But only VCG gives a dominant strategy to bidders to submit true valuations for all bundles. Bidders in CCAs can still speculate to a limited extent and try to earn a higher profit by deviating from reporting true valuations. If bidders do not submit many bids, efficiency as well as revenue can be comparably low.

The contribution of this work is the lab experiments with realistic settings, in which we compared the CCA to the SMRA. We used different settings which closely resemble the environments of European spectrum auctions: One setting uses the exact bandplan of the 2.6 GHz band in Europe, the other settings resemble environments in which several bands are sold at the same time, as discussed, e.g., in Switzerland. We showed that CCA was not superior to SMRA in the smaller base setting and significantly worse than SMRA in the multiband settings in terms of efficiency. Revenue was lower due to the payment rule of CCA. Performance suffered from the low number of bids submitted with CCA, especially in the larger multiband settings that offered hundreds and thousands of different bundles. Bidders submitted only 0.35% of all possible bundle bids in the larger multiband setting and 1.84% in the smaller multiband setting. Bidding on a larger number of bundles might appear impracticable and bidders might not submit the required number of bids for the auction to terminate with high efficiency. In the lab, in the smaller base setting with fewer options to choose from (48 different bundles), the CCA performed better and efficiency was comparable to that of SMRA. The results of our experiments indicate that CCA appears less suited for large settings in which several bands are sold at the same time. This is in line with, e.g., Hoffman (2011), who questions the suitability of clock-based combinatorial formats for settings with many different regional licenses as in the US or Canada.

In the field, we also observed similar problems. Cramton (2008) showed for the L-band auction in the UK that mobile operators decided to bid on only a small number of bundles in a setting with hundreds of thousands of possible bundles. They did so despite enough preparation and time. One reason might be that determining the valuation of many different bundles is hardly possible since the valuations depend on business cases. Such calculations are very extensive because expectations of future market shares and profits and estimations of the costs involved are required to establish the valuation of a license. If that is the case, preference elicitation is indeed the "bottleneck in the real-world deployment of combinatorial auction formats" (Parkes, 2006). In large settings with lots of different bundles, combinatorial auctions might not lead to superior results.

In our experiments, bidders did not follow a straightforward bidding strategy even though they had the incentive to do so. Instead, they followed simple heuristics and their selection of bundles was mainly driven by the complementarities in the value models. Due to the small number of bids the performance of CCA was not superior to that of SMRA, in contrast to expectations with rational bidders. Such observations question the validity of assumptions of purely rational bidder behavior in game-theoretical models.

An area for future work in this field is the analysis of different approaches to foster preference elicitation and collect more relevant bids from the bidders. Eliciting more valuations could relieve the observed problems of the CCA. Altering some of its rules could allow the CCA to collect more bids. For instance, by allowing more than just one bid per round in the clock phase (comparable to the single-phase Simultaneous Clock), bidders could specify more preferences for different bundles, which would support efficiency and also increase revenue. We do not know of any experimental comparison of the CCA and the single-phase Simultaneous Clock which could highlight the benefits of eliciting more bundle bids.

The bidding language can also be altered. The XOR bidding language lets bidders precisely state their preferences. But at the same time, it requires a huge number of bids to state preferences. Brunner et al. (2010) and Scheffel et al. (2010) have shown that this can be a source of inefficiency. Especially in larger settings with several bands, bidders have to submit an enormous number of bids if they want to express preferences which differ in the number of blocks for several bands. Nisan and Ronen (2001) suggested using dummy items in combination with the OR language to express various preferences, which is then called OR*. Boutilier and Hoos (2001) suggested the $\mathcal{L}_{\mathcal{GB}}$ language, which allows the use of the combinatorial $k - of$ operator applied to a set of atomic bids. That would require fewer bids to reveal more preferences. In addition to submitting bids, bidders could be allowed to specify other types of constraints, such as budget or capacity limits. These constraints could be directly represented in the winner determination.

Independent of the choice of the actual auction design and the specific auction rules, the problems of mobile operators in determining the valuation for many different license bundles remains. Determining a valuation is not easy in the domain of spectrum sales because it involves financial analyses. Bid preparation and also the communication of the bids can be very expensive (Parkes, 2006). With a growing number of possible packages, mobile operators may not be able to determine the valuations for all bundles that are required for high efficiency. Bidders may require help and guidance in the selection of relevant bundles worth determining the valuation for.

In this context, Hoffman (2011) points out the importance of bidder-aide tools. Such tools can be rule-based decision support systems which automatically suggest relevant bundles or even generate bids from input parameters describing the preferences of the bidder. These tools can hardly fit all possible domains but must rather be tailored to the specific needs of the application. In spectrum auctions, they can adopt the structure of business cases to guide the mobile operators. Parkes (2005) also suggested designs in which bidders state preferences that are translated into packages and bid prices using a support tool. This can be an iterative process in which the tool makes suggestions, and the bidder revises his input until he is satisfied with the output. Then he can submit the bids to the auctioneer. The practical implementation also needs to address questions of liability in the translation from preferences into bids. More research is required in this field, especially in the case of high-stake auctions such as spectrum sales.

Altogether, we need to better understand the behavior and limitations of bidders in the field and incorporate these in future designs. Bidder behavior in our lab experiments and also in the field did not follow game-theoretical assumptions of purely rational bidders for the reasons mentioned above. Comprehensive auction rules as those of the CCA might overcharge not only subjects in the lab but also bidders in the field (Cramton, 2009b; Hoffman, 2011). Thus, we argue that more empirical work in this field is necessary to pin down bidder characteristics and their limits. Mechanism design cannot obstinately build on the assumption of purely rational choice behavior when it comes to the design of auction rules which should perform well in the field.

Appendix A

Pre-study with competitions

This appendix provides detailed information on the pre-study (explained in section 4.4.3) in which we analyzed the effect of the level of bidder preparation on bidding behavior and auction outcome.

A.1 Experimental setup

This section explains the auction rules as well as the economic environment used in the lab and defines the value model, which was based on utility points.

A.1.1 Auction rules and economic environment

We implemented almost all of the auction rules of the German 4G auction in 2010 as described in section 4.4.3.1 to preserve the complexity of the decision space faced by bidders. Nevertheless, minor simplifications were necessary, since the field auction lasted for more than 3 weeks, and we aimed at a duration of less than 45 minutes per auction.

We allowed all bidders to bid on and win at most two blocks in the 0.8 GHz band and at most four blocks in the 2.6 GHz band. All blocks were abstract, only the fourth and fifth blocks in the 1.8 GHz band were concrete. This was the case as they were of specific interest to some of the bidders (see figure A.1) and selling them abstractly would have changed the market structure considerably. All bidders started with maximum eligibility, i.e., they could bid on all blocks. The activity phases were reduced to 3 stages (50%, 75%, and 100%) to reduce the time required for an auction. The experiments used an ***artificial currency (AC)*** to reduce the order of magnitude from the field. The entries for the click-box were adjusted accordingly: The bidders could use jumps of 1, 2, 5, 10, 20, or 50 AC. Start prices were set at 20 AC per block, the minimum increment at 15 AC. The round duration was set at 10 minutes for the first round and 3 minutes for subsequent rounds, which gave subjects enough time to decide on and to place their bids.

To recreate closely the situation in the field, we defined four different ***types of bidders***: Very Big (VB), Big (B), Small (S), and Very Small (VS). These four types differed with respect to their valuations, budget constraints, and the spectrum they already owned prior to the auction. One bidder of each type participated in each auction.

We restricted the set of auctioned licenses to the paired licenses (i.e., 28 blocks), which is in line with other spectrum auction experiments (Seifert and Ehrhart, 2005). The organization of the blocks into four bands and the distribution of the pre-owned spectrum was preserved, which strongly influenced bidder preferences (section A.1.2). Figure A.1 shows the bandplan with the spectrum bands in which blocks were sold: The white color indicates blocks to be auctioned in the experiment, while the shaded blocks indicate spectrum already owned by bidders. This corresponds exactly to the situation encountered in the field (figure 4.1).

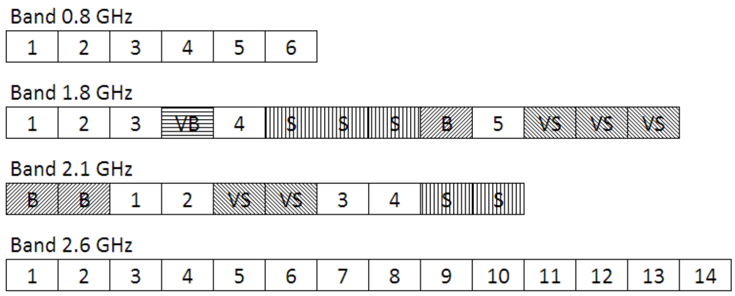

Figure A.1: Bandplan in the lab including pre-allocated spectrum

A.1.2 Value model

The bidder valuations in the German 4G auction had some key characteristics: Some of the spectrum on sale was located in between pre-owned spectrum. Therefore, the valuations for the relevant blocks differed among bidders. Valuations exhibited strong complementarities due to the technologies to be implemented. Especially in the 0.8 GHz and 2.6 GHz bands, the bidders required two or four blocks respectively to fully support the upcoming LTE standard[1] and to guarantee peak data rates for users. Implementing LTE on fewer blocks was less valuable. We assume at least some of the bidders had budget constraints across all bands rather than pure private values.

Therefore, in our experiments, we provided each bidder with an overall budget limit and a utility ranking of all possible allocations. The relative strengths and aspirations of competitors in the German 4G auction were discussed in the media[2] and we can assume that bidders had an understanding of the ranking of the budgets of all bidders. Similarly, we modeled budget constraints for the different bidder types with uniform distributions, and the parameters were common knowledge:

[1]LTE (Long Term Evolution) is a technological standard of the fourth generation which promises higher bandwidth for mobile communication services than older standards

[2]E.g., http://www.spiegel.de/wirtschaft/unternehmen/0,1518,688040-2,00.html

- Very big bidder: 600 to 900 AC
- Big bidder: 450 to 650 AC
- Small bidder: 300 to 500 AC
- Very small bidder: 200 to 350 AC

Bidders could bid up to their budget limit and try to win the most preferred allocation. If the budget limit was exceeded at the end of an auction (budget break), the corresponding bidder utility for this auction was zero. Temporarily exceeding the budget limit during the auction had no negative effect for the bidder. No additional payoff was created by unused budget.

The bidders received ***utility points (UP)*** from winning blocks with higher utility for sets of adjacent blocks. The smallest possible set is a single block which is not located next to an existing block owned by the winning bidder. In general, the more adjacent blocks within a band a bidder won, the higher the utility of this band, i.e., the more utility points he would gain.

The ***chunk utility*** $c_{i,m}(s)$ of bidder i for such a set s of adjacent blocks in band m is a uniformly distributed random variable drawn from $[c_{i,m}^{min}(s), c_{i,m}^{max}(s)]$. The bounds for the uniform distribution of $c_{i,m}(s)$ can be found in table A.1.

Band (m)	0.8 GHz		1.8 GHz					2.1 GHz				2.6 GHz			
No. adjacent blocks (s)	1	2	1	2	3	4	5	1	2	3	4	1	2	3	4
$c_{i,m}^{max}(s)$	5	75	2	8	15	15	17	5	11	11	20	4	6	10	50
$c_{i,m}^{min}(s)$	0	70	0	4	9	10	10	0	6	9	15	1	4	7	40

Table A.1: Ranges for chunk utilities

Since table A.1 gives the $c_{i,m}(s)$ for the combination of pre-owned and new spectrum of the bidder, e.g., winning two blocks in the 2.1 GHz band would give four adjacent blocks to the bidders B, S, and VS, but only two adjacent blocks for VB (see figure A.1). The utility resulting from winning these two blocks would therefore differ as well. We get bidder i's utility $u_{i,m}$ of an entire band m by adding up all chunks $c_{i,m}$ owned by bidder i within band m: $u_{i,m} = \sum_{k=m} c_{i,k}(s)$. Free disposal was given, but acquiring more spectrum than defined in table A.1 did not result in higher utilities.

The total utility U_i of bidder i's allocation is the sum of the utilities of all bands: $U_i = \sum_{m=1}^{4} u_{i,m}$

This deviates from quasi-linear utility functions as they are used in game-theoretical analysis, but can be motivated by the crucial value of the spectrum to participating companies. The valuation structure depending on pre-owned spectrum serves well for the purpose of this pre-study, i.e., it helps create a complex environment.

A.2 Treatment structure and organization

In total, we ran eight auctions in lab experiments and eight auctions in competitions using eight different value model instances. The experiments were conducted at the TU München from November 2009 through July 2010 with the MarketDesigner (www.marketdesigner.org) software. Altogether, 16 subjects were involved. The lab experiments and the competitions differed only in the level of bidder preparation.

No subject in the lab experiments ***(Lab treatment)*** had ever participated in a lab experiment on auctions before. Lab participants did not have to prepare for the experiment in advance. On the day of the experiment, the subjects were first introduced to the experimental setting, the auction rules, and the value model. Correct understanding of the auction rules was ensured with a questionnaire which all subjects had to fill in. Prior to the first auction, the software was explained and a test auction was conducted to familiarize all subjects with the user interface. The complete introduction took about one hour. At the beginning of each auction, participants received their individual valuations and budget limits. Subjects were compensated financially: The total compensation was made up of a 20 Euro show-up reward and an allocation reward. The utilities of the final allocations were translated into Euros with a conversion factor of 15 utility points to 1 Euro. On average, each subject received 67.62 Euro.

The competitions ***(Comp treatment)*** were conducted with subjects who went through extended training: Bidders were recruited among students who attended a lecture on auction theory. Two weeks before the auctions were conducted, they received the same introduction as in the Lab treatment, expanded with a broad overview of spectrum sales through SMRA, known strategies and past experiences. Participants were assigned to groups of three. During the two weeks prior to the experiment, they were asked to prepare comprehensive strategy papers (up to ten pages in size) outlining goals and tactics for each bidder role. The strategy papers were graded. The results of the competitions were rewarded as in the lab: Each participant received a show-up reward of 20 Euro and the utilities of final allocations were converted into Euro. On average, each participant earned 78.29 EUR.

A.3 Results

Basic tactical instruments in SMRA are discussed in the literature (e.g., Cramton et al. (2006a), Porter and Smith (2006), Salant (1997), Boergers and Dustmann (2003)): The auction rules give room for various types of signaling, budget bluffing, budget binding, eligibility parking and demand reduction. Some of the tactics used in the German 4G auction, such as signaling and budget bluffing, can be analyzed using the publicly available data. However, most of the tactical instruments are difficult to quantify without knowing the exact budgets and valuations of the bidders. Take demand reduction as an example: It can be caused either by a tactical decision or simply by a budget limit.

The goal of this pre-study was to investigate differences in bidding behavior due to differences in the preparation level of bidders in the Lab and Comp treatments. Therefore, we focus our analyses on various signaling activities, measures of budget bluffing, and eligibility management. We also briefly report the differences in the overall auction results. Where possible, we compare both treatments to field data from the German 4G auction. We applied the nonparametric Wilcoxon rank sum test (Hollander and Wolfe, 1973) to test the significance between the treatments: $\sim$ is used to indicate an insignificant order, $\succ$ indicates significance at a 10% level, $\succ^{*}$ indicates significance at a 5% level, and $\succ^{**}$ indicates significance at a 1% level.

A.3.1 Auction outcomes

In both treatments, subjects were incentivized to maximize utility based on a given budget limit in the auction. Therefore, we compare the treatments by *overall utility* gained in the auctions, measured in utility points (UP), and the *used budget* as a share of the total budget of each bidder.

One would expect that the preparation prior to the experiment and the application of tactics during the auctions would lead to higher overall utility or lower revenue. But this must not necessarily be the case.

Result 1a: *Comp bidders achieved significantly higher utility than Lab bidders (Comp $\succ^{*}$ Lab, p=0.0249).*

Comp bidders won an allocation worth 377.75 utility points on average, while Lab bidders' allocation achieved a utility of only 316.25 utility points on average. That implies that Lab bidders were not able to coordinate the distribution of spectrum among themselves as well as the Comp bidders. Furthermore, if we measure coordination by the number of high-value bundles (as defined by technological requirements, e.g., 4 blocks in the 2.6 GHz band), we find that Comp bidders won more such bundles than Lab bidders (Comp $\succ$ Lab, p=0.0780).

At the same time, Comp bidders utilized their allocated budget more efficiently (Figure A.2).

Result 1b: *Comp bidders paid lower prices for the spectrum they won. They saved a larger share of their budget (Comp $\succ$ Lab, p=0.0575).*

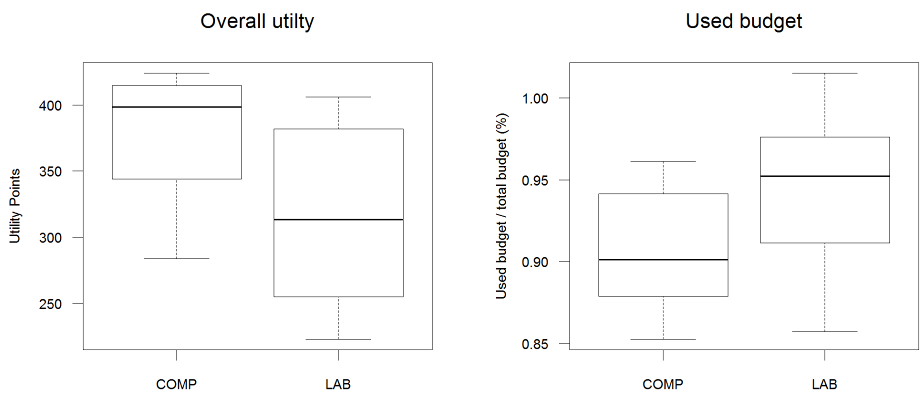

Figure A.2: Overall utility and used budget

In the Comp treatment, an average of 90.7% of the bidders' budgets was paid to the auctioneer. Lab bidders paid an average of 94.4%. Hence, Lab bidders paid significantly more for less attractive allocations.

Another observation is the distribution of the budget over spectrum bands. Figure A.3 shows the development of average prices by band over the auction duration, which is scaled to 100% to facilitate the comparison. Similar to the observations in the field, the 0.8 GHz band had the highest utility for all bidders in the experiment (table A.1): Winning two blocks resulted in up to 75 utility points. The second highest utility reward (up to 50 points) was provided by four blocks in the 2.6 GHz band. Thus the relation between the potential

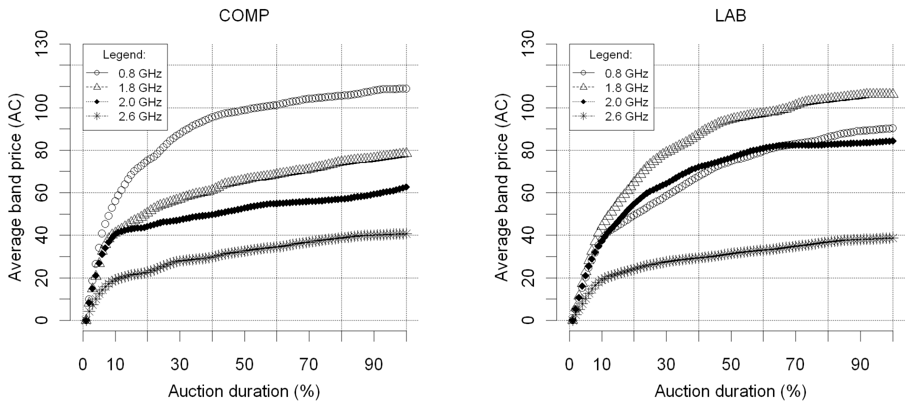

Figure A.3: Average band prices for Comp and Lab

values of these two bands was $75/50 = 1.5$ according to the value model. In the Comp treatment the levels of the final prices reflected this relationship very well: The price of one block in the 0.8 GHz band was the highest (approx. 110 AC) and in the 2.6 GHz band the second highest (approx. 40 AC). The relationship of prices for the two most valuable allocations in 0.8 GHz and 2.6 GHz bands was $(2 * 110)/(4 * 40) \approx 1.4$ which is close to the 1.5 of the underlying value relationship. Lab bidders, on the other hand, did not focus their bidding to the same extent: The price of the 0.8 GHz band was just 90 AC (while the 1.8 GHz band was more expensive) and one block in the 2.6 GHz band cost 40 AC on average. This equals a price relationship of ≈ 1.1.

A.3.2 Signaling

Signaling was the most often used tactic in the field. Mobile operators released public statements before and during the auction which gave some indication of their goals and their assessment of the market. During the auction, jump bids were used heavily. In the public data, we found that 8.1% of all bids were jumps, i.e. higher than required by the auction rules. 2.2% of bids were placed on bidders' own blocks, i.e. on blocks for which the bidder was the provisional winner. This is obviously a form of signaling since, according to the auction rules, the bidder need not raise the bid in such a case. Bids were also placed on blocks which were not the cheapest within a band of identical blocks. This tactic could be used to intentionally overbid the previous winner, which is a signal visible to all bidders.

Applying these tactical instruments successfully requires preparation and a clear goal for the auction. As expected, in our experiments Comp bidders applied more of these tactics:

Result 2: *Comp bidders placed more bids on their own blocks than Lab bidders (Comp $\sim$ Lab, p=0.2010).*

We found that in Comp treatments 0.21 bids per round were placed on bidders' own blocks, which compares to only 0.12 bids in the Lab setting. In the field, this tactic was heavily applied by TO2 (perceived to be the weakest bidder), which placed fourteen bids on its own blocks. One application of this tactic is to avoid the situation of binding budget constraints. By raising his own bid, bidder A can reach a price which prevents bidder B from placing the same bid and becoming the new high bidder. Without using this tactic, bidder A would have to bid at least another minimum increment to win back this block. Since this tactic requires a sound strategic goal and an estimation of the competitors' budget constraints, it was less often applied by Lab bidders.

Result 3: *Lab bidders placed significantly more bids on blocks which were not the cheapest (Lab $\succ^{**}$ Comp, p=0.0068).*

Straightforward bidding implies choosing the cheapest block within a band of identical spectrum (section 2.6.2). However, there were deviations from this behavior both in the field and in our experiments. Such bids can be used to specifically target a selected bidder in order to find a compromise. We counted 0.66 bids per round that were not on the cheapest available blocks in the Comp treatment and 1.14 in the Lab treatment. In the field, bidders placed 1.39 bids per round on blocks which were not the cheapest within the corresponding band. Interviews with bidders of the Lab treatment revealed that participants did not pay a lot of attention to the selection of the blocks, especially in the 2.6 GHz band, when prices differed only a little. Comp participants, on the other hand, pointed out that they checked price levels thoroughly and deliberately did not bid on the cheapest block in a band, which was possible because of better task management within a bidding team compared to individual bidders in the Lab treatment. They were also aware that such behavior would be interpreted by their opponents. Such bids observed in the field can be attributed to tactical considerations.

Result 4: *Comp bidders used jump bids more effectively than Lab bidders.*

Jump bids can be applied to quickly raise the price level in a band (high jumps), to avoid ties (small sized jumps), or to effectively demonstrate or signal the willingness to pay a high price for the block (medium to high jumps). At the same time, a considerably high jump puts the bidder at risk of overpaying.

Measure	Comp	Lab	p-value
Number of high jumps per auction	3.94	7.08	0.0638
Average share of jumps in 0.8 GHz	50%	40%	0.0329
Average jump premium (in AC)	3.2	16.2	0.0325

Table A.2: Jump bids

The sunk cost assumption for budgets in the experimental setting led to a comparatively high level of jumps in Lab and Comp, because bidders had no incentive to save any of their budget (Table A.2). Data from the field is not directly comparable to the experimental data, since the the German 4G auction lasted more than 3 weeks and 224 rounds.

Comparing the experimental treatments, we find result 4a:

Result 4a: *Lab bidders used high jumps to a significantly greater extent (Lab $\succ$ Comp, p=0.0638).*

We define high jump bids as bids that exceed the required minimum increment by 10, 20, and 50 AC (click-box). Lab bidders placed an average of 7.08 high jumps per auction, which compares to only 3.94 for Comp bidders.

Even though the overall number of high jumps was higher for the Lab setting, Comp bidders used the jumps strategically and applied them for the most valuable spectrum.

The total number of jump bids alone is not sufficient for an understanding of differences in bidding behavior. The desired effects and risks of a jump bid depend on its position and its relation to the average price in the corresponding band. Therefore, we also compared the bands in which jump bids were used (result 4b) as well as the average jump premium paid (result 4c).

Result 4b: *Comp bidders focused their jump bids on the most important blocks, i.e., the 0.8 GHz band (Comp $\succ^*$ Lab, p=0.0329).*

We found a significant difference in the ratio of jump bids that were placed in the hot spot band 0.8 GHz: Comp bidders recognized the high importance of the 0.8 GHz band and the need to coordinate in this band. Therefore, they concentrated their comparatively smaller total number of jump bids on this band: They placed 50% of their jump bids in the 0.8 GHz band, while Lab bidders did not recognize this importance and spread their jumps across all bands (only 40% in the 0.8 GHz band). This result is in line with findings on average final prices for bands: Comp bidders paid a significantly higher price for the 0.8 GHz band (p=0.0015) and significantly lower prices for the 1.8 and 2.0 GHz bands (p=0.0035 and p=0.0249 respectively). The price for the second most important 2.6 GHz band was higher but not significantly. This implies that Lab bidders were not able to estimate possible final allocations given the market structure.

Jump bids can be a useful strategy, but they bear a certain risk of overpaying. In the following, we consider the jump bids which won at the end of the auction, and define ***jump premium*** as the difference between the jump bid price and the average price of all other blocks in the corresponding band. Following this definition, the jump premium represents the lost budget which the bidder could have saved by making a lower bid.

Result 4c: *Lab bidders paid a significantly higher jump premium than Comp bidders (Lab $\succ^*$ Comp, p=0.0325).*

We found that Lab bidders paid, on average, a premium of 16.2 AC, which compares to only 3.2 AC for Comp bidders. This difference is significant. As pointed out before, using jump bids is far from easy. The preparation of Comp bidders resulted in a better understanding of auction dynamics and estimations of competitors' budgets, which allowed for a more effective use of jump bids. Lab bidders had less preparation and were less able to assess the implications of jump bids. They used jump bids more imprudently and paid a high price for it. In addition, Lab bidders were less aware of the risks of jump bids and overestimated their advantages.

A.3.3 Budget bluffing

Since binding budget constraints are crucial to the auction outcome, bidders in the field spend a great deal to estimate competitors' budget limits prior to and during the auction (Bulow et al. (2009)). Bidders do not want to reveal their budget constraints and make it as difficult as possible for competitors to estimate their budgets. Therefore, they might deliberately exceed their budget temporarily to make their competitors believe they are stronger than they are. This is called ***budget bluffing***. We cannot be sure whether budget bluffing was used in the German 4G auction, but the smaller players definitively had the incentive to do so. In the experimental setting, we know the exact budget constraints and can analyze such bluffs.

Successful applications of budget bluffing require that the bidder still remain within the budget at the end of the auction, which implies a reliable estimate of the financial power of other bidders, their targets, final prices in different bands, and the remaining auction duration. Only with such estimates is a bidder able to avoid exceeding his budget at the end of the auction, which results in zero utility.

Result 5: *In both treatments, budget bluffing was used to a similar extent, but Comp bidders succeeded more often in staying within their budget limits at the end of the auction.*

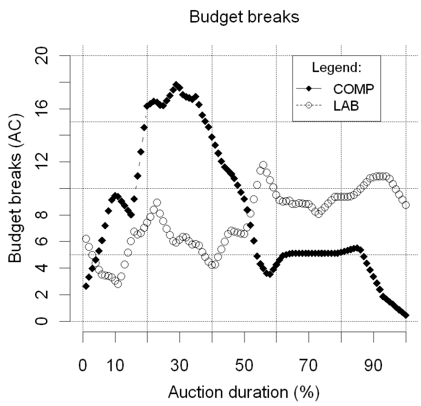

Figure A.4: Budget breaks during the auction

We found that Comp bidders considerably overdrew their budgets in the first half of the auction, up to 17.8 AC per bidder on average, but usually managed to be within budget limits at the end of the auction. At the auction end, they exceeded the budget by only 0.5 AC per bidder on average (figure A.4). In contrast, Lab bidders exceeded their budget by 6.2 AC per bidder at the beginning and instead of resolving this situation, they ended up overdrawing their budget by 8.8 AC on average at the end of the auction. Although the difference was not significant, it supports the conclusion that Lab bidders more often failed to judge the market situation correctly. In absolute numbers, at the end of the auction budgets were exceeded four times in the Lab setting and only once in the Comp setting.

A.3.4 Eligibility management

In both treatments of our experiments and in the field, bidders had to adhere to activity rules in order to maintain the right to participate in the auction. The SMRA with a stacked activity rule gives bidders a lot of freedom in managing the eligibility points, for instance by using a parking strategy and bidding on blocks of minor interest in the early stages of the auction.

Result 6: *Comp bidders actively managed eligibility points while Lab bidders bid to maximize eligibility points.*

Comparing the number of bids and the available eligibility, we found that Lab bidders submitted a higher number of bids per round (6.89) than Comp bidders (3.93). While Comp bidders used their highest number of activity points, 12.44, in round nine (normalized auction duration to 100 rounds), Lab bidders kept up activity longer and achieved a maximum of 17.50 in round twelve. From the peak, the Lab bidders constantly decreased their eligibility until the end of the auction, which was caused by the budget limits. Comp bidders, on the other hand, reduced eligibility to the level of the final allocation shortly after half of the auction duration. This can be attributed to proactive eligibility management.

We conjecture that, due to lack of preparation time, Lab bidders did not have a specified target allocation and eligibility requirement at the beginning of the auction. Thus, Lab bidders bid on more blocks to maximize their flexibility for later rounds. The different approach to eligibility management is also illustrated by the convergence of the auctions. Auctions in the Lab treatment finished on average three to four rounds earlier, which is significantly less, because by bidding on more lots they caused prices to rise more quickly. This is supported by the fact that the number of bids submitted per round by Comp bidders (3.93) more closely matches those encountered in the field (3.27). The Lab bidders submitted 6.89 bids per round.

Appendix B

Experimental study of CCA and SMRA

B.1 Example valuation sheets

Login: participant17 (Mustermann) **Datum:** 13.12.2010
Passwort: qe4689
URL: http://131.159.41.70:8080/MDFrontend/

Auktionsformat: SMR
Value model: woBC
Wave: B
Run: 1
Bieter-Rolle: a

Grundwertigkeit A: 152 (gezogen aus [120; 200])
Grundwertigkeit B: 107 (gezogen aus [90; 160])

Wertigkeiten: A-Bereich

#Güter	Gesamt	Pro Gut	Grundwertigkeit	Bonus
1	152	152	152	0
2	365	183	304	61
3	638	213	456	182
4	1.094	274	608	486
5	1.246	249	760	486
6	1.398	233	912	486

Wertigkeiten: B-Bereich

#Güter	Gesamt	Pro Gut
1	107	107
2	214	107
3	321	107
4	428	107
5	535	107
6	642	107

Figure B.1: Valuation sheet, base value model

Login: participant200 (Mustermann) **Datum:** 04.02.2011
Passwort: qe9089
URL: http://131.159.41.70:8080/MDFrontend/ Auktionsformat: PC
Value model: Set2

Grundwertigkeit A: 170 (gezogen aus [100 bis 300]) Wave: A
Grundwertigkeit B: 98 (gezogen aus [50 bis 200]) Run: 1
Grundwertigkeit C: 111 (gezogen aus [50 bis 200]) Bieter-Rolle: a
Grundwertigkeit D: 170 (gezogen aus [50 bis 200])

Wertigkeiten im Bereich: A

#Güter	Gesamt	Pro Gut
1	170	170
2	544	272
3	765	255
4	935	234
5	1.105	221
6	1.275	213

Wertigkeiten im Bereich: B

#Güter	Gesamt	Pro Gut
1	98	98
2	314	157
3	441	147
4	539	135
5	637	127
6	735	123

Wertigkeiten im Bereich: C

#Güter	Gesamt	Pro Gut
1	111	111
2	355	178
3	500	167
4	611	153
5	722	144
6	833	139

Wertigkeiten im Bereich: D

#Güter	Gesamt	Pro Gut
1	170	170
2	544	272
3	765	255
4	935	234
5	1.105	221
6	1.275	213

Figure B.2: Valuation sheet, multiband value model

Login: participant308 (Mustermann) **Datum:** 28.06.2011
Passwort: qe4948
URL: http://131.159.41.70:8080/MDFrontend/ Auktionsformat: PC
Value model: Set3

Bereich	Anzahl Güter	Gw	2er Bonus	3er Bonus	4er Bonus
A	6	495	43%	43%	57%
B	6	213	\		
C	6	172	51%	38%	47%
D	6	134	/		

Wave: B
Run: 4
Bieter-Rolle: a

Variable	Intervall
GwA	200 bis 500
GwB,C,D	100 bis 250
Bonus	0 bis 120%

Wertigkeiten im Bereich: A

#Güter	Gesamt	Pro Gut
1	495	495
2	1.203	602
3	1.911	637
4	2.688	672

Wertigkeiten im Bereich: B

#Güter	Gesamt	Pro Gut
1	213	213
2	535	268
3	829	276
4	1.142	286

Wertigkeiten im Bereich: C

#Güter	Gesamt	Pro Gut
1	172	172
2	432	216
3	669	223
4	922	231

Wertigkeiten im Bereich: D

#Güter	Gesamt	Pro Gut
1	134	134
2	336	168
3	521	174
4	718	180

Figure B.3: Valuation sheet, $\text{multiband}_{\text{small}}$ value model

B.2 Screenshots of the bidding interfaces

Figure B.4: Bidding interface SMRA

Figure B.5: Bidding interface CCA

B.3 Relative efficiency

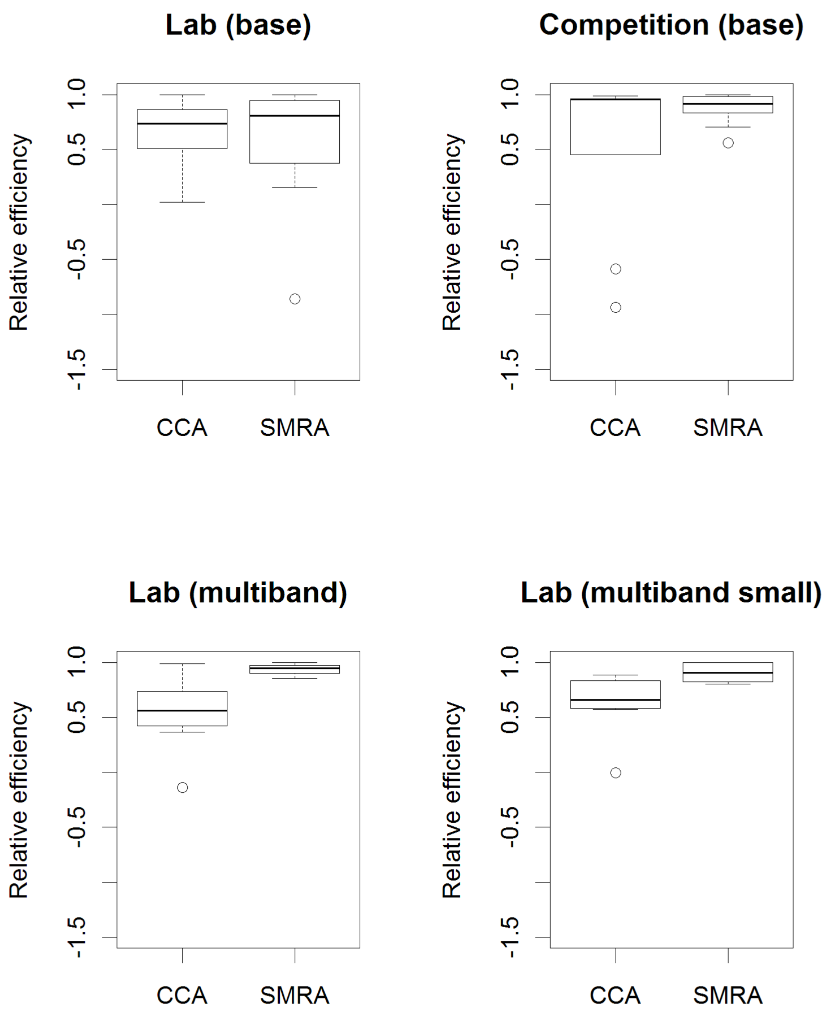

Figure B.6: Relative efficiency

B.4 Bidding behavior in CCA: Additional plots and tables

B.4.1 Base value model

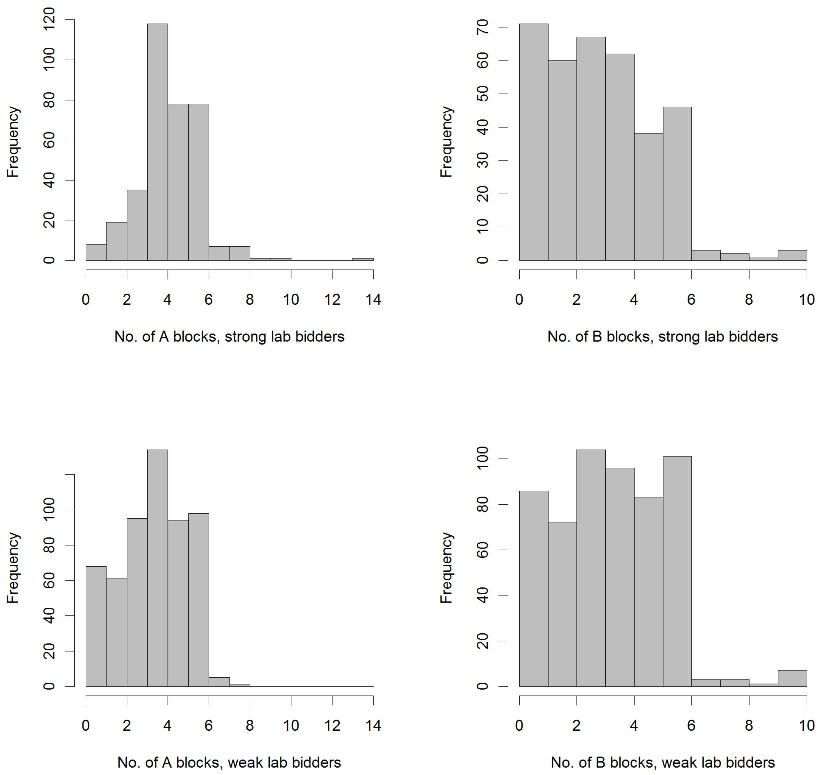

Figure B.7: Number of items in supplementary bids per band, strong vs. weak bidders, base value model, lab

B.4.2 Multiband value model

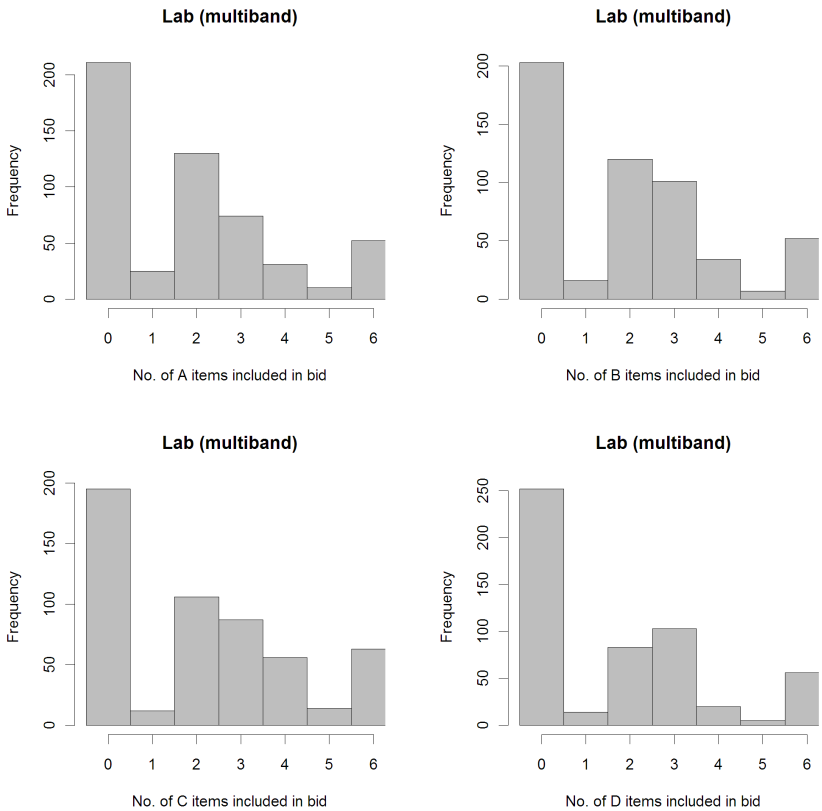

Figure B.8: Number of items in supplementary bids per band, multiband value model

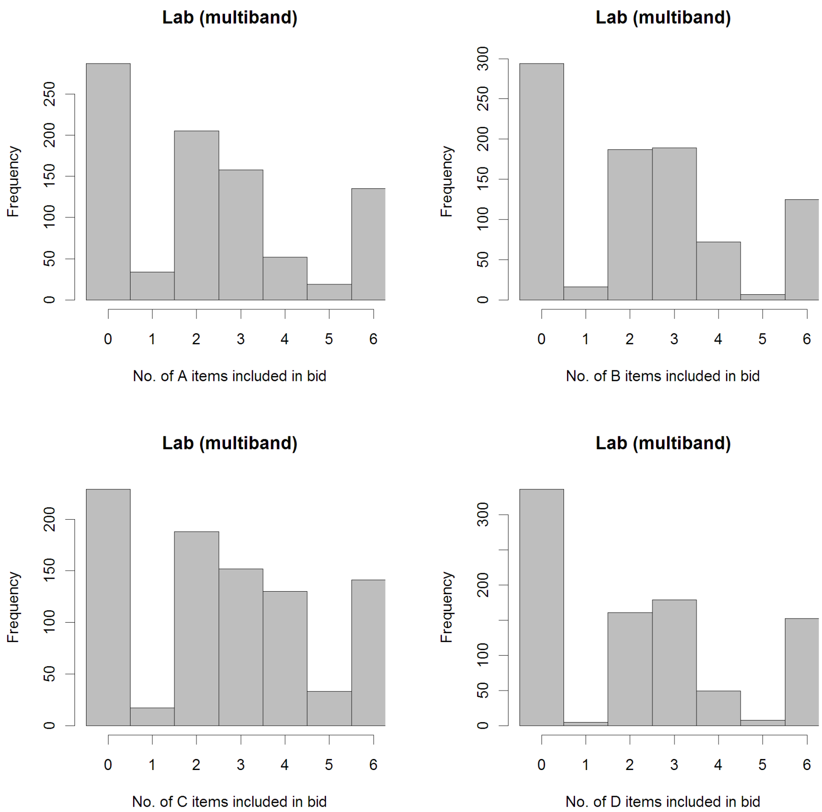

Figure B.9: Number of items in primary bids per band, multiband value model

B.5 Additional results of the competition

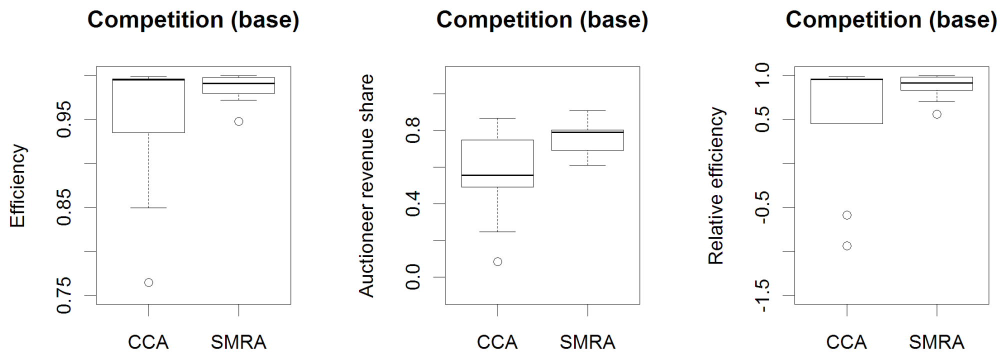

Figure B.10: Aggregate performance measures, competition

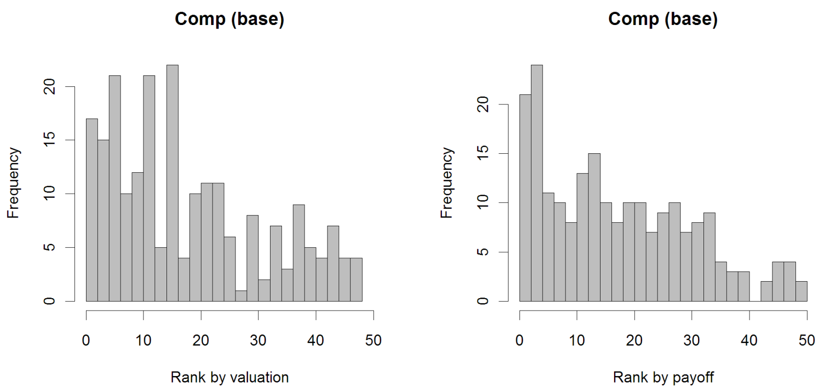

Figure B.11: Rank of supplementary bids by valuation and payoff at final clock prices, base value model, competition

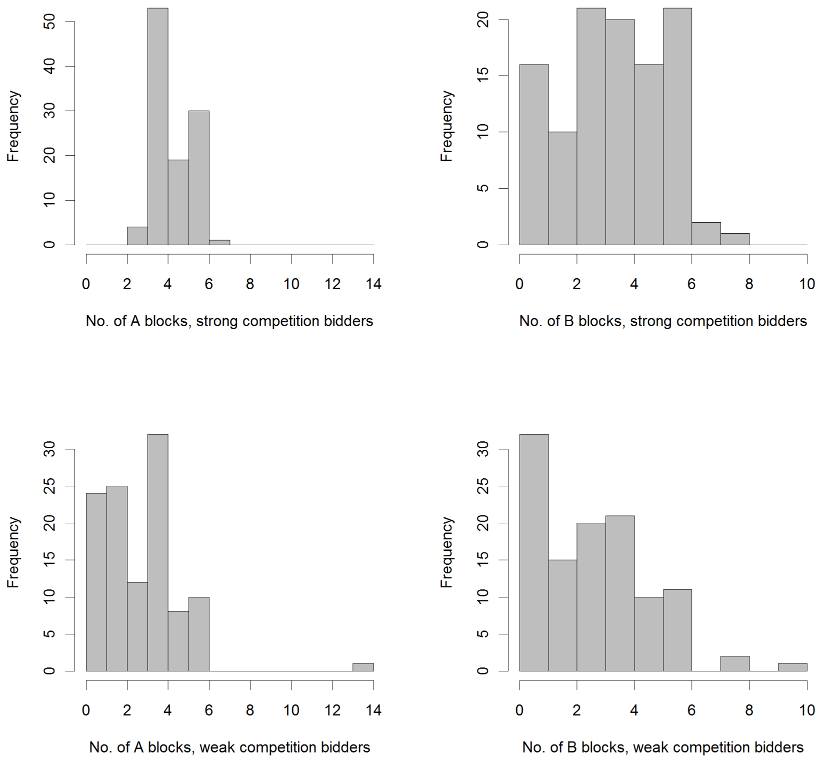

Figure B.12: Number of items in supplementary bids per band, strong vs. weak bidders, base value model, competition

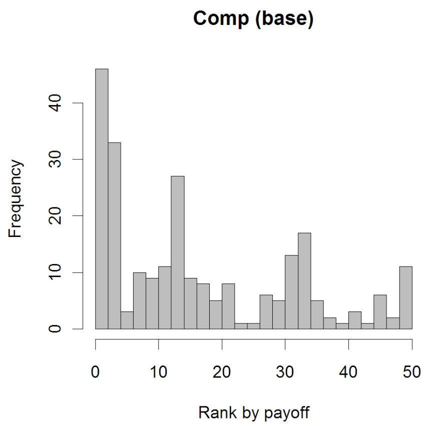

Figure B.13: Rank of primary bids, base value model, competition

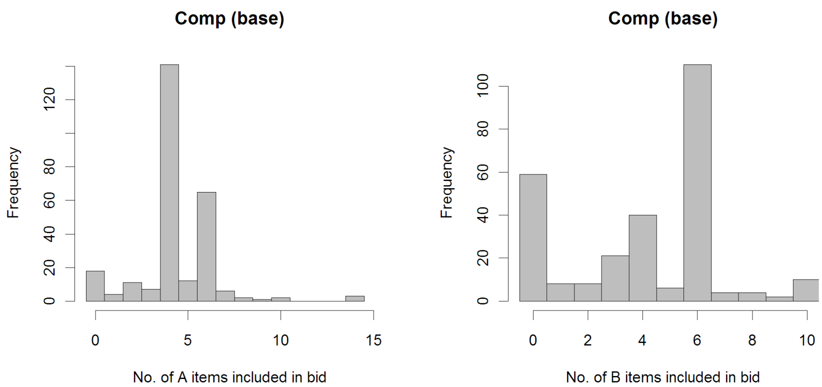

Figure B.14: Number of items in primary bids, base value model, competition

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