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Large-scale Multi-item Auctions

Evidence from Multimedia-supported Experiments

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by
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July 2012 *Sascha Schweitzer*

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1 Introduction

1.1 Multi-item Auctions: Applications and Designs

Auctions of multiple items are of increasing importance. Two prominent auction applications are the sale of radio spectrum rights and the sale of emission permits. The latest versions of these auctions incorporate advanced features such as proxy bidding, which allows bidders to predefine their actions for alternative scenarios; or package bidding, which allows bidders to express wishes for packages of items. For a long time, most of these advanced features were only the object of academic debate. In recent years, though, new and innovative auction designs have gained some traction in the field.

For example, in 2008, the British regulator employed a package auction for the sale of radio spectrum rights in the niche band of 10 to 40 GHz, in 2010, the Austrian regulator employed a package auction for the sale of spectrum in the significant 2.6 GHz spectrum band, and in 2012, the Swiss regulator employed a package auction for the simultaneous sale of spectrum in the 800 MHz, 900 MHz, 1.8 GHz, 2.1 GHz, and 2.6 GHz bands. The results of these spectrum auctions have shaped the future of the wireless communications industry, which plays a vital role in society's development. The value of the radio spectrum is suggested by the fact that, by the end of 2011, the total auction revenue for the sale of spectrum rights by the Federal Communications Commission (FCC) alone exceeded US$78 billion.[1]

Auctions for the allocation of greenhouse gas emissions permits have been implemented in the USA and Europe, and in future the Australian government plans to auction a substantial number of emissions permits in the Carbon Pollution Reduction Scheme. Emissions permits enforce the reduction of climate-damaging emissions by cap-

[1] Details on past FCC spectrum auctions are available at http://wireless.fcc.gov/auctions.

ping emissions at an amount that corresponds to the number of permits issued. The auctions help to channel emissions permits to the "right" emitters, charging emitters whose emissions would be too expensive to avoid, while forcing other emitters to carry out affordable abatement measures.

The design of appropriate auctions has been the subject of political and academic debate. Klemperer (2002b) noted that "auction design is not one size fits all." Rather, the optimal design of an auction very much depends on the specific market situation at hand. So, what is the right auction design for a given application?

The Uniform-price Sealed-bid Auction (USBA) relies on a simple pricing rule (Section 2.3.1). Basically, the auctioneer determines a price at which demand equals supply, and all units of an item are sold for that price. However, for heterogeneous items, the USBA does not provide appropriate heterogeneous prices. Furthermore, bidders who want more than one unit of an item may be incentivized to bid below their true values in order to obtain a lower item price.

The Vickrey-Clarke-Groves (VCG) mechanism—which has been investigated extensively in the literature—exhibits some profound theoretical advantages over the USBA. In particular, Vickrey (1961) emphasized that the mechanism motivates bidders to report their true valuations of an item. This is a crucial advantage, since it helps the auctioneer to obtain the information necessary to allocate the items to those bidders who value them most. However, in multi-item applications, the VCG design remains largely unused. Reasons for the mechanism's lack of practical success are that it is difficult to implement, that it can yield zero revenues, and that it is vulnerable to manipulation by the bidders as well as by the auctioneer (Ausubel and Milgrom, 2006).

The open, dynamic version of the USBA, the English Clock Auction (ECA), modifies the USBA by breaking down the submission of bids to a step-wise bidding process that is relatively simple as well as transparent and generates intermediate price signals. Similarly, the Simultaneous Ascending Auction (SAA) and the Package-clock Auction (PCA) both apply an open, ascending bidding process. In contrast to uniform-price auction designs, bidders bid on individual units in the SAA and on packages in the PCA. Package bidding allows bidders to express interdependencies between items.[2]

[2] In the terminology of auction theory, auctions employing package bids are called combinatorial auctions.

The main chapters of this thesis investigate economic laboratory experiments on two applications of multi-item auctions: Study 1 and Study 2. Study 1 deals with the auctioning of *emission permits* in the context of the Australian Carbon Pollution Reduction Scheme. A white paper by the Australian government estimated that the emissions trading scheme would cover around 1,000 firms (Commonwealth, 2008). Although smaller firms may not participate in the auction—instead, they purchase permits on secondary markets—the potential number of participants is in the range of tens to hundreds of firms. Compared with typically more specialized multi-item auctions, such as for the allocation of radio spectrum rights, this is a high number of participants. Indeed, most auction experiments that were reported in the literature featured between two and six bidders. To emulate a larger market, the emissions permits experiment featured 14 bidders, which was the maximum laboratory capacity at the Karlsruhe Institute of Technology (KIT).

In order to allow firms to plan ahead, the regulator intended to sell permits simultaneously for several years in advance These are called vintages. The multiple vintages in the real-world application were represented by two items in the experiment. For each item, multiple units were sold, representing the single permits of a vintage. In the real world, the firms' valuations of the emissions permits stem from the costs of the emissions abatement measures. Permits can be used alternatively to conducting abatement measures. Naturally, firms will first replace the most expensive abatement measures with emissions permits. Therefore, their valuations of the first emissions permits, which they purchase, correspond to the costs of the most expensive abatement measures, and the marginal utility function for the permits is typically decreasing. The experimental design of Study 1 employed a simple linear function to represent the decreasing marginal utilities. Thus, in economics terminology, the units exhibited the characteristics of (imperfect) *substitutes* (see Section 2.1).

Study 2 deals with the application of multi-item auctions for the sale of *radio spectrum rights*. These high-stake auctions shape the telecommunications industry, which is one of the key industries of the current innovation cycle. The specific motivation for Study 2 were the German 2010 and the Austrian 2010 radio spectrum auctions, which were the first in an upcoming series of European spectrum auctions. Although both auctions happened in the same year in neighboring countries and both included the sale of 2.6

GHz spectrum rights, the regulators used fundamentally different auction designs. The aim of the spectrum auction experiment was a structured comparison of the auction designs used in the two countries.

The 2.6 GHz spectrum band consisted of two different sub-bands which were intended for different technical uses and could not be combined. In the experiment, these two sub-bands were represented by two items. In the real-world application, within each sub-band, the spectrum was divided into blocks of 5 MHz. These blocks were represented in the experiment by multiple units of each item. Since a telecommunications service provider needed to acquire several spectrum blocks in order to offer a technically attractive service with a sufficiently high bandwidth (for instance for realizing a broadband internet connection), the units within each sub-band were modeled as complements in the experiment.

Table 1.1 provides an overview and a comparison of the two studies presented in this thesis. Both studies deal with large-scale auctions of multiple units of two types of items. Also, in both applications, governments conduct auctions, in order to allocate scarce natural resources. On the other hand, the number of bidders and the bidders' values of the items differed between the studies. For this reason, the auction designs tested in the experiments differed as well, which is why two separate experiments were conducted. However, both experiments presented very similar challenges with respect to their design and implementation.

Moreover, in both applications, uncertainty about the values of the items played an important role. In the emissions permits case, the uncertainty was mainly due to the unknown prices of the permits on future secondary markets. In the spectrum rights case, the uncertainty stemmed from the unknown development of the new technologies and markets the radio spectrum will be used for. Historically, these uncertainties were the primary reason for the employment of open, ascending auction designs that generate intermediate price signals (e.g. McMillan, 1994). Therefore, the experiment in Study 1 included a treatment with secondary markets and the experiment in Study 2 featured an explicit uncertain value component.

Table 1.1: Overview of the experimental studies

	Study 1	Study 2
General application	Emissions permits	Radio spectrum rights
Types of items	Vintages *(characterized by common validity period)*	Spectrum bands *(characterized by common location in the spectrum band)*
Specific motivation	Australian Carbon Pollution Reduction Scheme *(in preparation)*	European Long-Term-Evolution (LTE) auctions *(2010 to today)*
Number of bidders (per auction)	14	4
Number of units sold (per item)	100 + 80	7 + 4
Substitutes vs. complements	Substitutive items and units	Substitutive items, complementary units
Exchange value	Secondary markets (treatment)	No secondary markets
Compared auction designs	Sequential / USBA; Sequential / ECA; Simultaneous / USBA; Simultaneous / ECA	Simultaneous / SAA; Simultaneous / PCA

1.2 Research Questions and Structure of the Text

This thesis investigates the auction designs proposed for the sale of spectrum rights and emissions permits with respect to *three criteria*.

> **Research Question 1:**
> *How do the auction designs proposed for two specific large-scale applications differ with respect to efficiency, revenue and price signals?*

First, from the perspective of a social planner, items should be allocated to the bidders who value them most. This is equivalent to maximizing the sum of the market participants' values, the so-called social surplus. When the social surplus is maximized, no participants in the market can improve their situation without making some other participants worse off. The corresponding allocation is called efficient.

A second criterion is the generation of revenues for the auctioneer. A rational, profit-maximizing auctioneer seeks to maximize the auction revenue. If the auctioneer is the state, social welfare may be more important than revenue. However, social welfare may exceed the scope of an auction. For instance, the auction revenues allow the government to redistribute some part of the bidders' surplus to the society and, in return, to reduce distortional taxes (cf. Section 2.2.2).

A third criterion for the evaluation of auction designs is whether and to what extent an auction provides price signals to the market. Firms use price information for planning and accounting purposes, and the exchange value of an item is approximated by its market prices. Further, in the course of the auction process itself, if the auctioneer calculates and publishes prices during the auction, bidders gain information on the valuations of the opposing bidders. They can then incorporate this information into the estimation of the market value of the items and improve their bids accordingly.

Seeking to answer Research Question 1, this thesis is structured as follows. Chapter 2 explains the three criteria for the evaluation of the auction designs in more detail, and presents auction designs that are relevant for the applications studied in this thesis.[3]

[3] Readers familiar with the basic concepts and auction designs may want to skip Chapter 2 and focus on Chapters 3, 4, and 5.

Chapter 3 is devoted to the methods of experimental economics which are required for answering Research Question 1. As the core of this thesis, Chapters 4 and 5 report the experimental Studies 1 and 2 on emissions permits and spectrum rights applications of multi-item auctions. Finally, Chapter 6 concludes by providing a summary of the results, stating open questions and pointing out aspects of future research.

Studies 1 and 2 are also an example of the limits of the experimental approach in economics, and of how these limits can be moved. Factors like the substitutive or complementary nature of the auctioned goods, the presence of uncertainty and sometimes elaborate auction rules complicate an experimental situation. In order to answer Research Question 1, Chapter 3 develops several *extensions of the toolkit of experimental economics*. This leads to a second, methodological research question.

> **Research Question 2 (Methodological Research Question):**
> *How can experimenters guarantee control, reproducibility and validity in large-scale testbed experiments?*

Traditionally, economic experiments serve to test theoretical models or constructs which are well arranged and clearly structured. These experiments seek to isolate effects by modeling a market situation in the laboratory. With the goal of studying the effects of certain parameters of interest, only these parameters are manipulated between treatments, while holding all other parameters equal—in order to obtain a maximum of control and comparability throughout all the observations in the experiment.

The employment of laboratory experiments for investigating more complicated real-world markets was introduced in the 1990's, when Plott (1994) argued that laboratory experiments should serve as a *testbed* for the design of markets. In principle, the scientific criteria of control, reproducibility and validity also hold for the evaluation of market designs for large-scale applications. However, it may be difficult to guarantee control in highly complex environments. For example, one major problem is guaranteeing the subjects' comprehension without interacting with them in an uncontrolled way.

Chapter 3 proposes and implements a set of extensions of the toolkit of experimental economics for the investigation of large-scale applications by applying the empirical and theoretical results of cognitive research. Reverting to state-of-the-art technological and psychological research, the proposed instruments seek to improve and control the subjects' comprehension. The proposal includes modularized video instructions, comprehension tests, a software integrated learning platform, a graphical one-screen user interface and comprehension-based group matching.

2 Multi-item Auctions

2.1 Common Valuation Models in Auction Theory

For the investigation of multi-item auctions, the bidders' values structures for the items are crucial. In particular, the criteria of efficiency and price signals (Sections 2.2.1 and 2.2.3) are meaningful only against the background of a given values structure. In the following sections, the basic concepts of substitutes and complements, and three major strands of valuation models from the auction literature will be summarized.

Substitutes and Complements

An important textbook concept—which is also of high relevance in practice—is the categorization of the bidders' values into *substitutes* and *complements* (e.g. Varian, 2010). These labels describe interdependencies between the items. Two Items, A and B, are *complements* if a bidder's values for these items are *super-additive*:

$$v(A \cup B) \geq v(A) + v(B). \tag{2.1}$$

In this case, the bidder's valuation of a bundle of the items is higher than the sum of the individual values of the items. One example of complements is left and right shoes. In contrast, two Items, A and B, are *substitutes* if a bidder's values of these items are *sub-additive*:

$$v(A \cup B) \leq v(A) + v(B). \tag{2.2}$$

In the case of substitutes, a bidder's value of a bundle is lower than the sum of the individual values of the items. A typical example is butter and margarine.

The same set of items can be complements to one bidder, but substitutes to another bidder. For example, consider a spectrum auction with an incumbent and a new entrant. The entrant might need several lots in a certain frequency range to build an efficient network, whereas the incumbent might be satisfied with only one of the lots in order to enlarge his already established network. In this example, the lots represent complements to the first bidder, but substitutes to the second bidder.

In the case of complements, one major challenge of auction design is the *exposure problem*. The exposure problem can occur in sequential auctions, as well as in simultaneous auctions in which package bids are not allowed (e.g. Kwasnica et al., 2005). In particular, the exposure problem was a crucial design element of the experiment in Study 2 (Chapter 5). In order to win a package, bidders might feel the need to bid above their values of an individual item. In this case, not winning all of the desired items will result in losses. The fear of the exposure problem, can motivate bidders to hold back bids and may therefore affect the allocation and revenues of the auction.

Example 2.1 (The exposure problem)
Consider a Simultaneous Ascending Auction (SAA, Section 2.4.1) with two items A and B, and two bidders 1 and 2. For Bidder 1 the items are perfect substitutes (she is interested in only one item), whereas Bidder 2 needs both items. Let's assume Bidder 1 values either item A or B at €200, and does not gain any additional value from a second item. On the other hand, Bidder 2 values the bundle of both items at €100 (Table 2.1), while a single item is of no value to her. The bidders do not know the opposing bidder's values.

Table 2.1: Example for the exposure problem.
The cells of the table denote the bidders' values for the individual Items A and B or the bundle of both items.

	{A}	{B}	{A,B}
bidder 1	€200	€200	€200
bidder 2	€0	€0	€100

Bidder 1 and Bidder 2 might outbid one another—Bidder 2 trying to obtain both items and Bidder 1 bidding on one item, the one with the lowest price. At some point, the prices of both items reach €50, and bidder 2 holds the highest bid for at least one of the items. Now, Bidder 1 continues to bid on one item, but Bidder 2 reaches her budget limit for her desired package and has two options. Either she stops bidding and ends up paying € 50 for an item she has no use for, or she keeps on bidding, in the hope that she can lower her losses if Bidder 2 drops out of the auction soon. However, in both cases, Bidder 2 would suffer a loss.

If Bidder 1 dropped out in the next bidding round, Bidder 2 would win both items, suffering a loss of €10 (€100 - €50 - €60 = - €10). However, this will not happen, as Bidder 1's value for either item is €200, so that she continues to bid. When the price of the items reaches €100, Bidder 2's loss will increase with every further bidding round—even if she wins both items.

Independent Private Values Model

Vickrey (1961) based his seminal work on the formal analysis of auctions on the Independent Private Values (IPV) model. This model assumes that the bidders' values for an item are drawn independently from a common and commonly known probability distribution. The term *private* refers to the assumption that a bidder knows her value of an item, but does not know the values of the other bidders. In this sense, the values are private information.

In the IPV model, differences amongst bidders' values stem from actual differences in their tastes. The assumption of private values is applicable for auctions in which non-durable consumer goods, as for example food, are sold or if the value is derived only from using the item. In that case, it is plausible that the value is known only to the bidder and that the bidders' values depend entirely on their personal taste (Milgrom and Weber, 1982). Another popular example of the applicability of the IPV assumption is the selling of a painting, since personal taste plays a decisive role in this context. However, Krishna (2002) notes that the example is questionable, since it only works under the assumption that the painting is viewed as a consumption good only and not as an investment that is likely to be resold.

Remarkably, in a single-unit auction,[1] theory predicts that the expected revenue and the price will be the same in all standard auctions.[2] This result, known as the *revenue-equivalence theorem*, was first presented by Vickrey (1961) and then generalized by Riley and Samuelson (1981) and Myerson (1981) to cover a broad class of auctions. The theorem rests on the assumptions that the bidder with the highest value always wins the item, that the surplus for the bidder with the lowest value is zero, that the bidders are risk-neutral, and that the bidders' private values are drawn independently from the same distribution. With respect to multi-unit auctions, Maskin and Riley (1989) extended the theorem to situations with multi-unit supply, but single-unit demand. However, for most situations with multi-unit demand, Krishna (2002) demonstrated that the theorem does not hold, because under multi-unit demand different auction designs tend to deliver different allocations.

Seifert and Ehrhart (2005) remarked that the IPV assumption is quite common in the literature on multi-item auction experiments. Aside from the argument that most of the literature related to spectrum auctions assumes an IPV model, the authors also gave a practical reason: Because in a private values model the bidders receive only a single, one-dimensional piece of information which their value for the item depends on, this model "is easier to present and for the subjects to understand" (p. 234). In the present thesis, IPV models were employed in Study 1 and in some of the auctions in Study 2.

Common Value Model

The Common Value (CV) model was first introduced by Rothkopf (1969) and Wilson (1969, 1977). The textbook example of a CV situation is the selling of oil drilling or mineral mining rights. The exact amount of oil or minerals in the ground is not known, but it is the same to all bidders, and bidders do have at least some information that allows them to estimate the real value.

[1] Here and in the following, the term "unit" was used to refer to the homogeneous units of an item.

[2] Standard auctions include the first-price sealed-bid auction, the second-price sealed-bid auction, the Dutch auction and the English auction. The revenue-equivalence theorem also holds for many non-standard auctions where the same set of valuations of the bidders leads to the same equilibrium allocation.

Observing the bids of the other bidders or the development of prices can provide the bidders with useful information about the actual value. Bidders can incorporate this information into their estimation of the value and improve their decision making. This is especially relevant with respect to a phenomenon known as the *winner's curse*. Since the actual value is unknown to the bidders at the time of the bidding, the bidders need to estimate the value. Some estimates will be too low, others will be too high. The winner's curse is caused by the fact that by design the bidder with the highest bid—which is likely to be the bidder with the highest estimate—will win the auction. If the bidders do not condition their bids on the event of winning the auction and discount their bids accordingly, they may win at a price that is higher than the true value, which implies a negative profit. Capen et al. (1971) first observed the winner's curse in the oil drilling industry. Kagel and Levin (1986) listed further examples of the winner's curse in Outer Continent Shelf lease sales, cooperate takeover battles and auctions for book publication rights. In laboratory experiments, Kagel and Levin showed that the winner's curse persists and even experienced participants cannot elude it.

As Thaler (1988) pointed out, even if the bidder is aware of the danger of overestimating the value, it is still very difficult to estimate it correctly. For example, in a first-price auction, the participants must bid more aggressively with an increasing number of bidders, but at the same time the bidders should bid less aggressively since, with more bidders, the probability increases that the winner will overestimate the value. It is unclear, though, whether the provision of price signals during the auction provides helpful orientation to the bidders or whether it increases the cognitive load.

Interdependent and Uncertain Values

Neither the IPV model nor the CV model adequately describe the value structures that are observed in reality. Typically, real goods may exhibit characteristics of both models. In the oil-drilling example, companies might have different costs of production, different capacities and different opportunities in the oil market. Analogously, in the art auction example, a bidder might use the work of art to decorate her home. In this scenario, it is very likely that the appreciation of the object by the general public is an important part of the bidder's own valuation. Study 2 of the present thesis dealt with a similar situation and explicitly modeled these interdependencies in the design of the experiment.

For the single-unit case, some models incorporate uncertain value components and interdependencies between the bidders' values. Pioneering the research on value interdependencies, Milgrom and Weber (1982) introduced the *affiliated-values model*. Here, the item has a different value to each bidder, but the values are affiliated. The IPV model and the CV model are special cases of the more general affiliated-values model.

Coining the term "almost common value auction," Bikhchandani (1988) extended the classic CV setting by an IPV component. In this line of research, experimental studies investigated the explosive effect of slight private values advantages predicted by Bikhchandani's theory. For example, Avery and Kagel (1997) studied almost common value auctions with a second-price sealed-bid mechanism, and Rose and Levin (2008) investigated the explosive effect in an English clock auction. In contrast to the theoretical predictions, in the experiments, bidders tended to bid proportionally to their values.

Goeree and Offerman (2002) took an approach different from Bikhchandani by using a two-dimensional signal. The authors noted that "by focusing on the 'extreme' cases, the literature has inadvertently spread the belief that auctions generally lead to efficient allocations" (p. 625). Goeree and Offerman argued that, when bidders process two-dimensional information on separate private values and common value components, inefficient outcomes should be expected. The author suggested that "a bidder with an inferior private value but an overly optimistic conjecture about the common value may outbid a rival with a superior private value" (p. 625). In this sense, auctions with private and common value components need to cope with the efficiency concerns of the IPV world as well as with the winner's curse of the CV world. In their experiment, Goeree and Offerman found that the observed bidding behaviour was roughly in line with the theoretical predictions. Yet, in contrast to theoretical predictions, the provision of more information did not increase the allocative efficiency of the auctions.

Two further issues related to uncertainty and interdependency of valuations are bidders' risk aversion and cognitive limitations. If bidders are asymmetric in their risk attitude, in the theoretical equilibrium rational bidders will act asymmetrically. This can result in inefficient allocations (Kagel and Levin, 2002b). Also, uncertainty is likely to increase the challenge to the cognitive capabilities of the bidders, since uncertainty requires bidders to estimate values and to incorporate stochastic components into their calculations.

In the case of multi-unit auctions, under uncertain and interdependent values, general equilibrium results do not exist and might be difficult to develop. Engelbrecht-Wiggans and Kahn (1998) remarked that auctions in which individuals can purchase more than one unit of the good being sold differed in striking ways from multi-unit auctions in which individuals may purchase only one unit. A major addition in the case of multi-unit demand is the incentive for strategic demand reduction. Bidders may be inclined to understate their demand in order to influence the price of the items purchased. However, Engelbrecht-Wiggans and Kahn report equilibrium results only for the IPV case.

Uncertain, common value components induce additional incentives for demand reduction in multi-unit-demand auctions. This is due to the effect of a bidder's bid on the value estimation of the opposing bidders. When a bidder reduces her demand on an item, she provides information on the common value component that the other bidders will include in their own estimation. Thus, bidders can influence the bids of their opponents by influencing their opponents' estimates.

Consider an example known as Klemperer's wallet game. In the wallet game, the auctioneer sells a common value item in an English auction with $n = 3$ bidders $i = 1, 2, 3 \in N$.[3] Each bidder i obtains a signal s_i. The bidders' signals are uniformly and independently drawn from $[0, 1] \subset \mathbb{R}$. The value $v \in \mathbb{R}$ of the item is identical for all bidders and calculated as the mean of the bidders' signals as defined by the formula

$$v = \frac{1}{n} \sum_{i=1}^{n} s_i \tag{2.3}$$

With K denoting the set of Bidders k that have dropped out of the auction revealing their signal s_k, Bidder i's equilibrium bid $b_i \in \mathbb{R}$ is given by Equation (2.4):[4]

$$b_i = (n - |K|) \cdot s_i + \sum_{k \in K} s_k \tag{2.4}$$

[3] In the original wallet game by Klemperer (1998), only two bidders were considered. An extension to multiple bidders was introduced by Bulow and Klemperer (2002).

[4] Bulow and Klemperer's (2002) notation differed from the notation used here in not using a closed form expression.

Analogously to calculating her equilibrium bid, Bidder i can also calculate her estimated value $v_{\text{est},i} \in \mathbb{R}$ of the good, improving her guess every time a bidder drops out:

$$v_{\text{est},i} = \frac{1}{n} \cdot \sum_{k \in K} s_k + \frac{1}{n} \cdot s_i + \frac{n - |K| - 1}{n} \cdot 0.5 \tag{2.5}$$

By the same token, a bidder's action influences the estimation of the opposing bidders. If she drops out early, the estimation of the opposing bidders will be lower than it would be if she dropped out later. Yet, in this example with single-unit demand, a bidder cannot exploit her influence on the opposing bidders' estimates. Because, once she reduces her demand, she drops out of the auction and cannot benefit from lower prices. In the case of multi-unit demand and supply, however, lowering the opposing bidders' estimates can lead to lower prices that affect the bidder's profit.

Secondary Markets

The heading "secondary markets" may be surprising in a section on values structures. The reason for this is that the presence of secondary markets affects the perception of values in the primary market. Consider the auctioning of an antique that is to be resold by the new owner, an example presented in McAfee and McMillan (1987). In this example, the future exchange value on secondary markets induces a CV component into the original IPV market. Thus, by transforming the item into an exchange good, secondary markets can contribute to the uncertainty and interdependence of the valuations on primary markets. In the worst case this may contribute to complicating and confusing the market situation on the primary market.

The impact on the value structure in the primary market may even call into question the principle benefit of secondary markets. In a Coasean world without transaction costs, secondary markets will establish efficiency (Coase, 1960). However, when trade entails transaction costs to the participants in the secondary market, not all beneficial trades will take place and efficiency will not be obtained. Due to their distortional effects on the primary market, it is then unclear whether secondary markets do actually increase overall efficiency, or whether they may even decrease overall efficiency. To the author's knowledge, no study that explicitly addresses the question of combined primary and secondary market efficiency is reported in the literature. In order to isolate the effects of secondary markets, Study 1 of this thesis investigated secondary markets in dedicated experimental treatments.

2.2 Evaluation Criteria

2.2.1 Efficiency

> *"At the core of economics is the concept of efficiency."*
>
> (Leibenstein, 1966, p. 392)

The allocation of scarce resources, the generation of welfare and the distribution of the generated welfare belong to the most fundamental questions of economic activity. Therefore, *auction efficiency* and *auction revenue* are essential measures for evaluating auction performance. While revenue is defined simply as the sum of payments to the auctioneer, auction efficiency is more difficult to grasp.[5] In micro-economic theory, one notion of efficiency is Pareto efficiency. A situation is Pareto efficient if nobody's utility can be improved without making another individual worse off. Note that in an auction situation, a social planer judging the Pareto efficiency of an allocation needs to evaluate the situation under the assumption that alternative transfer payments are possible. Otherwise, virtually every allocation would be Pareto efficient, since re-allocations would always deprive some bidders of their value without allowing for compensation.

Holmström and Myerson (1983) apply the Pareto concept to double auctions, and in the early experimental literature on auctions, further examples of the application of this concept can be found (Kagel and Levin, 2002a). However, Pareto efficiency offers only a binary measure of yes or no without allowing for a more gradual judgement of the level of efficiency. Furthermore, in a sufficiently complex situation, it may be practically impossible to fulfill the criterion. Therefore, the experimental literature frequently reports efficiency in terms of relative allocative efficiency which is measured in terms of utalitarian social surplus, also called welfare (e.g. McCabe et al., 1990). Social surplus is defined as the sum of the cardinal utilities of all members of society and therefore assumes interpersonal comparability of utilities. Relative allocative efficiency

[5] See Section 2.2.2 for the discussion of auction revenue and its relation to auction efficiency.

is defined as the percentage of social surplus that is created relative to the social surplus that could have been created in the best case. Note that from a relative efficiency of 100% follows Pareto efficiency, since the utility of single individuals can be improved only by redistributing from other bidders.

With respect to the valuation models introduced in Section 2.1, efficiency concerns are most relevant under the presence of IPV components. Indeed, in the pure CV case, any allocation leads to the same social surplus—as long as all items are allocated. Therefore, IPV components must be included, in order to investigate efficiency in a laboratory experiment.

Definition of Efficiency Measures

The efficiency measures used in this thesis are defined as follows. There are n bidders $i \in N \subset \mathbb{N}$ bidding for m items $k \in M \subset \mathbb{N}$. The supply of item k is restricted to a quantity of $s_k \in \mathbb{N}$ units, while each bidder's demand is restricted to a quantity of $d_k \in \mathbb{N}$ units. An allocation $\mathrm{q} = (q_1, q_2, ..., q_i, ..., q_n) \in A \subset Q^n$ defines the quantity vectors $q_i = (q_{i,1}, q_{i,2}, ..., q_{i,k}, ..., q_{i,m}) \in Q \subset \mathbb{N}^m$ allocated to each bidder i. The realized allocation is denoted with $\hat{\mathrm{q}}$. Bidder i's value for a given quantity vector q_i is denoted with $v_i(q_i) \in \mathbb{R}$.

The *social surplus* $w(\mathrm{q}) \in \mathbb{R}$ is defined as the sum of the bidders' and the auctioneer's surplus. Since the prices $p = (p_1, p_2, ..., p_i, ..., p_n) \in P \subset \mathbb{N}^n$ are mere transfer payments from the bidders to the auctioneer, they are canceled out by the auctioneer's revenue, and the social surplus depends exclusively on the value of the allocation.

Definition 2.1 (Social Surplus)
The social surplus $w(\hat{\mathrm{q}})$ *under a given auction outcome* $\hat{\mathrm{q}}$ *is calculated as the sum of all bidders' values* $v_i(\hat{q}_i)$*:*

$$w(\hat{\mathrm{q}}) = \sum_{i \in N} v_i(\hat{q}_i)$$

Definition 2.2 (Efficient Allocation)
An allocation q^* *is called an* efficient allocation*, if it solves the following maximization problem:*

$$\begin{aligned} &\max_{\mathrm{q}\in A} \sum_{i\in N} v_i(q_i) \\ &s.t.\ \ \forall k,\ \sum_{i\in N} q_{i,k} \leq s_k \\ &and\ \ \forall i \wedge k,\ \ q_{i,k} \leq d_k \end{aligned}$$

Definition 2.3 (Relative Allocative Efficiency)
The relative allocative efficiency $e(\hat{\mathrm{q}})$ *is defined as the ratio of the realized social surplus* $w(\hat{\mathrm{q}})$ *divided by the potential social surplus* $w(\mathrm{q}^*)$ *in an efficient allocation* q^**:*

$$e(\hat{\mathrm{q}}) = \frac{w(\hat{\mathrm{q}})}{w(\mathrm{q}^*)}$$

In the experiments reported in Chapters 4 and 5, all induced values are non-negative. Therefore, the lower bound for efficiency in the experiment is zero and the space of potential efficiency results $e(\hat{\mathrm{q}})$ is $E = [0, 1]$.

2.2.2 Revenue

"The only difference between grandfathering and auctioning is that in grandfathering the energy companies, not the taxpayers, pocket the extra revenue."

(Cramton and Kerr, 2002, p. 335)

The auction revenue is probably the most tangible result of an auction. It is therefore prominently reported in the media and is the subject of intense political debate. Formally, the revenue equals the sum of the *prices* that the bidders pay to the auctioneer. From the perspective of welfare economics, revenue is a transfer payment from the bidders to the auctioneer. It determines the split of the social surplus without changing the total surplus.

Since revenue equals the auctioneer's profit, a rational, profit-maximizing auctioneer is also a revenue-maximizing auctioneer. Private firms are typically seen as an example of this type of auctioneer. Yet, in the large-scale auction applications reported in Chapters 4 and 5, the auctioneer is a government agency. Ideally, the government assumes the role of a benevolent social planner. In contrast to a profit-maximizing auctioneer, the social planner seeks to maximize social surplus, instead of auction revenue. In fact, revenue does not matter to the social planner, since it is a mere transfer payment which cancels out in the calculation of social surplus.

As defined in Section 2.2.1, an efficient allocation of the items maximizes social surplus. Indeed, governments tend to stress the goal of efficiency. For example, the US Congressional Budget Office has stated that spectrum rights auction *"goals include ensuring efficient use of the spectrum, promoting economic opportunity and competition, avoiding excessive concentration of licenses, preventing the unjust enrichment of any party, and fostering the rapid deployment of new services, as well as recovering for the public a portion of the value of the spectrum"* (Congressional Budget Office, 2000, p. 117). This statement downplays revenue goals and emphasizes efficiency-related objectives (with respect to allocative and overall market efficiency). Most economists agree that efficiency should be the primary goal in spectrum auctions (for example McMillan, 1994; McAfee and McMillan, 1996; Cramton, 2002).

However, given the existence of secondary markets, some economists consider efficiency less important and identify revenue as a primary objective. The sale of emissions permits presented in Chapter 4 is an example. Cramton and Kerr (2002) stated that auctioning was to be preferred to grandfathering, because it generated higher revenues.[6] Ockenfels (2009) challenged this opinion with the argument that firms should pay as little as possible for emissions permits in order to keep costs for environmental measures low. Following this argument, some economists may even consider revenue minimization as a legitimate goal of auction design.

Ockenfels' argument is reminiscent of the discussion of potential consumer price increases due to high auction prices in the context of spectrum rights. For instance, a European Commission's greenpaper stated that *"auctions should not lead to an excessive transfer to the public budget or for other purposes to the detriment of low tariffs for the users"* (Commission, 1994, p. 42). In response to this claim, McMillan (1995)

[6] *Grandfathering* is an alternative allocation mechanism that awards emissions permits to some past polluters for free.

argued that auction prices are fixed costs to the communications provider and do not affect consumer prices, since a profit-maximizing firm bases its prices on its marginal costs. In McMillan's opinion, even potential increases in the capital costs of the firm due to higher borrowing for the acquisition of spectrum rights, can have only a minor impact on consumer prices.

Another argument in favor of raising revenues is the necessity of financing the state and its social system. Governments soften inequalities and raise money in order to redistribute wealth and to fulfill their public duties. Cramton (1997) argued that auction revenues were preferable to taxes, because one dollar of revenue raised through taxes resulted in 17 to 56 cents of welfare loss due to distortional effects (Ballard et al., 1985). Therefore, in some cases, increases in revenue can justify slight decreases in auction efficiency.

Further, public opinion is typically opposed to giving away public resources to wealthy firms for a very low price or even for free. For instance, Mueller (1991) reported the case of the first spectrum auction in New Zealand. The auction resulted in a media disaster, since spectrum rights were allocated at ridiculously low prices. This example emphasizes the political nature and relevance of the auction revenue.

2.2.3 Price Signals

> *"A fortune in fabulous prizes may go to these people today, if they know when the Price is Right!"*
>
> (Intro to "The Price is Right," as aired on CBS since 1972)

When publishing *auction prices*, an auctioneer provides information to the bidders and their stakeholders in the market. This information increases the transparency of the auction process, increases the trust in the auctioneer and helps bidders estimate the market value of the items. If prices are published during the auction process, the bidders can incorporate this information into their estimates of the values of the items and adjust their bids accordingly. If prices are published after the auction, they are often used as an indicator of the "objective" value of an item for resale and accounting purposes.

Prices can be referred to as signals because they provide a proxy of the bidders' valuations. Prices are good signals if they reflect the valuations closely. Quantitatively, "reflecting valuations" closely means a high positive *correlation* between the valuations of an item and the item price. Yet, since the value of an item can be different for different individuals—while prices are aggregated to the level of one item—measuring their correlation is not always a straightforward process. For example, the correlation can be measured with respect to the average valuation, the minimum or maximum valuation or virtually any other aggregation.

The information provided by prices is particularly relevant in situations with incomplete information and informational asymmetries.[7] Causes of incomplete information are the uncertain future development of technology, the uncertain adoption of the products by the consumers and the uncertain development of the market. Even when values can be estimated, the acquisition of corresponding information and the calculation of estimates may incur costs to the bidders.

Cramton (2009b) stated that "in the case of spectrum auctions, there is much uncertainty about what things are worth." Further he suggested that bidders can gather "collective market insights, which can be revealed in a dynamic auction process." Depending on the informational characteristics of the auction design, these market insights can stem from intermediate prices, final prices or even details on the opponents' bidding activity. As Goeree and Offerman (2003) showed, theory does predict inefficient results for auctions with uncertain value components. The provision of price signals by the auctioneer can reduce this uncertainty.

For CV auctions, Milgrom and Weber showed that policies of revealing information increase the average seller revenue. This principle is known as the *linkage principle* and it constitutes an incentive for the auctioneer to facilitate information discovery in the auction. For example, McMillan (1994) based his argument for conducting an open, ascending auction for the multi-unit sale of spectrum rights on the linkage principle. However, Perry and Reny (1999) showed that the linkage principle does not hold for multi-unit demand.

[7] McAfee and McMillan (1987) remarked that situations with asymmetries of information between buyers and sellers are also those when auctions are typically employed.

When the presence of secondary markets induces an uncertain common value component, price signals become more important in the primary market. As pointed out above, revealing information helps to mitigate the winner's curse (Milgrom and Weber, 1982). Also, future participants in the secondary market who do not participate in the auction may rely on the auction prices for planning purposes, and initial prices are relevant for the functioning of secondary markets by setting a first anchor point for the market price.

However, price signals might be less crucial in the pure IPV case than in the CV or in the mixed case. Since bidders are in possession of complete information when they act on their valuations, they do not need to acquire additional information during the auction. Note that even if a bidder knew the opposing bidders' values, the value she gave an item would not be influenced by this knowledge.[8] Therefore, in order to investigate the role of price signals in a laboratory experiment, uncertainty is an important design element.

2.3 Static Auctions

The static auctions presented in the following two sections are one-shot games. All bidders submit their bids simultaneously, and are not allowed to communicate with each other. After the submission of the bids, the auctioneer determines the allocation and the prices.

2.3.1 Uniform-price Sealed-bid Auction

In the Uniform-price Sealed-bid Auction (USBA) bidders simultaneously submit sealed price-quantity bids composing their demand schedules. After the submission of bids, the auctioneer calculates a market-clearing price and all bids at or above the market price are served at the uniform market price. In this thesis, the USBA was investigated in Study 1 (Chapter 4) on the sale of emissions permits, as the USBA design has been proposed for this application in the scientific literature (e.g., Ockenfels, 2009).

The idea and the academic discussion of the USBA date back to Vickrey (1961). Vickrey proposed a USBA with a Highest Rejected Bid (HRB) pricing rule for the sale

[8] However, price signals may be relevant to the auctioneer and other market participants.

of multiple homogeneous goods in an independent private values world under single-unit demand. Analogously to the Vickrey-Clarke-Groves (VCG) mechanism (Section 2.3.2), the USBA prevents bidders from strategizing by decoupling a bidder's bid from the price the bidder has to pay if she wins the auction.

For the case of *two-unit demand*, Noussair (1995) reported equilibria of the USBA with a HRB pricing rule under independent private values.[9] Noussair showed that bidders tend to bid lower than their true valuation for the second unit. The bidders' incentive to under-reveal their true values stems from the case when a bidder's higher bid is served, while the bidder's lower bid is the highest rejected bid, which determines the uniform price. It can be shown that under multi-unit demand a uniform-pricing rule cannot induce demand revelation (Vickrey, 1961; Green and Laffont, 1977).

Engelbrecht-Wiggans and Kahn (1998) extended Noussair's analysis to a broader class of equilibria and identified pooling strategies at a bid of zero. For common value auctions, Back and Zender (1993) showed that zero-bids can occur analogously to the independent private values scenario. In practice, zero-bids correspond to not bidding at all—in spite of a positive valuation—which is also called *demand reduction*. This phenomenon is discussed more broadly in Ausubel and Cramton (2002).

Demand reduction exacerbates inefficiencies. It is possible that units will not be allocated to the right bidders (those who value them the most), and what is worse, units may even not be allocated at all. Therefore, theory predicts a lower expected efficiency for the USBA than for incentive-compatible mechanisms, such as the VCG mechanism. In the case of complementary values, efficiency is reduced even further, since the bidding language of the USBA does not enable the bidders to express their preferences for bundles of units. List and Lucking-Reily (2000) compared the USBA with a VCG auction in a Sportscard field experiment with multi-unit demand. In line with the theoretical predictions, they find significantly more zero bids in the USBA. With respect to revenues, List and Lucking-Reily reported no significant difference between the auction formats.

[9] While the theoretical literature discussed in this section analyzes and recommends a HRB pricing rule, in actual applications the Lowest Accepted Bid (LAB) rule is more common (Cramton et al., 2009). With risk-averse bidders, Cramton et al. mentioned higher expected revenue as an advantage of the LAB rule. Also, the LAB rule appears to be more intuitive.

Despite the theoretical disadvantages described above, the USBA is certainly relevant in practice, and it was included in the experiment in Study 1. Two advantages of the USBA are its relative simplicity (Noussair, 1995), and its ability to state scarcity prices for items. With respect to final prices, unlike the VCG mechanism, the USBA provides item-wise scarcity prices. However, the one-shot design of the USBA does not provide any intermediate price information to the bidders.

As the original USBA was intended only for the sale of multiple homogeneous units of the same type of item, a modified version featuring two separate prices was developed for the sale of two different items in the experiment in Study 1.[10] In principle, the auction consisted of two USBAs that were conducted simultaneously. In order to keep the simplicity of the original mechanism, the experiment design did not allow for combinatorial bids. Details on the implementation are provided in Appendix A, and the experiment software is available for download from http://www.sascha-schweitzer.de/download/co2.

2.3.2 Vickrey-Clarke-Groves Mechanism

> *"Why is the Vickrey auction design, which is so lovely in theory, so lonely in practice?"*
>
> (Ausubel and Milgrom, 2006, p. 18)

Vickrey (1961) demonstrated that in a single-unit auction, if the bidder with the highest bid obtains the item at the second highest bid price, the bidder maximizes her profit by reporting her true valuation of the item. This is independent of how the opposing bidders bid. In the terminology of auction theory, in the second-price auction, truthful bidding is a dominant strategy. The dominance of truthful bidding is due to the fact that the second-price rule guarantees that a bidder's bid will not affect the price she has to pay if she wins the item.

Analogously, in auctions of multiple units, a uniform-pricing rule based on the HRB induces truthful bidding if each bidder demands only a single unit. Clarke (1971) and Groves (1973) extended Vickrey's approach to the general case of the sale of multiple units with multi-unit demand. In the VCG mechanism, preferences for bundles can be expressed. The principle idea of extending the second-price rule to the multi-unit case

[10] Strictly speaking this was not a uniform-price auction, but rather a two-prices auction.

is to decouple a bidder's bid and the price she has to pay if she wins a bundle. Again, a bidder's price is calculated solely based on the opposing bidders' bids. As there is no single second highest bid in the multi-unit case, the price is calculated as the opportunity costs that her winning imposes on the opposing bidders.[11]

The following model describes the VCG mechanism in the multi-unit case. Analogously to Section 2.2.1, the notation refers to the case of multiple homogeneous units of multiple items. An item represents a type or a class of goods with approximately identical characteristics. There are n bidders $i \in N \subset \mathbb{N}$ bidding for m items $k \in M \subset \mathbb{N}$. The supply of item k is restricted to a quantity of $s_k \in \mathbb{N}$ units, while each bidder's demand is restricted to a quantity of $d_k \in \mathbb{N}$ units. An allocation $\mathrm{q} = (q_1, q_2, ..., q_i, ..., q_n) \in A \subset Q^n$ defines the quantity vectors $q_i = (q_{i,1}, q_{i,2}, ..., q_{i,k}, ..., q_{i,m}) \in Q \subset \mathbb{N}^m$ that indicate how many units of each item k are allocated to a bidder i. The value function $v_i(q_i) : \mathbb{N}^m \mapsto \mathbb{R}$ maps a quantity vector q_i to bidder i's valuation for the given quantity.

The VCG mechanism asks each bidder to state her bid price for every bundle. Bidder i maps a quantity q_i to a bid by the bidding function $b_i(q_i) : \mathbb{N}^m \mapsto \mathbb{R}$. The auctioneer decides on the allocation q of goods by choosing the binary decision variable $\gamma_i(q_i) \in \{0, 1\}$ for all bidders i and all quantity vectors q_i. The variable $\gamma_i(q_i)$ takes on the value 1, if q_i is allocated to bidder i, and 0 otherwise. A complete set of decision variables is denoted by γ.

The auctioneer calculates her decision γ^* by maximizing the sum of all reported bid prices. Equation (2.6) states the maximization problem (following Krishna, 2002, p. 230). The condition in Equation (2.7) ensures that bidder i gets at most one of the quantity vectors q_i she bid for. Equation (2.8) ensures that the supply restrictions for all items k are met.

$$\max \quad \sum_{i \in N} \sum_{q_i \in Q} b_i(q_i)\gamma_i(q_i) \tag{2.6}$$

$$\text{s.t.} \quad \forall i, \sum_{q_i \in Q} \gamma_i(q_i) \leq 1 \tag{2.7}$$

[11] Remarkably, Green and Laffont (1977) showed that—under the assumption of rational bidders—the VCG mechanism is the only auction design that both admits dominant strategies and results in a Pareto efficient allocation.

$$\forall k, \sum_{i \in N} \sum_{q_i \in Q} \gamma_i(q_i) q_{i,k} \leq s_k \tag{2.8}$$

To calculate Bidder i's price, the auctioneer needs to determine the opportunity costs of the opposing bidders according to their reported values (also called social costs). First, the auctioneer calculates the reported value of the opposing bidders under the decision γ^*. Then, by solving the maximization problem given by Equation (2.6) for $N \backslash i$ instead of N, she calculates the reported value that the opposing bidders would have obtained if Bidder i had not participated in the auction. This hypothetical decision is denoted is denoted with γ'. The price $p_i \in \mathbb{R}$ Bidder i has to pay equals the difference of these two values, described by Equation (2.9).

$$p_i = \sum_{j \in N \backslash i} \sum_{q_j \in Q} b_j(q_j) \gamma'_j(q_j) - \sum_{j \in N \backslash i} \sum_{q_j \in Q} b_j(q_j) \gamma^*_j(q_j) \tag{2.9}$$

At first glance, the rules and calculations of the VCG mechanism seem complex. Yet, for bidders, the effect of the mechanism is quite the opposite, once they know their dominant strategy. Since truthful reporting of their valuations is the dominant strategy under VCG, bidders do not need to perform elaborate calculations. Therefore, despite its complexity, VCG offers bidders a certain simplicity.

Despite its advantages, the VCG mechanism comes with some serious pitfalls. Reviews of theoretical and practical disadvantages were given in Ausubel and Milgrom (2006) and in Rothkopf (2007). A potential problem with respect to *efficiency and revenue* generation is the mechanism's susceptibility to various forms of cheating. Rothkopf (2007) listed not less than four different kinds of cheating, three of which may be relevant in the types of auctions considered in this thesis: conspiracies between the bidders, cheating by bidder through false names and cheating by the auctioneer. In the first two cases, revenues decrease and the allocation becomes potentially inefficient. In the case of cheating by the auctioneer, revenue increases without changing the allocation. But on the long term, the third form of cheating erodes trust into the auctioneer, undermines the dominance of truthful bidding, and finally results in lower participation, lower revenues and inefficient allocations.

With respect to *information provision and price signals*, the static VCG mechanism performs poorly. Because it is a one-shot auction design, a VCG auction does not provide intermediate price signals. Seeing this shortcoming, Ausubel (2004) proposed an open, ascending version of the VCG mechanism. However, in all variants of the VCG mechanism, the final prices are bundle prices, making it difficult to attribute market values to individual items.

A major problem when it comes to its implementation is the computational burden that the mechanism imposes on the bidders and the auctioneer (Krishna, 2002, p. 230). The bidders face the problem of determining their valuations for all $\prod_{k \in M} d_m$ packages. While theory usually assumes that those values are given, in practice, the costs for estimating the values can be high. In contrast to the original one-shot design of the mechanism, in the ascending auction designs described in Sections 2.4.1 to 2.4.3, the bidders can narrow the set of realistic outcomes during the course of the auction. This allows the bidders to work with rough estimates for the least likely auction outcomes and to focus their more detailed and hard-won estimates on the most likely outcomes. For the auctioneer, the winner determination problem and the payment calculation is similarly difficult to solve. Especially for the sale of low value items, the mechanism's complexity may increase transaction costs unreasonably.

2.4 Open Ascending Auctions

In the course of an ascending auction, the prices of the items increase continuously or over multiple rounds. An auction is called an open ascending auction, if the bidders obtain information, such as the bids of the opposing bidders, during the course of the auction. The main advantage of open, ascending designs (compared with static designs) is the provision of intermediate price signals. Milgrom and Weber (1982) strongly recommended an *open* auction, since "[...] that maximizes the information made available to each participant at the time she places her bids." After each round the participants are able to update their own valuations of the items and their estimates of the final prices. In the following round bidders can adapt their bids based on the new information.

2.4.1 English Clock Auction

The English Clock Auction (ECA) employs an open, ascending bidding process. The auctioneer posts a price and bidders indicate the quantity of an item they are willing to buy at the given price. As long as the aggregated demand exceeds the aggregated supply, the auctioneer increases the price, either continuously or in discrete steps. When the clock stops, the final price is calculated either according to the Highest Rejected Bid (HRB) or to the Lowest Accepted Bid (LAB) pricing rule, analogously to the USBA described in Section 2.3.1.[12] Cramton et al. (2006) recommended the use of an ECA for the sale of emissions permits, which was also the subject of the laboratory experiment in Study 1 (Chapter 4).

Theoretical insights into the ECA were provided by McCabe et al. (1990), who identified equilibria under multi-unit supply and single-unit demand under independent private values. For single-unit demand, the auction is incentive-compatible and yields efficient allocations. McCabe et al. also reported experimental data that showed no significant difference between the bids predicted by theory and the bids observed.

Empirical evidence in favor of the open auctioning of a single-unit item under affiliated private values was provided in the experimental study by Kagel et al. (1987). The authors reported that the ECA leads to behavior closer to the equilibrium strategy than the USBA. However, an increased risk of collusion is attributed to open auction designs. Yet, contrary to these apprehensions, Kagel and Levin (2001) reported that in an experimental comparison of a USBA and an ECA under non-increasing two-unit demand. Despite both auction designs having identical normal form representations (which was also true for the USBA and the ECA without revelation of aggregate demand designs in Study 1), the open auction performed much closer to equilibrium. The authors reported further increased efficiency results when employing a dynamic VCG auction. Kagel and Levin (2005) reported similar results for two-unit demand with synergies between the two units. Again, the open auction performed closer to equilibrium, obtaining higher efficiency values than the sealed bid version of the auction.

In order to accommodate two types of items, in the experimental Study 1 of this thesis, a modified version of the ECA featuring two separate price clocks for the two

[12] Ausubel (2004) noted that most ascending bid auction designs can be collapsed down to a uniform-price sealed bid auction.

types of items was employed. In principle, the auction consisted of two ECAs that were conducted simultaneously. In order to take into account interdependencies between the items, and to provide sufficient flexibility, bidders were allowed to shift their demand from one item to another during the course of the auction. Details of the implementation are provided in Appendix A. Please use http://www.sascha-schweitzer.de/download/co2 for downloading the experiment software.

2.4.2 Simultaneous Ascending Auction

In 1976, William Vickrey suggested the use of multiple simultaneous ascending auctions for the sale of multiple items. In the early nineties, Paul Milgrom, Robert Wilson and Preston McAffee designed the first full-fledged version of the Simultaneous Ascending Auction (SAA) for the Federal Communications Commission (FCC) sale of paging licenses. In 1994, the FCC conducted this auction successfully and exceeded revenue expectations (McAfee and McMillan, 1996). Since its introduction, many regulatory authorities worldwide have used the SAA for the assignment of spectrum (see Study 2, Chapter 5), and for the auctioning of divisible goods in other markets, for example the electricity market (Cramton et al., 2006).

The SAA generalizes the single-unit English auction for the sale of multiple units. The main characteristics of the SAA are the following. First, the auctioneer auctions all units of all items *simultaneously*. Second, the bidding process takes place in *in multiple rounds*. A bidding round lasts for a period of time defined by the auctioneer and allows bidders to debate with their teams and calculate their next bids. The bidders are not allowed to communicate with the opposing bidders and do not gain any information on the opposing bids submitted in the current round. Third, the bidding process is *open*, meaning that the bids are published after each round. The level of detail provided can vary. In the "most open" auctions, the auctioneer announces all bids including the bids' values and the bidders' identities, while in the "least open" auctions, the auctioneer discloses only the value of the highest bid without revealing the bidder's identity. Last, bidders bid on *individual units*. Package bids are not allowed.

In addition to the basic properties, there are a number of micro-rules that need to be defined. Table 2.2 provides a summary of the most relevant micro-rules.

Table 2.2: Micro-rules of the SAA. For an elaborate description see Cramton (1997).

Micro-rule	Description
Stopping rule	The stopping rule determines when the bidding phase of the auction ends.
Minimum bid increment	The minimum bid increment dictates the minimum amount by which bidders have to increase their bids. It is implemented to keep the duration of the auction within certain limits. The auctioneer can adjust the minimum bid increment according to the advancement of the bidding phase. Typical increments are in the 5 to 10 percent range (Cramton et al., 2006).
Activity rule	The activity rule is installed to prevent the bidder from waiting to bid until the last minute, which deprives her opponents of valuable information. The activity rule forces the participant to bid in a consistent manner and with a certain level of activity. The level of activity determines what percent, depending on the advancement of the bidding phase, of her current eligibility the bidder must be active on. This can range from the simple requirement that the activity may not increase from round to round to more complicated versions that include comprehensive restrictions.[13]
Bid information	Bid information is the information that is published before, during and after the auction. The amount of released information can vary from only little—e.g. the identities of all the bidders before the start, the highest bid after each round and in the end the winner is revealed—to full transparency about the identities of the bidders and the deposits they made beforehand, the highest bids and who made them and all the bidders' eligibility after each round.
Bid withdrawal	The possibility of bid withdrawals in return for withdrawal penalties can be implemented in order to mitigate the exposure problem. The penalty amounts to between 0 and the difference between the withdrawn bid and the final bid.
Tie-breaking rule	Ties occur, when several bidders bid the same highest price on the same unit. One solution for this instance is to award the unit to the bidder who submitted her bid first. These time-based rules come with the (often welcome) side-effect that bidders have an incentive to submit their bids faster. Alternatively, ties can be solved by a random draw.

[13] There have been several different versions installed by the FCC. In some auctions the bidders were in possession of a certain number of waivers that could be used in a round like a "time-out" in which they were not required to submit a bid.

Auctioning the items *simultaneously* eliminates the uncertainty about future prices of substitutional items, that occurs in sequential auctions, and allows the bidders to bid more aggressively. It also enables the bidders to shift their bids to the most beneficial items (Cramton et al., 2006).

If bidders have complementary valuations, allowing only *individual bids* on the units of the items can inflict the risk that bidders will acquire only a subset of a desired package. This is called the *exposure problem*. This problem is especially prominent if the items are complementary. Allowing bids on packages solves the exposure problem. Yet it also increases the complexity for the auctioneer and the bidder and additionally bears the risk of the so-called *threshold problem*. This problem describes the difficulty of a group of bidders to outbid a global bidder, when every single bidder in the group seeks to keep her contribution to the total bid low. Weighing the advantages and disadvantages of package bids, in 1994, the FCC saw the danger of the exposure problem as the lesser evil relative to the complexity and the potential threshold problem (Cramton, 1997).

Milgrom and Weber's (1982) argument for open auctions also holds for the SAA. As in the ECA, after each round the participants are able to update their own valuations of the items and their estimates of the final prices. Therefore, Cramton et al. (2006) identifies the SAA's price discovery performance as the auctions design's key success factor for its predominance in certain applications.

Yet the advantage of intermediate price signals comes with an increased risk of collusion. For instance, bidders may try to communicate through their bids by entering characteristic numbers that represent the desired number of spectrum rights or the postal code of a desired region. This maneuver is called bid signaling. In order to prevent collusive bidding through bid signaling, most recent spectrum auctions—notably the German spectrum auction analyzed in Chapter 5—have made use of so-called click-box bidding. With click-box bidding, the bidders can only bid on a predefined selection of values above the minimum bid increments. This prevents bidders from communicating their preferences disguised as numbers in their bids.

Although the SAA is well established in practice, the theory on this auction format is less developed. Milgrom (1999) showed that for settings with more than three bidders, if at least one bidder has demand in which items are not mutual substitutes, no competitive equilibrium prices exist. Remarkably, Kagel et al. (2010) stated the lack of SAA equilibrium strategies explicitly in the instructions to their auction experiment. After describing the strategic options and pitfalls in the instructions to their SAA treatment of their spectrum auction experiment, they informed the subjects explicitly about the lack of equilibrium strategy: "What should you do? If we knew that we would not have to run the experiment" (Kagel et al., 2010, p. 3).

Due to its practical relevance, there is a large body of empirical literature on the SAA. Cramton et al. (2006) saw practical proof of the SAA's *efficiency* in the fact that the resale of spectrum rights is uncommon. In an experimental comparison of the SAA with the VCG mechanism, under independent private values, Brenner and Morgan (1997) did not find significant differences in allocative efficiency. Between the SAA and variants of a so-called Anglo-Dutch Auction, under independent private values with an uncertain common value component, Abbink et al. (2005) did not find significant differences in allocative efficiency. All in all, the empirical evidence suggests that the SAA leads to efficient results which are on a par with, albeit not better than the efficiency results shown by competing auction designs.

Referring to the US spectrum auctions, Cramton et al. (2006) stated that *revenue* expectations had often been exceeded. Klemperer (2002a) analyzed the revenue results of the SAAs that took place in several European countries in 2000 and 2001 for the sale of spectrum rights for so-called 3G (third-generation) networks. Klemperer criticized the majority of these auctions for not living up to their revenue potential.

Klemperer identified a gap between the actual spectrum *values* and the auction *prices*. The estimates before the auctions and the promisingly high prices in the British and the German 3G auctions indicated values of 400–650 euros per capita, while countries like Austria, Switzerland, Belgium, Denmark and Greece received embarrassingly low revenues of 100 euros or less per capita.

Klemperer identified several flaws in the auction designs and in the supporting policies, which he blamed for the low revenues. Since the bidders participated repeatedly in very similar market situations, bidders learned to anticipate the auction outcomes and to behave collusively. The increased danger of collusion was further facilitated by the open design of the SAA. Furthermore, smaller firms were frightened away from participation, reducing competition in the auction. The auctioneers, on the other hand, failed to learn from the high revenues in the early auctions and did not set sufficiently high reserve prices. To sum up, revenue and the quality of price signals in the SAA seem to depend crucially on the specific market situation. Repeated auction events and a small number of bidders are problematic in this respect.

2.4.3 Package-clock Auction

Cramton (2009a) proposed the Package-clock Auction (PCA) for the sale of radio spectrum rights.[14] In a "best of both worlds approach," the auction design merges a clock-bidding stage with a package-bidding stage—the first stage being similar to the ECA described in Section 2.4.1 and the second stage being similar to the VCG mechanism described in Section 2.3.2.

In recent years, the PCA has gained some traction in large-scale field applications. Cramton and Ausubel used the auction design to conduct several auctions in the gas and electricity sector as well as in a spectrum allocation context, the Austrian regulator employed the PCA in the 2010 spectrum rights auction of the 2.6 GHz spectrum, in 2012 the Swiss regulator employed the PCA for the sale of multiple spectrum bands, and further auctions are planned in other European countries (e.g. Ireland). The ascent of the PCA points to the importance of an experimental investigation of this new auction design, and Study 2 (Chapter 5) contributes to this exercise.

In the first stage of the PCA, the auctioneer posts a clock price for each item. This clock price is increased until the demand does not exceed the supply for each item. In contrast to a traditional clock auction, the auctioneer interprets the clock bids as package bids. This guarantees that no incomplete subsets of the quantity combinations bid for in the clock stage are allocated. In the second stage of the auction, the bidders submit conventional package bids. By sequentially conducting these two stages of the auction, the PCA combines an open and dynamic design with package bids.

Auction Process The *clock stage* consists of multiple rounds. At the beginning of a round, clocks for each item announce the current price for one unit of an item. After a round, the prices increase for those items for which the demand exceeds the supply.

[14] Predecessors of the PCA auction design were presented in Porter et al. (2003) and Ausubel et al. (2006).

The increment of the increase is determined by the auctioneer. The clock stage ends, if there is no excess demand for any of the items. As in the SAA, the bidding rounds are discrete, giving the participants time to react to the new information. Since the demand vector of each bidder is interpreted as a package bid in each round, the bidders indirectly bid on packages in the clock stage.

The main purpose of the clock stage is the provision of *price signals*. As discussed in Section 2.2.3, price signals are particularly relevant with respect to uncertain value components. Also, it is helpful for a bidder to learn about the preferences of her opponents, since the items received by the opposing bidders can have a positive or a negative impact on the bidder's valuation of the items. The bidders are supposed to use the information on prices and quantities acquired in the clock stage to improve their bids in the supplementary stage (Ausubel et al., 2006).

In the *supplementary stage*, bidders get the opportunity to revise their bids from the clock stage or to bid on additional packages. For example, a bidder who bid on two units in the clock stage is able to express her demand for a single unit at a lower price in the supplementary stage. The supplementary bids are sealed bids and all made in a single round. At the end of the supplementary stage, the auctioneer calculates the value-maximizing allocation according to Equation (2.6) presented in Section 2.3.2 on the VCG mechanism.

Activity Rule In principle, bidders can bid on any valid bundle. However, there is no obvious reason why bidders should make the effort to submit bids in the clock stage—revealing their demand—if they can also wait to submit their bids until the supplementary stage. Therefore, bidders could be inclined to refrain from bidding in the clock stage and bid only at the very end of the auction, a behavior called "bid-sniping." To prevent this behavior, an activity rule requires all bids to be consistent between the clock stage and the supplementary stage. The *activity rule* is a critical, though also a complex part of the PCA.

The original *revealed preference activity rule* was introduced by Ausubel et al. (2006). In every bidding round Bidder i's bids must satisfy the following formula:

$$\left(p_i^t - p_i^s\right) \cdot \left(q_i^t - q_i^s\right) \leq 0, \tag{2.10}$$

in which s and t ($s < t$) are two points in time, p_i^s and p_i^t the price vectors and q_i^s and q_i^t the demand vectors at these times.[15] This means that at any point t in time Bidder i can switch from a package q_i^s to the package q_i^t, only if q_i^s is relatively more expensive. Since the activity rule also applies to the supplementary round, the bids made in the clock stage constrain the bids that the bidders can submit in the supplementary round. So, in order to be able to bid up to their true valuation for a package in the supplementary stage the bidders must bid according to their true valuation in the clock stage.

In practice, the revealed preference rule turned out to be difficult to employ. In experiments conducted by Cramton (2009b), bidders who had not bid truthfully in the clock stage faced problems adjusting their bids in the supplementary stage. They struggled to identify which of the constraints of the activity rule were being violated. Another problem with the revealed preference activity rule is its restrictiveness when there is uncertainty about the valuations. This can lead to the problem that “the bidders' values may change over the course of the auction for example as the result of common value uncertainty” Cramton (2009b).

In order to reduce the complexity and the restrictiveness of the original revealed preference rule, Cramton modified the original activity rule including fewer constraints. The modified rule is called the *simplified revealed preference rule*, and implemented in the present experiment. In the clock stage, it is possible to bid on packages of the same size or smaller without any constraint. Bids on larger packages have to satisfy the following inequation:

$$q_i^t \cdot (p_i^t - p_i^{t-1}) \leq q_i^{t-1} \cdot (p_i^t - p_i^{t-1}). \tag{2.11}$$

This means that in order to switch at a point t in time to the bigger package q_i^t, this package has to become relatively cheaper than the package q_i^{t-1}.

The rules for the supplementary stage are also simplified. Let $b_i(q_i^f)$ be the final bid of the clock stage on the package q_i^f. Then, all bids $b_i(q_i)$ in the supplementary stage on packages q_i of the same size or smaller then q_i^f need to satisfy the following constraint:

$$b_i(q_i) \leq b(q_i^f) + (q - p_i^f) \cdot p_i^f, \tag{2.12}$$

[15] For the derivation see Ausubel et al. 2006.

and all bids in the supplementary stage on packages larger than q_f the constraint:

$$b_i(q_i) \leq b_i(q_i^s) + (q_i - p_i^s) \cdot p_i^s, \tag{2.13}$$

where s is the round in which bidder i bids for the first time on a package q_i^s smaller than q_i. Since the bidders cannot know which round in the clock stage will be the last, they have to bid consistently with what they intend to bid in the supplementary stage. Otherwise they will not be able to submit their intended bids at the end of the auction.

Cramton (2009b) also tested the simplified version in a series of experiments. Those experiments support the suggestion that the desired properties of the original rule carry on to the simplified version of the rule. The simplified version of the activity rule was used in the Austrian spectrum auction in 2010, and was also used in the experiment reported in Chapter 5.

Pricing Rule The PCA pricing rule modifies the VCG pricing rule discussed in Section 2.3.2, in order to avoid a notorious problem associated with the original rule. In the case of complementary items, situations can occur in which the sum of the prices charged for a subset of units is below a price offered by an opposing bidder or a coalition of opposing bidders. In the terminology of game theory, the prices are not in the core. In a renegotiation of the auction outcome, this result would not be stable.

Cramton (2009a) tackled this problem modifying the Vickrey prices to conform with a set of side conditions. These conditions guarantee that the final auction prices are in the core. In the first step of the price determination, the auctioneer calculates VCG prices. She then determines the final PCA prices by choosing the prices with the smallest Euclidean distance to the VCG prices that still fulfill the core-conditions. This modified pricing rule is called Closest-to-Vickrey (CtV) pricing. The principle idea behind this procedure is to minimize the incentives for deviating from truthful bidding.

Advantages and Disadvantages A major advantage of the PCA over the SAA is the elimination of the exposure problem through the use of package bids. A second advantage over the SAA is the PCA's speed, since clock bidding is faster than bidding on individual units. The SAA is especially slow toward the end of the auction, because few bids are then placed on the units and it takes several bidding rounds to increment the price on all units. As a third advantage over the SAA, the clock stage is easier to oversee and clearer in its structure than the plethora of individual bids in the SAA, since the bidder only needs to answer an easy demand query: "how many units to purchase at the current price."

Ausubel et al. (2006) named limited information as another advantage of the PCA. The current price and the excess amount of each item is the only information released to the bidder after each round. This prevents the bidders from using bid signaling to communicate with other bidders, from retaliating with bids and from excessive strategizing. However, the exclusiveness of this advantage is disputable. One could argue that the SAA can be designed to provide as much or as little information.

The PCA is not without potential disadvantages. The complexity of the activity rule can be problematic for the bidders. This may require more intensive training sessions than in the SAA. An analogous problem for the auctioneer is the complexity of the winner and price determination. There are several optimization problems to solve, which means the PCA needs more computational time than the SAA.

Also, since the PCA is a relatively new auction design, potential auctioneers and bidders do not have much experience with it, whereas the SAA has been conducted countless times. This concern played a major role in the decision of the German authorities against the PCA in favor of the SAA in 2010 (Bundesnetzagentur, 2009).

The incentive to deviate from a straightforward bidding strategy under CtV pricing can be very pronounced. For a continuous, incomplete-information environment, Goeree and Lien (2009) showed that core-selecting auction formats yield lower and less efficient outcomes further from the core than do Vickrey outcomes.[16] An example analogous to the one described by Goeree and Lien is provided below.

Example 2.2 (Incentives for deviating from truthful bidding in the PCA)
The following example illustrates the nature of deviations from truthful bidding under CtV pricing in a complete-information environment. Two units of an identical item are auctioned among three Bidders $i \in \{1, 2, 3\}$. $k_i \in \{0, 1, 2\}$ denotes the number of units purchased by Bidder i and $v_i(k_i)$ denotes the value Bidder i places on her purchase k_i.

[16] Although Goeree and Lien's (2009) result sounds drastic, it does not mean the end of the PCA. The PCA solves an important political issue and competing auction formats like the SAA do not look much better from a theoretical perspective.

Bidder 1 places a value of 100 on the purchase of both items, but no value on the purchase of a single item. In contrast, Bidder 2 and Bidder 3 each place a value of 80 on the purchase of a single item, while the purchase of an additional item does not increase the bidders' valuations. While the two units are complements for Bidder 1 they are perfect substitutes for Bidders 2 and 3. This situation is depicted in table 2.3.

Table 2.3: Valuations in Example 2.2

i	value of one unit $v_i(k_1)$	value of two units $v_i(k_2)$
Bidder 1	0	100
Bidder 2	80	80
Bidder 3	80	80

Provided that all bidders bid according to their true valuations, the auction outcome in the PCA is as follows. No unit is allocated to Bidder 1 who accordingly pays zero. Bidders 2 and 3, who jointly hold the highest value for the two units auctioned, each obtain one unit. The price for a unit is 50. The original Vickrey price is 20, while the additional 30 stem from the CtV-pricing-rule which imposes an increase on the original in order to meet the core criterion. If both bidders did pay only 20, the total payment would be only 40, which is less then Bidder 3's bid of 100. Due to the symmetry of the situation the increase of the price is split equally between Bidders 2 and 3.

However, Bidder 2 could considerably improve herself by unilaterally bidding below her true valuation. If Bidder 2 submits, for instance, a decreased bid of 21, the final allocation will not change. Yet, the price Bidder 2 has to pay decreases from 50 to about 20. The bidder's profit almost doubles from 30 to about 60. Luckily for Bidder 2, in the new situation Bidder 3 has no incentive to deviate from her original truthful bidding strategy. If Bidder 3 decreased her bid as well, then, neither she nor Bidder 1 would obtain a unit of the item. Therefore, the new situation constitutes an equilibrium.

Indeed, all splits of the CtV total minimum price for Bidders 2 and 3 of the total CtV price of 100 represent an equilibrium, with the only symmetric equilibrium being the equal split of 50-50. In any equilibrium, the reported total valuation is 100, which is well below the actual valuation of 160.

3 Methodology

3.1 Comparative Experiments

> *"If a mechanism does not work acceptably in a simple case created in a laboratory, then there may be no reason to think that it will work in the complex cases found in a field application."*
>
> (Plott, 1997, p. 607)

Informal experiments are an integral part of children's everyday life. They put things into their mouths to compare their feel and taste, or they throw objects from the table to observe their behavior under the laws of gravity. The goal of those experiments is to fight boredom, to observe nature and to learn about the relationship of cause and effect. Exploring similar questions of cause and effect, scientists perform experiments in a systematic way. The tradition of comparative experiments goes back as least as far as the 10$^{\text{th}}$ century, when the Arab scholar Alhazen employed experiments for his inquiries in optics (Alhazen, 1989).[1]

In a comparative experiment, researchers conduct multiple treatments, varying selected variables between the treatments, while holding all other variables or environmental conditions constant. Different observations across treatments are explained by variation of the treatment variables. Often, comparative experiments are conducted in a laboratory environment in order to obtain maximum control over the relevant variables, so that an observed effect can be attributed to a specific variable. Control means the ability to *set* and to *know* the values of the relevant variables.[2]

[1] Over the centuries, the experimental method and its philosophical foundation was further developed by Western scholars, such as Roger Bacon, Galileo Galilei and Karl Popper.

[2] According to the Merriam Webster dictionary definition of "control," the term has the two meanings: *having power* and *checking or testing* (www.merriam-webster.com. 2012, February 26, 2012).

The environment in the field is often complex and a whole plethora of variables changes between the single observations. It is usually impossible to hold all variables—other than the treatment variables—equal. Even more troubling, it is usually not possible to identify all relevant variables and to measure their change. An illustrative example is provided by the German and the Austrian spectrum auctions conducted in 2010 (Chapter 5). In both cases, the respective regulator auctioned spectrum in the 2.6 GHz band. Since the two regulators employed two fundamentally different auctions, the auctions' designs could be compared on the basis of the available field data.

Indeed, as the auctions in the example took place in a very similar technological and cultural environment in neighboring countries, the conditions for a comparison seem favorable. Unfortunately, however, there are still so many differences between the two situations that a direct comparison of the two real-life auction events is almost infeasible. First, the researcher's knowledge of the participants' valuations and their motivation is incomplete. Second, different bidders with different business models participated in the auctions, additional spectrum bands were offered in the German auction, the markets differed in size and structure, and the geological environments differed. And third, when the Austrian auction took place, the participants were able to incorporate the knowledge of the earlier German auction.

3.1.1 Control in Economic Experiments

Experimental economics gains control over the relevant variables by conducting the auctions in the controlled environment of a laboratory. Vernon Smith, the founding father of experimental economics stated: *"Control is the essence of experimental methodology"* (Smith, 1976, p. 275). This section presents several existing instruments for guaranteeing control in the economic lab.

One crucial instrument for establishing control in economic laboratory experiments is the use of *induced values* in economic experiments (ibid.). Instead of trading with physical goods, subjects in the experiment trade with tokens or certificates that are exchanged for a predefined resale value at the end of the experiment. The use of tokens allows the experimenter to induce supply and demand structures and to ensure that these variables are equal between the treatments (or that they differ in a controlled way).

A second instrument of control is the use of identical procedures for all treatments. For instance, the laboratory hardware, the interface of the experiment software and the instructions should be identical between the treatments. Yet, the extent to which these and other procedural parameters can be controlled is limited. In contrast to experiments in the natural sciences, experiments in social sciences are limited in the control of humans and their complex environment. Also—as will be explained in the following sections—control over the physical content of instructions and software does not automatically imply control over the perception of these media and over the experiment situation in the human mind.

The subjects in an experiment are (usually) individual humans who participate in the experiments voluntarily. In principle it is not possible to hold these subjects constant across treatments. If the same subjects participate in all treatments (*within-subject* design), they will be biased in the later treatments due to their experience of the earlier treatments. If, on the other hand, different subjects participate in the separate treatments (*between-subject* design), they will also be different in personality, cognitive capability and other human traits. One mechanism for controlling for sequence and learning effects in within-subjects studies is varying the sequence of treatments within one experimental session—for instance, for Treatments A and B, two alternative sequences could be ABBA and BAAB (Friedman and Sunder, 1994, p. 26).

Another common solution of the issue of subject heterogeneity is *randomization* of the subject selection in combination with repetition and a between-subject design (ibid., p 22ff). This approach allows for an indirect or stochastic type of control. It rests on the conjecture that the differences between the subjects are distributed stochastically and cancel each other out if there are sufficient independent observations. To support a systematic and rigorous randomization, standardized software tools for the invitation of subjects are becoming increasingly popular. An example is the online recruitment system, ORSEE, which automates the administration of the subject database and the random selection of subjects, and contributes to the development of standards in experimental economics (Greiner, 2004).

An aspect related to control is the *reproducibility* of the experimental results. If the results of one specific experiment conducted by one specific research institution possess universal validity, the same results should recur, when other institutions—at different locations and at later times—*replicate* the experiment. Replicating an experiment can serve to test the robustness of past results or to test the effect of additional parameters. In order to replicate exactly the same conditions as in the original experiment, the information on the details of the original experiment needs to be as complete as possible. This is an issue of documentation and communication, especially if the institution that seeks to replicate an experiment is a third party. Most journal articles on economic experiments hardly discuss the instructions used in their studies. Yet often (but not always), the instructions are available in the appendix or from the author on request.[3]

3.1.2 Testbed Experiments

Smith (1976) stated two central functions of experimental economics. First, "laboratory studies can serve as a rigorous empirical pretest of economic theory." And second, the "results of experiments can be directly relevant to the study and interpretation of field data." Plott (1994) saw an additional role for economic laboratory experiments. He suggested that experiments should serve to test markets designed by economists and intended for actual applications. Plott coined these experiments *testbed experiments*.

Plott (1997) distinguished between several types of testbed experiments. First, experiments serve to test the "broad rules that might be implemented" (p. 605). A broad comparison of rules and auction designs is also the main goal of the experimental studies in this thesis. Plott mentioned two more functions of testbed experiments, which he encountered when consulting the Federal Communications Commission (FCC) on the choice of an auction design for the sale of radio spectrum rights. After the FCC had decided on the broad rules of the auction design, experiments were employed in order to test the detailed rules. These experiments were run with the actual software that was developed for the auction, and "at this stage, the experimental methods were, in a sense, part of debugging" (p. 608). In addition, during the actual operation of the

[3] The author's personal experience with requests for instructions is negative. In some instances, the instructions were claimed to be lost or burnt. To ensure reproducibility, it would seem appropriate to require the publication of the instructions and the software along with a research article.

FCC auction, insights from the experiments were used to adopt details of the running auction process. For instance, during the auction, the experimenters contributed their experience to adjust the speed of the auction by setting appropriate bid increments.

Any form of testbed experiment is typically more *specific* to a given situation than a traditional theory-based laboratory experiment. Furthermore, in contrast to stylized models, real large-scale applications are typically more *complicated* and more obscure. First, real bidders and items are worlds of their own with a plethora of attributes and unique features. The real world is never homogeneous and one usually does not know all of its properties and conditions. Second, there are additional aspects—apart from bidders and items—which are interwoven with the market. For instance, law, politics, and emotional aspects might play a role and affect the market situation.

The relevant domains in the context of experimental economics—theory, experiment and the external world—constitute a triangle, as depicted in Figure 3.1. Which *inferences* are valid *within and between those domains* is discussed under the term "validity." *Internal validity* refers to the validity within the experiment, which is "whether a given laboratory phenomenon or mechanism has been correctly identified" (Guala, 2005, p. xi). *External validity*, on the other hand, refers to the validity of the results for the external world, which is "whether the results can be generalized from the laboratory to the outside world" (ibid.). In formal terms, Guala described internal validity as the ability to infer that A causes B within the domain of the experiment E, while he described external validity as the ability to make the same inference in another domain F.

To some degree there is a *trade-off* between internal and external validity. The more closely the experiment situation represents a real market, the more complicated the experiment will get. But a more complicated situation is also very likely a situation which is more difficult to control. When deciding on this trade-off, one might keep in mind that internal validity is a prerequisite of external validity. Therefore, it may not be possible to obtain an arbitrarily high level of external validity without losing the internal and therefore the overall validity of the experiment.

Despite their long tradition in psychological research, the concepts of internal and external validity were not introduced in experimental economics until the 1980's and 1990's (Heukelom, 2009). And still, the issue of external validity is not clear cut. Although there may be many differences between the inside world of the laboratory and

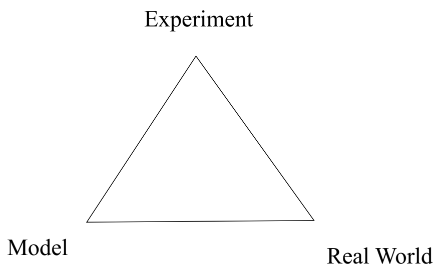

Figure 3.1: Domains of economic experiments.[4]

the outside world, it may also be true that the two worlds have more in common than they have differences. For instance, Plott (1982) stated that “laboratory markets are ‘real’ markets in the sense that principles of economics apply there as well as elsewhere. Real people pursue real profits within the context of real rules” (p. 1520).

Sometimes, a link between theory and experiment is demanded for an experiment to be internally valid. For instance, Plott (1997) worried that a mechanism might work purely “for accidental reasons” (p. 607). However, this does not affect internal validity as defined above, as (even if there is no theory) the experiment will still allow for statistical inferences from cause A to effect B, if the level of control is sufficient. Naturally, in testbed experiments, the theoretical foundation is often weak or does not exist at all. Still, some theoretical background may be helpful to give meaning to these inferences. As McAfee and McMillan (1996) stated, “the real value of theory is in developing intuition” (p. 172).

3.1.3 Traditional Experimental Instructions and Software

One condition for internal validity is that the subjects *understand* a given task. For example, Fiore (2009) stated that an experiment is considered internally valid—“in the sense that the causal relations derived from it can be considered as fundamentally true and replicable” (p. 26)—if the following conditions are fulfilled: “adequately motivated subjects, put in a controlled environment, where they are not deceived, but rather are

[4] The idea of this figure was adopted from Sugden (2005).

given the opportunity to *understand properly the task they are required to perform* and given the opportunity to acquaint themselves with it" (p. 25–26, emphasis added). This section discusses how experimental economists traditionally ensure subject comprehension and how their instruments develop.

Usually, an economic lab experiment is presented to the students in the form of a *written instruction text*. It is a common practice to make the instructions available to the subjects at the beginning of an experiment and to read them out aloud once. Reading out the instructions ensures (or at least makes more likely) that all subjects obtain the same information and do not skip text passages.

The design of the instructions is a crucial part of the preparation of an experiment. Davis and Holt's (1993) textbook on experimental economics stated that "It is worthwhile to spend a lot of time working on instructions" (p. 27). The authors advised young researchers "to begin with standard, often-used instructions, and to modify them for the purpose at hand." For testing and optimizing the instructions, Davis and Holt recommended "[p]ilot experiments and individual 'debriefing' sessions." They also said that instructions should be "specific about all aspects of the experiment" (p. 26). Davis and Holt reasoned that a failure to provide detailed information—for instance on the duration of the experiment—would lead the subjects to engage in conjecture and behavior out of the experimenter's control.

What cannot be found in Davis and Holt's textbook (or in any textbook on experimental economics) is a discussion of the insights provided by psychology on learning and cognition in complex environments. One reason might be that typical instructions for traditional theory-based experiments include only a few pages of text, which does not require overly sophisticated training instruments. A second reason may be that, even if more sophisticated instruments could improve comprehension, their implementation would require dedicated effort.

In order to verify the subjects' comprehension, many experimenters conduct a *comprehension test* before the beginning of the experiment (Friedman and Sunder, 1994, p. 52). Usually, the subjects are also allowed to ask the experimenter questions (after reading the instructions as well as during the experiment). The form of this interaction between experimenter and subjects varies from open discussions to disclosed questions—sometimes with selected publicly announced answers. While, occasionally, the test questions are published along with the experiment instructions, experimenters usually do not systematically document or report the questions that were posed by the subjects.

Testbed experiments—such as the auctioning of multiple items with sub-additive values and multiple units with super-additive values in a combinatorial auction (Chapter 5)—are typically more complicated than traditional theory-based experiments (cf. Section 3.1.2). Naturally, the tackling of these elaborate scenarios requires elaborate instructions. As Clark et al. (2006) put it "[m]ore information and more complex tasks demand greater skills, which require more training" (p. 7). This implies a major challenge to instruction design and to the subjects participating in the experiment. Friedman and Sunder (1994) drew the analogy that "[e]xperimental instructions often compete with apartment lease forms in length and complexity of their fine print" (p. 40).

For example, Cramton (2009b) provided his student test subjects with 38 pages on the rules of his Package-clock Auction (PCA) experiment. The PhD-student subjects could handle this task, as they were given as much time as they wanted to read the instructions at home and prepare for the experiment.[5] Unfortunately, the number of observations for this type of experiment is naturally limited by the size of the potential subject pool and the level of control is much lower than in a traditional experiment, since communication and collusion cannot be prevented completely. Also, experimenter demand effects can be more prominent in the familiar environment of the PhD-student subject pool, making it necessary to monitor this issue very carefully.[6] An alternative would be to employ regular students and to instruct them in the controlled environment of the laboratory. Yet, given the extent of the instructions in the case of Cramton (2009b), it seems likely that the subjects would be overwhelmed by the amount of material they had to learn and understand in the limited time available in a traditional laboratory experiment.

After receiving the experimental instructions, the second major instance of information and interaction in an economic experiment is usually moderated by the *experimental software*. The issue of software and interface design is similar to the one of instruction design, and most of what has been said about the design of the instructions might also be said of the interface. The didactic requirements are basically the same, and in fact, a major task of the instructions is to explain the interface.

[5] Source: Private correspondence with the experimenter in February 2010.

[6] The *experimenter demand effect* occurs when subjects try to act according to the behavior that is supposedly desired by the experimenter.

Friedman and Sunder (1994) emphasized that "[s]oftware is the key resource in a computerized economics laboratory in terms of both the time and money it takes to develop and maintain" (p. 66). Nevertheless, neither Friedman and Sunder's, nor Davis and Holt's (1993) textbooks provided detailed guidelines for the design of experimental software. Since the publication of these popular textbooks, software and interface standards have been driven mainly by the development of software toolkits by the community of experimental economists—such as *Multiple Unit Double Auction* (MUDA) by Charles Plott (Plott, 1991), *Multistage* by Thomas Palfrey, *Python Experimental Economics Toolkit* (PEET) by Ben Saylor, *Willow* by Jaap Weel and Kevin McCabe, and *z-Tree* by Urs Fischbacher (Fischbacher, 2007). This list is far from being complete, which is also the case for the process of software standardization for economic laboratory experiments.

One of the most popular tools for the development of experimental software is z-Tree—on February 26, 2012, Google Scholar indicated 2,727 citations of the corresponding journal article Fischbacher (2007). Also, both of the studies reported in Chapters 4 and 5 were programmed and conducted using z-Tree (plus custom plug-ins). The software toolbox provides a graphical interface which facilitates the development of simple programs, and it also offers the opportunity to write additional program code and to include external programs.

Besides the practical advantage of simplifying software development and saving some of the software costs, as stated by Friedman and Sunder (1994), z-Tree also had a big impact on the standardization of the user interfaces of experimental software. All standard interface elements, such as buttons and input boxes, are provided by the toolbox and do therefore look the same across all experiments. Furthermore, the client interface always runs in full-screen mode, features a characteristic neutral grey color scheme, and requires interface developers to use one-screen designs that do not involve multiple levels of menus. These restrictions lend every z-Tree program a visually similar appearance. Also, they force developers to use well-structured, tidy designs.

From a *historical perspective*, the standards for instructions and software tools for economic experiments *evolved* over time to enable the fulfillment of the scientific requirements of control, reproducibility and validity. The basis for the development of most of the discipline's instruments were common sense and experience. "To some extent and from a given perspective, experimental economics seems to be still a discipline ‘under construction’, subjected to continuous refinements and improvements, even if gradually, on some issues, a tacit consensus at the beginning, and a more explicit consensus afterwards, has grown up” (Friedman (1988) as cited in Fiore (2009) p. 3).

With respect to this evolutionary approach, the development of the instruments of experimental economics resembles the *design science* approach coined by Hevner et al. (2004). Hevner et al. stated that the “design-science paradigm seeks to extend the boundaries of human and organizational capabilities by creating new and innovative artifacts” (ibid., p. 75). Being used mainly in information systems research, the term *artifact* usually refers to a computer software system or to a software-supported system. Applied to the tools of experimental economics, the artifacts are the experiment software and the instructions.

The evaluation of design science artifacts relies mainly on the experience reported by the software engineers and the test users of the artifact. As Hevner et al. (2004) put it, “knowledge and understanding of a problem domain and its solution are achieved in the building and application of the designed artifact” (p. 75). This learning by doing approach (plus the establishment of a more or less tacit consensus) resembles the evolution of scientific methods.

The following sections will develop several (at least partly) new instruments for the effective instruction of subjects and the running of experiments. Yet, since some of the proposed changes may exceed the scope of evolutional development—quite naturally provoking all kinds of caution and resistance—it seems advisable to provide a stronger theoretical and empirical basis than is usually devoted to advances in experimental instruction and software design. Therefore, although no validation of the overall implementation can be provided within the scope of this thesis, the following sections will provide a foundation for the individual instruments, mostly reverting to the comprehensive results of cognitive research.

3.2 Insights from Learning Theory

> "[. . .] *the unaided observer is severely limited in terms of the amount of information he can receive, process, and remember. However, it is shown that by the use of various techniques* [. . .] *this informational bottleneck can be broken.*"
>
> (Miller, 1957, p. 2914)

The science of cognition is a well established and self-contained discipline with a strong theoretical and empirical foundation. Much of the literature in this field focuses on the design of instructions, and the study of this literature is of interest to anyone involved with the systematic teaching of learning objectives. In principle, the findings of cognitive learning theory also apply to the instructions in economic experiments—even more so since the empirical evidence in cognitive research is mostly the result of laboratory experiments.

As bad weeds grow tall, so the training industry offers an abundance of myths and folk wisdom. From edutainment to discovery learning, most of these practices have not been empirically evaluated and some have even been proved wrong through scientific evidence (cf. Clark, 2006). The goal of the following sections is to present a short survey of the scientific literature on the working of the mind and the principles of instruction that can improve learning under the constraints of the laboratory situation in an economic experiment.

3.2.1 Approach and Background of Cognitive Theory

Cognition is the *science of the mind*—concerned with the mind and its processes, such as perception, memory and reasoning. The methods of the cognitive sciences include the construction of theory and the empirical validation or falsification of the theoretical predictions. Although many of the great philosophers—such as Plato, Descartes, and Kant—engaged, over the course of centuries, in the study of the workings of the human mind, the modern discipline of cognition emerged only in the second half of the 20$^{\text{th}}$ century.

Emphasizing the necessity of causal models for the understanding of learning, Mayer (2005a) stated that the design of instructions is inevitably connected with a cognitive concept of the mind. “Decisions about how to design a multimedia message always reflect an underlying conception of how people learn—even when the underlying theory of learning is not stated” (p. 32). Further, the understanding of that concept improves the design of instructions, as “instructional messages that are designed in the light of how the human mind works are more likely to lead to meaningful learning than those that are not” (ibid.).

The dominant role of the cognitive sciences within psychology today can be traced back to the *cognitive revolution*. Before the rise of cognitive science, behaviorism prevailed in the analysis of behavior and learning. Behaviorists saw learning as a black box that mediates between a stimulus and the behavioral response. The process of learning itself was considered as out of the reach of research, since it occurs in the covert world of the mind and cannot be directly observed. Indeed, radical behaviorism ignored any causal role of the mind in human behavior (Paivio, 1986).

In the 1950’s, behaviorism was challenged by authors like George A. Miller, Noam Chomsky and Donald Broadbent. These authors drew some of their inspiration and of their arguments from the young disciplines of information science and from the research on artificial intelligence, which naturally require conceptual models of the mind. Steven Pinker (2002) summarized the core ideas of the cognitive approach. He stated that “[t]he mental world can be grounded in the physical world by the concepts of information, computation, and feedback” (p. 31) and that “[t]he mind cannot be a blank slate because blank slates don’t do anything” (p. 34).

The cognitive approach is constructive, as it constructs hypothetical models of the mind. Yet, the cognitive approach is also empirical, as it derives those models on the basis of empirical observations and validates the models by the means of experimentation. For an example of how empiricism and theory construction work together in cognitive science, consider the discovery of the associative nature of memory organization by Bousfield (1953). The experimenter presented words in a random order. Despite the random order of presentation, the subjects recalled these words in conceptually related clusters. These empirical observations in the free-recall task suggested that information is reorganized by the mind in a certain way. Although a set of models can explain this phenomenon, this set can be narrowed down by empirical observations and the subsequent elimination of incompatible models.

3.2.2 Multimedia Learning

Multimedia learning refers to the learning through multiple channels, such as pictures and words. Note that (somewhat counterintuitively) the term *multimedia* learning usually refers to the multiple channels of perception and cognition rather than to actual physical media. In this sense "words" include text as well as narration and "pictures" include still pictures as well as animations.

In a survey of multiple empirical studies, Mayer (1997) emphasized the evidence that the effect of multimedia learning does not depend on the actual media that the learning material is presented in, but rather on the engagement of multiple cognitive processes. Nevertheless, the requirements of control in economic experiments—such as the limited amount of time and the necessity to document and to reproduce the learning materials if required—may advise against some media. For instance, methods employing human instructors are generally difficult to control due to the learning processes of the instructors themselves and due to the interaction between instructors and subjects.

Mayer (2005a) stated that "People learn more deeply from words and pictures than from words alone" (p. 31). Exploring the question why one should expect the multimedia principle to work, Fletcher and Tobias (2005) referred to the philosophy of the 18^{th}-century bishop, George Berkeley, who suggested that words and pictures evoke different thought processes. While the word "tree" makes one think of the abstract *concept* of a tree, a picture of a tree evokes a concrete *image* in one's mind. The verbal concept may also be associated with different attributes and images for different people, while the image of a tree implies a very specific and strong meaning.

Paivio (1986) extended this thought by suggesting the *dual coding theory* which assumes that the mind processes visual and verbal information differently and along distinct and mostly independent channels. Evidence for the independence of the channels is provided by so-called dual-task experiments, in which subject have to accomplish a secondary task, while working on a primary task (Clark et al., 2006, p. 34). For example, the subjects listen to a series of numbers which they are supposed to remember, while they also wait for a signal tone, at which point they have to press a button. These experiments showed that performance in the primary task suffers considerably, if the secondary task occupies the same channel as the primary task, while secondary tasks on different channels imply only a minor decline in performance.

Independent channels can also complement each other (e.g. Fletcher and Tobias, 2005). For example, images can facilitate the recall of nouns. Furthermore, the capacity restrictions described in Section 3.2.3 apply channel-wise. Therefore, the overall processing capacity increases, when more channels are employed. This is one of the primary reasons why multimedia instructions lead to improved learning results (e.g. Low and Sweller, 2005).

With respect to the verbal channel, there is strong evidence that narration (acoustic information) is easier to process than printed text. Clark et al. (2006) cited not less than 17 separate studies that were conducted in several countries and contexts which support this statement. Remarkably, the advantage of narration is most pronounced for complex learning materials, while it vanishes for very simple topics.

Another central and well-established principle of learning is the distinction between *working memory* and *long-term memory*. Somewhat contrary to general language use, in cognitive terminology, working memory refers only to the instant recall of given information—usually within the time frame of a single minute. Long-term memory is anything beyond that. While working memory is restricted (cf. Section 3.2.3), long-term memory is generally considered to be an unlimited resource (Baddeley, 1997).

Learning requires information to pass from working memory into long-term memory. Yet, long-term memory works much differently from the memory on a computer disk, which just receives and stores information as it is. Instead, the human mind needs to actively *construct* and *(re)generate* the information (Wittrock, 1989). "Instruction, then, does not involve the transmission of intact 'chunks' of information from teacher to students, but rather the transmission of cues that students use to construct, verify and modify their models of the world" (Fletcher and Tobias, 2005, p. 119). The reason for this somewhat cumbersome storage process lies in the structure of long-term memory.

A well established model of the human memory structure is provided by the *schema theory*, which goes back to Bartlett (1932), and—in a modern, cognitive variant—to Chi et al. (1982). As Sweller (2005) put it, "[s]chemas are cognitive constructs that allow multiple elements of information to be categorised as a single element" (p. 21). Furthermore, schemas form a network and learning revolves around the association of the new information with existing schemas.

The dual coding theory, the schema theory, and the constructive nature of learning are key assumptions of both major theories of multimedia learning—Richard E. Mayer's *cognitive theory* and John Sweller's *cognitive load theory*. Another, and perhaps the most crucial element of those theories is concerned with the capacity and the limits of the learning process, in particular with respect to working memory. Capacity issues are the main obstacle that an effective instruction design needs to overcome. The following section presents the most prominent of those issues and ways to overcome them.

3.2.3 Processing Constraints and Counter-measures

One of the early and most robust findings of cognitive research is the limited capacity of the human short-term memory and processing. Miller (1956) suggested that the processing capacity of the human mind is limited to *four to ten* single items or *chunks* of information. The author based his conjecture on a survey of numerous experiments. For example, Pollack (1952, 1953) asked subjects to listen to tones and identify their frequency by assigning numbers to them. While for up to four different tones mistakes were very rare, a greater number of tones led to frequent confusion. For the design of instructions, these findings imply that the instructor should avoid high numbers of similar chunks of information.

The capacity restriction of four to ten chunks applies only to one-dimensional information. Empirical research showed that increasing the number of dimensions increases the overall capacity (Miller, 1956). For instance, Miller cited Klemmer and Frick's (1953) experiment on the judgement of points in a square, which represented a two-dimensional problem.[7] In the presence of a second dimension, the number of distinguishable positions increased from 10 to 15 to about 24 positions.

[7] As a remarkable aside, many of the studies Miller referred to in his seminal 1956 paper originated from non-university and also non-psychological research. For instance, Pollack (1952, 1953) were both published in the *Journal of the Acoustical Society of America*, and the study by Klemmer and Frick (1953) was conducted at a US Air Force base and previously classified as military research.

Klemmer and Frick's and later studies indicated that an increase in the dimensions of information increases the number of processable items. For instance, the human mind can easily identify one out of thousands of faces. This is possible, because face data provide several metrics, such as distances, shapes, and colors. Inferring some advice for practical instruction design, organizing the input into several dimensions may increase the number of processable chunks. For instance 20 bullet points sorted into a two-dimensional framework may be easier to overview at a glance than a long, one-dimensional list.

Quite naturally, the capacity-increasing effect of additional information dimensions is limited. First, with each additional information dimension the additional number of distinguishable categories becomes smaller (in economic language, the marginal capacity contribution decreases). Second, the number of distinguishable items in each dimension actually decreases with any further dimension, until the mind can distinguish only two characteristic values per dimension.

Miller (1956) suggested overcoming processing limitations through the use of *recoding*. Miller gave the example of memorizing a 18-digits binary number, which is almost an impossible task within the scope of working memory. Yet, recoding the binary number into 6 octal digits transforms the task into a problem that is easily trackable by the human mind. The trick behind this recoding procedure is that the human mind seems to possess long-term memories of complex concepts (such as higher numbers) which the short-term memory can access through a single reference. Sweller et al. (1998) fleshed out this concept and defined conceptual chunks of information as schemas (cf. Section 3.2.2). As the working memory interacts with the long-term memory, it employs existing schemas in order to enhance its capacity.

In a quite extensive research program, John Sweller and his colleagues further refined Miller's work on cognitive capacity by focusing on the load side of the capacity problem. Sweller et al. (1998) identified several distinct categories of load and proposed technics for their management. Roughly, cognitive load theory distinguishes between relevant and non-relevant load. Examples of non-relevant load—or in Sweller et al.'s terminology *extraneous cognitive load*—are unnecessary pieces of information, distracting graphical effects, and the crossing of cognitive channels (e.g. the choice of a verbal description of graphical information).

Sweller et al. distinguished between two types of relevant load. First, *intrinsic cognitive load* stems directly from the difficulty of the learning materials. For example, single-item auctions are intrinsically simpler than multi-item auctions. The instructor can manage this kind of load—for instance by breaking down the information to a sequence of smaller parts—however, the essential difficulty of a topic cannot be reduced completely.

The second type of relevant load—*germane cognitive load*—is created intentionally by the instructor in order to facilitate the process of schema construction described in Section 3.2.2. A counter-example from the author's personal experience is the learning strategy of many elderly people who wish to use a computer. Often they focus on pure rote learning by memorizing very specific click-paths which lead them to only a few selected ends (for instance opening one section of a specific news web site). Since they do not expose themselves to the load of a variety of tasks (often fearing that they will "damage" the computer), they cannot form a general schema of how a computer works.

Table 3.1: Cognitive principles.
(The listed literature does not include all of the studies that have investigated the individual principles, but rather seeks to provide an entry point into the literature for further reading.)

Cognitive Principle	**Literature**	**Description**
Dual Coding and Modality Principle	Paivio (1986) Mayer (2005a)	The use of multiple sensory or cognitive channels increases the total processing capacity.
Schema Learning	Bartlett (1932) Bousfield (1953) Chi et al. (1982)	Information in long-term memory is stored in the form of schemas which are associated with each other and can be accessed quickly by short-term memory.
Redundancy Principle	Mayer (2005b)	The duplication of information increases cognitive load, but does not improve learning.
Coherence Principle	Mayer (2005b)	Additional, unnecessary information increases cognitive load, but does not improve learning.
Dimensionality Effect	Miller (1956) Mayer (2005b)	The total number of distinguishable chunks of information increases with the number of informational dimensions.

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Table 3.1 – continued from previous page.

Cognitive Principle	Literature	Description
Split Attention Effect	Yeung et al. (1998) Mayer (2005b)	If corresponding chunks of information are spatially or temporally split, recombining this information imposes additional cognitive load.
Signaling Principle	Mayer (2005b)	Graphical or acoustical cues help to guide the attention to the most relevant information which reduces cognitive load.
Intrinsic and Germane Load	Sweller et al. (1998)	Intrinsic load is the inevitable load due to the inherent difficulty of a subject, while germane load is additional load that facilitates the development of robust schemas.

The reduction of extraneous load is a primary goal of instruction design. In a survey of the experimental literature, Mayer (2005b) identified five principles that support this goal. Almost suggesting itself, the *coherence principle* demands abstention from the provision of any unnecessary information (even entertaining information—which runs the risk of making Jack a dull boy). Mayer listed eleven experimental studies on the coherence principle, out of which ten supported the concept.

Second, the *signaling principle* is that graphical or acoustic cues can help to guide the subjects' attention to the most relevant information. This principle was supported in three out of three studies collected by Mayer. Third, the *redundancy principle* states that duplicating information increases the cognitive load on short-term processing. Therefore, Mayer advised abstaining from the use of on-screen text that duplicates the narration of a video. Note that the principle does not affect long-term memory and processing—for instance, the distribution of previously narrated information in the form of printed text (after the learning has taken place) may not have a negative effect on learning. The redundancy principle was supported in ten out of ten studies.

Fourth and fifth, the *spatial* and the *temporal contiguity principle* are that corresponding information is provided spatially and temporally close to each other. For instance, explanatory text to the elements of a picture should be printed right next to the corresponding elements, and graphics should be shown with the words explaining them. The reasoning behind this advice is that any spatial or temporal separation of interrelated information requires the mind to bring the information together for itself, increasing cognitive load. Again, each of the two principles was supported by multiple experimental studies.

The spatial continuity principle—also known as the *split attention effect*—is one of the most prominent findings of cognitive load theory. Indeed, the second term may be more accurate, since it seems that instructors can avoid the splitting of attention as well by means other than spatial contiguity. For example, Mazarakis (2007) provided experimental evidence that alternatively to joining graphical elements spatially, connecting lines between the corresponding elements or enclosing frames around them are equally effective in supporting the task of merging the relevant information.

3.3 New Instruments for Large-scale Applications

"The proof of the pudding is in the eating."

(old English proverb)

Due to the complexity of the market situations investigated in this thesis, the instructions and the software of the experiments are even more crucial than in many traditional laboratory experiments. This section seeks to advance the *toolkit of experimental economics* by applying the empirical and theoretical results of cognitive research to the design of those instruments (cf. Section 3.2). Its main contribution is the proposal of an *experiment environment* that enhances control, reproducibility and validity in complex market situations.

In order to fulfill the scientific standards defined above, two principles guide the design of the proposed experiment environment. First, it seeks control on the *overt* or outer level—the level of what is presented to the subjects, in what form and at what time. Second, the experiment environment seeks control on the *covert* or inner level—the level of how the subjects understand the situation and what pictures they form in their minds. Traditional experimental instructions and software as introduced in Section 3.1.3 typically achieve a sufficient level of control on the overt level, but are limited in achieving control on the covert level. The covert level is where the principles of cognitive research come into play, and should be implemented without sacrificing control on the overt level.

The proposed experiment environment includes modularized video instructions, advanced comprehension tests, a software-integrated learning platform, graphical one-screen user interfaces and comprehension-based group matching. In order to illustrate the nuts and bolts of these instruments, their implementations in the emissions permits experiment (cf. Chapter 4) and the spectrum auction experiment (cf. Chapter 5) serve as an example and as a proof of concept.

Table 3.2 provides an overview of the cognitive principles from Section 3.2 and their implementation in experimental instructions and software. All of these features were actually implemented in the spectrum rights experiment, and most of the features were also implemented in the emissions permits experiment. In the following sections, examples from those experiments will illustrate the details of what the implementations looked like and how they supported successful learning and participation in the experiment.

Table 3.2: Implementation of cognitive principles in the instructions and software.

Cognitive Principle	**Instructions**	**Software**
Dual Coding and Modality Principle	Use of video instructions that combine graphics and narration. Graphics are used for specific visual information, narration for abstract verbal information, not vice versa.	Depiction of graphical information in visual rather than in textual form. Explanation of the software in the instructions through a direct video demonstration.
Schema Learning	Familiar schemas are evoked if possible and not in conflict with neutral framing. Central concepts are repeated in different graphical and verbal representations, in order to enforce the forming of robust and meaningful schemas.	Use of familiar interface and interaction concepts. Consistent and graphically recognizable use of figures and design elements.

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Table 3.2 – continued from previous page.

Cognitive Principle	**Instructions**	**Software**
Redundancy Principle	Abandonment of on-screen text that duplicates the narration. Redundancy that does not affect short-term processing—e.g. distribution of transcripts of the narration—is admissible and may contribute to overt control.	Provision of information and interaction elements in a single, reasonable form and place.
Coherence Principle	Information is reduced to the essential, helpful or necessary.	Tidy user interface that offers the necessary information, but abstains from additional gimmicks. Non-essential rules and activities should be automatically (and transparently) controlled by software functions.
Dimensionality Effect	Graphical elements make use of two or three dimension, long lists of bullet points are avoided.	Use of several graphical dimensions, such as place, shape and color. Important: structure needs to stay tidy, otherwise conflict with the coherence principle ensues.
Split Attention Effect	Numbers and explanatory texts are placed close to the corresponding graphical elements. The narration always refers to the visual element that is currently highlighted.	Numbers and explanatory texts are placed right next to the corresponding graphical elements.
Signaling Principle	Relevant information is highlighted with color cues or movements.	Use of colors, unobtrusive animations, and notification messages to highlight currently relevant information.

Continued on next page.

Table 3.2 – continued from previous page.

Cognitive Principle	Instructions	Software
Management of Intrinsic and Germane Load	Instructions are segmented into modules of about ten minutes each. Between the modules, the subjects can repeat the videos at their own pace, in order to adapt the speed of learning to their individual processing capacity.	The timing of the experiment should be set endogenously by the subjects.

While a cognitively founded design applied to the experimental instructions and software can mitigate some of the complexity issues of testbed experiments, there are still natural limits to what is feasible, and the overall experiment should stay within these limits if possible. The crucial issue is less one of a single detail of the design, but rather whether the subjects can realistically cope with the general design with all of its elements—the market mechanism itself, the instructions, the software, etc. All the details and design decisions together decide on whether an experiment can or cannot be conducted successfully.

In the preparation of the emissions permits experiment in 2009, the author's experiment team faced the challenge of designing and communicating a multi-item auction with an elaborate two-dimensional values structure and corresponding bidding rules. Despite the fact that they collaborated with several experienced experimental economists to design the experiment, they had to abort the first pilot sessions because the sessions turned out not to be doable in the time allowed by the experimental session. One reason for this failure was that the experiment software required bids in the form of marginal values which had to be inserted into a textual list of contracts. Although in principle providing the most direct way to bid according to theoretical predictions, this form of bidding was unfamiliar and confusing to most of the subjects. Further, it was difficult to graphically overview and administrate the resulting list of bids.

The issue was resolved in the redesigned version of the experiment. Instead of freely configurable marginal bids, the software finally included a list of prices ranging from 1 to 30 with a graphical slider on the side of each price (Figure 3.5). The slider allowed subjects to set a quantity between 0 and 15 units of an item for each of the given prices. While the previous version of the software required subjects to understand every detail of the design in order to bid reasonably, the new version used familiar interface concepts, relieved the subjects of as many cognitive burdens as possible, and delegated the compliance to less crucial rules to the software. For instance, when a subject moved one of the sliders, the experiment software automatically adapted the prices above and below in order to ensure monotonicity. It was not necessary to explain the details of the monotonicity requirement as it was built into the software.

3.3.1 Video Instructions

Video instructions provide a versatile instrument to incorporate much of the advice of cognitive research. First, they allow for the simultaneous use of multiple sensory and conceptual channels, such as pictures, animations, text and narration. Second, they allow for the acoustical, graphical and temporal coordination of the channels presented. Third, videos convey verbal information by narration rather than text, which is strongly recommended for complex learning materials. Fourth, videos allow tight control over the sequence and completeness of the learning experience. Subjects can hardly skip any part of the instructions, since the video captivates all of their senses.

In the emissions permits experiment example described above, the software relieved the subjects of the burden of manually ensuring the monotonicity of their bids. In principle, the automatic monotonicity adaption of the bids by the software is intuitive and easy to understand. Yet, the verbal explanation of the idea in the textual instructions required explaining all of the possible cases and successive steps that were involved. The accumulation of similar *verbal* chunks of information confused the test readers.

The main problem with the task was that the principle of the slider movement was essentially of a *graphical modality*. Indeed, if a graphic display of the setting and the movement of the sliders was provided, the concept became clear and self-explanatory. Only in verbal form did the concept need to be cumbersomely constructed by forming a mental image from the verbal chunks, because there exist no single well-known term for the concept in common speech. Therefore, the solution for the instructional problem was

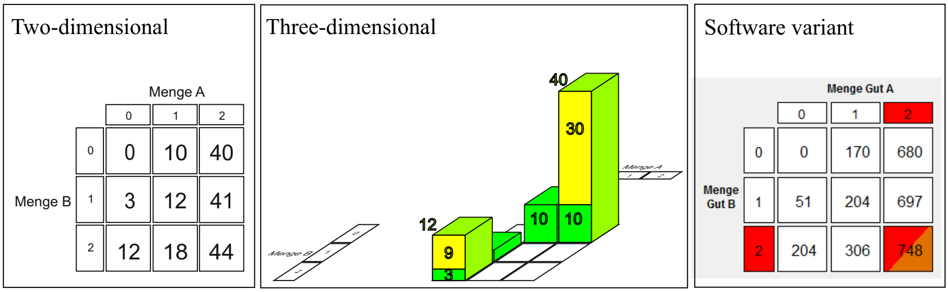

Figure 3.2: *Germane load* through alternative representations enforces robust *schema learning*.

to employ the *modality principle* by depicting the slider concept in a video demonstration of a working example.[8]

The spectrum experiment instructions systematically employed *germane cognitive load* for the construction of robust *schemas*. The central piece of information in the experiment was the values structure of the goods sold in the auction. This structure consisted of a two-dimensional 3x3 table that included sub- and super-additive values. The internalization of the values structure schema was crucial for the participation in the auction. In order to manage the cognitive load, the values structure was introduced step by step.[9]

The values structure table was first introduced in a two-dimensional view (left box of Figure 3.2). After explaining the meaning of the rows and the columns, the animated video slowly tilted the two-dimensional table into the third dimension and explained the values and their properties in the three-dimensional version of the table (center box of Figure 3.2). Besides offering an alternative view in order to accomplish a more robust construction of the values structure schema, the three dimensional display also allowed a more intuitive and graphical depiction of sub- and super-additivity.

Finally, for explaining further characteristics of the table, the video switched back to the two-dimensional view (right box of Figure 3.2). Later in the instructions, another version of the two-dimensional values table reappeared in the video demonstration of the software interface. Although the principle of the table was the same in the software as in

[8] http://www.sascha-schweitzer.de/download/co2/treatment_6/video_1.
[9] http://www.sascha-schweitzer.de/download/spectrum/pca/video_1.

the first part of the video instructions—since the table stood in the context of the software interface and had to include some additional features—it looked slightly different in terms of its size and colors. Yet, this additional perspective further contributed to the forming of a general schema of the values table. By switching between two-dimensional and three-dimensional views, different layouts and contexts, germane cognitive load was admitted in order to help the mind construct a robust schema of the values structure.

When summing up the explanation of the values structure table, the instruction video employed another advice from cognitive research by reverting to previously *existing schemas*.[10] The super-additive nature of two units of an item in the auction (cf. Chapter 5) was summed up by telling the familiar proverb: "The whole is greater than the sum of its parts."[11] This proverb evoked a concept deeply stored in most subjects' long-term memory. The hint also helped the subjects to associate the new values structure schema with existing knowledge, which served as a catalyst for sorting the new schema into long-term storage.

The spectrum experiment instructions also made generous use of *signaling by visual cues*, while thoroughly complying with the principle of *temporal contiguity* to avoid the *split-attention effect*. For instance, for the explanation of the software interface, the relevant areas of the screen which were currently explained were highlighted, while the other parts were faded out in order to focus attention on the relevant information. A screenshot of the fade-out effect is provided in Figure 3.3.

Intrinsic and germane cognitive load were further *managed* by segmenting the video instructions into several modules of about ten minutes each. After showing each module completely once, subjects had the opportunity to navigate through the chapters of the module and to replay any part of a module as often as required.[12] While the initial obligatorily presentation of the complete modules ensured that subjects did not skip parts of the videos, their personal video player enabled subjects to adapt their cognitive load to their individual optimum.

Figure 3.4 shows a screenshot of the video player which was embedded in the comprehension test. In the lower left section, a navigation area allowed the subjects to choose a

[10] http://www.sascha-schweitzer.de/download/spectrum/pca/video_1.

[11] Translated from the German instruction text: "Das Ganze ist mehr als die Summe seiner Teile."

[12] In order to allow the subjects to listen to different parts of the video without disturbing each other, they were equipped with headphones.

Figure 3.3: *Signaling* through fade-out effect (screenshot).

part of the video module by chapter, and below the video window, controls for playing, pausing and resuming the video were provided.

3.3.2 Comprehension Control

It is a common practice to conduct comprehension tests before the beginning of the experiment in order to ensure that the subjects understand the experiment situation. (Section 3.1.3). These tests have two goals. Firstly, they serve to deepen the learning experience by requiring subjects to actively think about the instructions. Secondly, they serve the experimenter to test whether a sufficient level of comprehension has been attained.

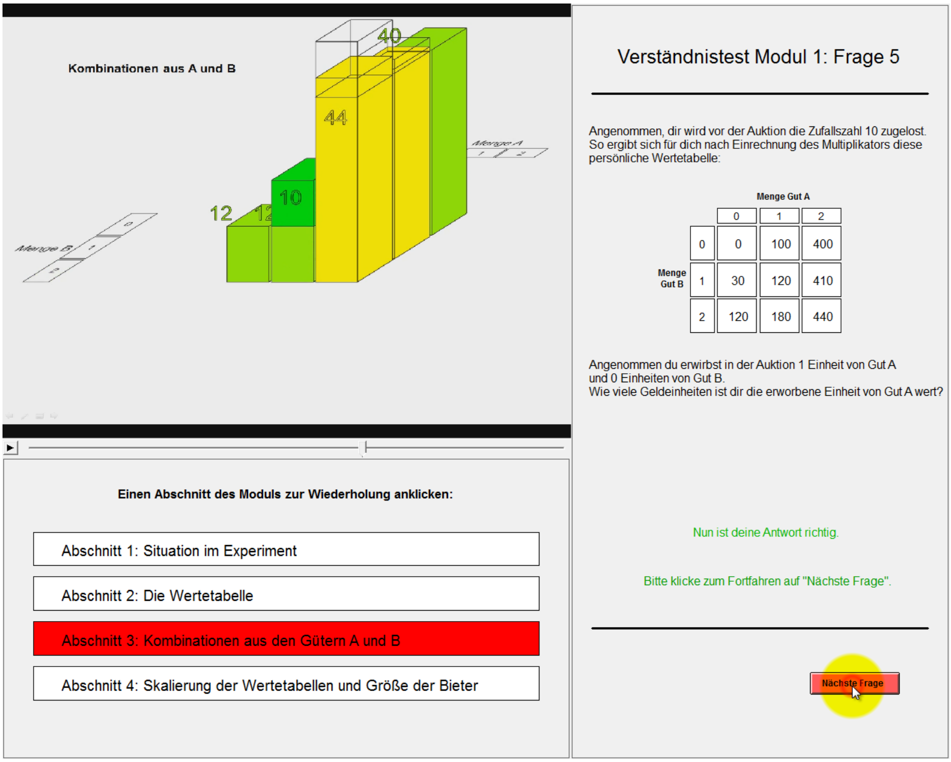

Figure 3.4: Individual video player for *cognitive load management* embedded in the comprehension test (screenshot).

In the case of complex testbed experiments, the question of sufficient comprehension changes from a yes or no statement to a more diverse measure. Naturally, the associative and individual nature of learning implies heterogeneity in the quality of knowledge acquired by the different subjects. For difficult learning tasks, and with heterogeneous subjects, the spectrum of knowledge is set to be very broad. Therefore, subject comprehension is necessarily gradual and—as comprehension is the basis of any informed decision making process—one should expect subject comprehension to affect the subjects' behavior.

As it is impossible to completely eliminate this diversity in subject comprehension, it is at least desirable to control for it. If the subjects in an experiment interact with each other, full control on subject comprehension can only be achieved on the level of the independent groups. *Forming groups* on the basis of their members' comprehension can help to isolate the effect of issues of comprehension. For example, in the spectrum experiment, subjects were distributed into groups of four, according to their comprehension level. Within each group a homogeneous level of subject comprehension was obtained. Alternatively, it could also be relevant to investigate different levels of heterogeneity or any other comprehension structure. The decision on this structure is a design choice and may also depend on the real market situation that the experiment is modeled after.

For the purpose of providing a meaningful indicator of subject comprehension (and also for doing justice to individual learning performance), the comprehension tests in a testbed experiment should enable the *gradual measuring* of subject comprehension. While traditional experimental comprehension tests often achieve a one-hundred-percent rate of correct answers, a sophisticated comprehension test can obtain gradual measures by employing questions of several difficulty levels. For example, the test in the spectrum experiment started with simple questions like "How many bidders participate in one auction?" and went on to more complicated logical questions and numeric examples. After failing to answer a question correctly for the second time, the subjects were given the correct answer by the experiment software.

In order to cluster subjects by their comprehension and to include a control variable for comprehension in the statistical analysis as proposed above, it is necessary to calculate a *quantitative comprehension measure*. Some relevant proxies for subject comprehension are the count $ans_{(1)}$ of questions that have been answered correctly at the first try, the count $ans_{(2)}$ of questions that have been answered correctly at a later try, and the time t that was required for completing the test. To rank the subjects by their comprehension, these proxies can be aggregated to a one-dimensional indicator. For example, in the spectrum experiment, the aggregation was chosen such that the order of indicators was first determined by $ans_{(1)}$, second (in the case of ties) by $ans_{(2)}$, and third (in the case of further ties) by t.

3.3.3 Software and User Interface

The user interface is the primary representation of the experiment situation to the subjects. Usually, it provides all necessary information during the experiment and it also serves for data input and interaction. Being such a prominent device, it is natural to expect the user interface to have a considerable impact on the behavior of the subjects and on the outcome of the experiment, and to affect overt as well as covert control.

Most of the cognitive principles presented in Section 3.3.1 apply just as much to the design of the user interface as to the design of the instruction videos. For instance, the *modality* principle recommends to present information in the “appropriate” cognitive channel. For the user interface, this means that graphical information should be presented by pictures, shapes or color, rather than text.

Further, *schemas* taught in the instructions should be made recognizable in the interface by employing an arrangement of their elements and a design language similar to that of the instructions. An example of the recurrence of both aspects is provided by Figure 3.2. It also seems advisable to reduce extraneous cognitive load as far as possible by abstaining from additional non-essential interface elements (*coherence principle*), placing graphical elements and corresponding textual information close together (avoiding the *split attention effect*), and using visual cues for highlighting important information (*signaling principle*).

Besides enhancing control on the covert level by complying with cognitive principles, a well-thought-out design of the user interface can also reduce the variance within and between the treatments on the observable level. Within a treatment a simple maneuver for reducing uncontrolled leaps and bounds in the subjects’ attention is the employment of a compact one-screen interface. While this is the state of the art in traditional laboratory experiments, some testbed experimenters tend to employ original software which was designed with a plethora of sub-screens and pop-ups. These gimmicks should be reduced to the necessary minimum.

Between treatments, unnecessary variance should be reduced by keeping the software interfaces as similar as possible. While, at first glance, this principle seems to suggest itself, in practice, it is often not that obvious. In both experiments presented in this thesis, the auction designs compared are quite heterogeneous and—had the software for the designs been developed independently—the resulting interfaces would certainly look different from each other in many ways. For example, in the emissions permits experiment, static and dynamic auction designs were compared. Naturally, the first drafts of the software looked like completely different computer programs.

Two simple tricks helped to considerably unify the user interface. First, the dynamic auction was supplemented by proxy bidding which allowed for the submission of complete bidding schedules in advance—just as in a static auction. Second, the static auction employed the same proxy bidding interface as the dynamic auction. Even the auction process of the dynamic auction was simulated in the static auction—with two functional differences. First, more time was provided for the initial bid submission. And second, after the initial submission, the bids could not be changed, while the dynamic auction process was conducted in time lapse mode. The screenshots in Figure 3.5 illustrate the similarity of the resulting software screens.

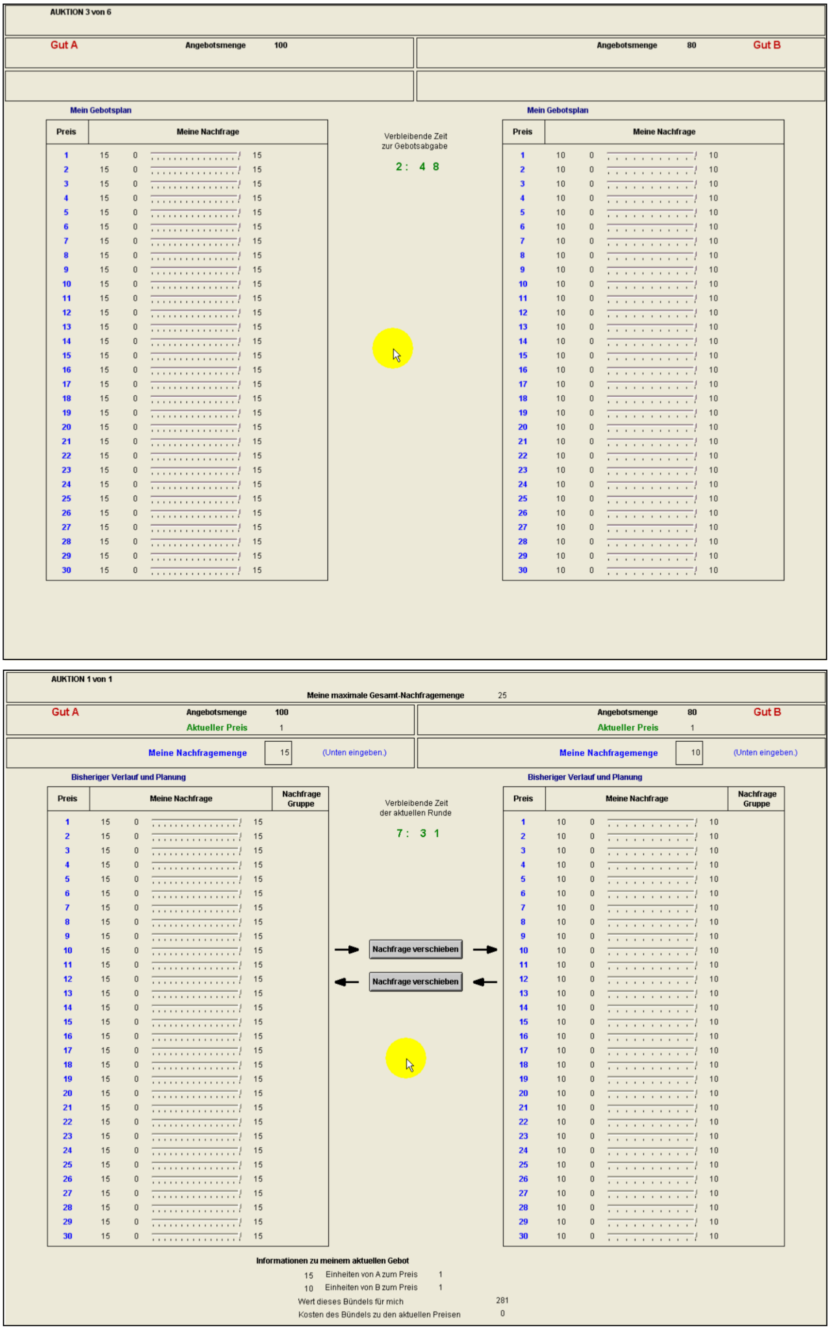

Figure 3.5: Unified user interface of static and dynamic auction designs in the emissions permits experiment.

4 Study 1: An Emissions Permits Application

4.1 Background

> *"The Government has decided that a large proportion of permits will be auctioned, highlighting the importance of auction design."*
>
> (White Paper Commonwealth, 2008, p. 9-1)

Most of the recent increases in global average temperatures—which threaten the environmental stability of many places on earth—were very likely caused by increases in human-made greenhouse gas concentrations (IPCC, 2007). In Kyoto, in 1997, 37 countries agreed to commit themselves to the reduction of climate-damaging emissions (United Nations, 1998). One of the instruments stipulated in the Kyoto Protocol is a *cap and trade* emissions trading system. This system constrains the emissions of climate damaging pollutants by capping them to a limited number of permits which are issued by the respective governments.

Some economists—for example Jensen and Rasmussen (2000), and Cramton and Kerr (2002)—argued that auctions allocate emissions permits to their best possible use, that they provide flexibility in the distribution of costs, and that auction revenues may contribute to reducing distortionary taxes. The EU emissions trading system, the US Regional Greenhouse Gas Initiative (RGGI), and the (proposed) Australian Carbon Pollution Reduction Scheme (CPRS) followed this advice by prescribing auctions for a proportion of their (prospective) permits allocation.

The present experimental study investigates several alternative auction designs proposed in the literature for the auctioning of emissions permits. The experiment was designed and conducted by a team of researchers, including the author, at the Karlsruhe Institute of Technology (KIT) and the University of New South Wales (UNSW), in order to advise the Australian Department of Climate Change and Energy Efficiency (DCCEE) on the primary allocation of emissions permits in an emissions permits trading scheme. Parts of this chapter were published in the final report prepared for the Australian Department of Climate Change and Energy Efficiency (Betz et al., 2010).

Details and plans for the Australian CPRS were laid out in the governmental White Paper Commonwealth (2008), which drew heavily on Evans & Peck (2007), commissioned by the National Emissions Trading Taskforce (NETT). The scheme was intended to cover about 75% of all greenhouse gases emitted in Australia. The majority of the affected companies already have to report their emissions under the Australian National Greenhouse and Energy Reporting Act (NGERA) of 2007 (Commonwealth, 2007). In March 2012, in sum, these companies reported an estimated 344 megatonnes of direct CO_2 emissions for the financial year 2010-11, roughly 80% of which were accounted for by 40 businesses.[1] Besides emitting firms, financial institutions and professional dealers would be allowed to participate in the auctions and the secondary permit markets.

Each permit would have a date stamp (vintage), indicating the year in which it became applicable. Permits could be banked without restrictions (used in later years), while borrowing (using permits earlier) was to be limited to a small amount (up to 5%). The majority of the permits were supposed to be auctioned off in advance, up to three years before the relevant vintage. There would also be a “wrap-up” auction after the end of a financial year, to sell permits of the current year one month prior to the final surrender date, thus allowing “liable entities to reconcile their permit requirements after emissions data are finalised each year” (Commonwealth, 2008, p. 9-16). All in all, in one auction event there could be up to five vintages auctioned off simultaneously—permits for the previous year, the current vintage, and three future vintages.

Figure 4.1 shows the auction schedule as proposed in the recent 2012 Position Paper by the Australian Government. The table shows the way the sale of emissions permits for a

[1] Further information and data is available on the regulator’s website: http://www.cleanenergyregulator.gov.au.

	Compliance Year								
Vintage	2013-14	2014-15	2015-16	2016-17	2018-19	2019-20	2020-21	2020-21	2021-22
2015-16	15 million units	37.5% -15 million units	50.0%	12.5%					
2016-17	15 million units	25.0% -15 million units	12.5%	50.0%	12.5%				
2017-18		12.5%	12.5%	12.5%	50.0%	12.5%			
2018-19			12.5%	12.5%	12.5%	50.0%	12.5%		
2019-20				12.5%	12.5%	12.5%	50.0%	12.5%	
2020-21					12.5%	12.5%	12.5%	50.0%	12.5%
2021-22						12.5%	12.5%	12.5%	50.0%

Figure 4.1: Proposed auction schedule (data from Commonwealth, 2012, p. 10). The proportions (cells) refer to the proportion of units of a given vintage (rows) that would be auctioned in a given compliance year (columns).

given year would be distributed to auction events in consecutive compliance years. The proportions expressed (cells) refer to the proportion of units of a given vintage (rows) that would be auctioned in a given compliance year (columns). In turn, within one compliance year, there would be multiple auction events, since the proposal suggested an auction frequency of four auctions per year.

The 2008 White Paper proposed that the preferred auction type would be a simultaneous multi-vintage English Clock Auction (ECA) with proxy bidding. The goal of the experiment described in this dissertation was to test the proposed simultaneous ECA, and to compare it with a simultaneous Uniform-price Sealed-bid Auction (USBA), as well as with sequential auctioning in an ECA, or in a USBA. The key objectives of the government were to "promote allocative efficiency (...) with a minimum of risk and transaction costs," to "promote efficient price discovery," and to "raise auction revenue" (Commonwealth, 2008, chapter 9-2). The first two objectives were given priority over the last one. Consistent with these goals, the criteria of the present experimental comparison were auction efficiency, revenue and price signals (cf. Section 2.2).

As the experiment was motivated by the discussion on the CPRS proposed in Australia, some specifics of the experimental design were related to this specific situation. However, the advantage of an economic experiment is that it is able to abstract many particularities of the natural environment. This study did not model any (transitional or permanent) price caps, reserve prices, international permit markets, product market decisions, abatement investments, compliance checks or penalties. Rather, it incorporated all these features into bidder preferences which were induced in a controlled way. This feature of a laboratory experiment makes it possible to come to conclusions about causal relationships. It may naturally limit the external validity of the results obtained in such a controlled environment—a caveat of any laboratory experiment—but at the same time it makes the results more general, and also relevant for other permit markets, and multi-unit auction designs in general.[2]

Shortly after the present study's completion, in April 2010, Kevin Rudd's labor government deferred its original CPRS proposal due to the loss of the liberal party's support for emissions pricing. Paradoxically, in 2011, the succeeding government of Julia Gillard—which initially was strongly opposed to any form of carbon pricing—had to perform the opposite of Rudd's move, in order to gain the Green Party's support, and finally introduced the "Clean Energy Act" emissions trading system to Australia (Commonwealth, 2011). In March 2012, the present study's proposal for the auctioning of the permits (Betz et al., 2010) made its way into the DCCEE's position paper for the implementation of the future auctioning of emissions permits (Commonwealth, 2012).

4.2 Price Signals in Emissions Permits Auctions

A firm's abatement costs for the reduction of greenhouse gas emissions are specific to that particular firm, and therefore may be best captured by an IPV model (Section 2.1). However, as there will typically be a liquid secondary market for emissions permits, the resale value of the permits may also be of high relevance to emitters and to resellers alike. However, especially in the beginning of an emissions permits trading scheme, the resale value is highly uncertain. Price signals obtained in the primary auctions can help to

[2] Confer with Chapter 3 for a more elaborate discussion of validity in economic laboratory experiments.

mitigate this uncertainty (ibid.). Therefore, governments may want to publish the prices generated during the emissions permits auctions and they may be concerned about the quality of these price signals.

Emissions permits are indistinguishable, homogeneous goods. Therefore, the most natural pricing of permits is one uniform price for all units of a vintage. Indeed, the literature seems to agree that permit auctions should apply uniform pricing—as used in the auctions in England, Ireland, Hungary, and in the U.S. RGGI and NO_x schemes (see Ockenfels, 2009, for an extensive discussion of the pros and cons of uniform and discriminatory pricing). Experimental studies—in particular in the context of emissions auctions—generally reported superior performance of uniform price auctions with respect to revenues and efficiency (e.g. Holt et al., 2007, 2008; Porter et al., 2009).[3] Further, besides the empirical evidence, there is also a political dimension to the employment of uniform pricing, as discriminatory prices for obviously homogenous emissions permits could give reasons to complain about favoritism. Hence, this study focused on uniform-price auctions.

The two most prominent auction designs within the class of uniform-price auctions are the Uniform-price Sealed-bid Auction (USBA) and the English Clock Auction (ECA) (Chapter 2). By revealing aggregate demand during the course of the auction, ascending clock auctions support the convergence of aggregate demand to supply, and therefore are said to have superior price discovery capabilities relative to sealed-bid auctions. This may be especially important in the beginning of a permit trading scheme when secondary markets are not yet operating efficiently (see Holt et al., 2007; Mandell, 2005; Ockenfels, 2009, for a corresponding argument that this advantage becomes less important once secondary markets exist).

A potential disadvantage of the additional information revealed in ascending clock auctions is that it may ease collusion between bidders. Holt et al. (2008) tested this objection in a laboratory experiment by conducting sealed bid and clock auctions in which participants could discuss any aspect of the auction in a chat room that was open prior to each round of bidding. The authors found significantly more collusion and lower prices in a clock auction than under other auction formats. In a follow-up

[3] With the exception of Goeree et al. (2009) and Shobe et al. (2010) who found in their settings that an ECA performed worse than a discriminatory auction with respect to revenue and efficiency.

study incorporating a rich environment with permit banking, secondary markets, and compliance penalties, Burtraw et al. (2009) compared clock auctions and uniform price sealed bid with and without an opportunity to chat, and found that clock auctions yield lower revenues than sealed-bid auctions in both environments, but the presence of an opportunity to chat reduced revenues under both formats.

In a similar design, Mougeot et al. (2011) assessed the effect of the presence of speculators on the ability of bidders to collude in ascending-clock and a sealed-bid auctions with a pre-auction chat. Speculators are essentially bidders with no private values for the permits, who buy only in order to sell later in the secondary market. Again, sealed-bid auctions led to higher revenues and less collusion than did ascending clock auctions. The inclusion of speculators increased revenues further by making the auction more competitive, but led to lower allocative efficiency (including spot trading on secondary markets). In contrast to the collusion experiments, Porter et al. (2009) found that when demand is relatively elastic, clock auctions are superior to sealed-bid auctions in terms of revenue (but not different in their efficiency properties).[4] No differences were observed with inelastic demand.

One means to curb collusion in clock auctions—while at the same time keeping their simplicity—might be to limit the information provided to bidders, i.e. not to reveal aggregate demand after each price step. Shobe et al. (2010) tested this assertion by comparing clock auctions with and without demand revelation in a “loose cap” environment, in which the number of auctioned permits was a high percentage of the demand at the reserve price. In this setting, the authors did not find any significant differences with regard to revenue or efficiency, and thus no indication for more or less collusion in any auction type.

In sum, as Holt et al. (2007, 2008) pointed out, there seems to be a trade-off between the effects of more information in promoting price discovery on the one hand and facilitating collusion on the other. The majority of auction designers seem to weigh the collusion argument more strongly. For example, in the 2004 Virginia NO_x auction aggregate demand was not revealed because of concerns that it would facilitate demand reduction (see Porter et al., 2009), and Holt et al. (2007, 2008) proposed a uniform-price sealed-bid auction for the RGGI scheme.

[4] Note that, for the single-unit case, Holt et al. (2007) could not replicate these results.

The present study compared the USBA with the ECA, both with and without revelation of aggregate demand. Furthermore, it investigated the impact of subsequent secondary markets on all three auction types.

4.3 Multiple Vintages

Real-world permit schemes typically issue several vintages of permits, and sell these vintages ahead of time. For instance, the Australian CPRS planned to auction vintages up to three years in advance.[5] The auction schedule presented in Figure 4.1 (Section 4.1) stipulated that the auctioning of a vintage be distributed over several compliance years, and to hold auctions of several vintages in the same year.

When only one vintage is sold, the units of this vintage are indistinguishable and homogeneous. Most of the experimental studies discussed above dealt with this case, and were concerned with multi-unit auctions of a single vintage. However, when multiple vintages are issued at once, these vintages must be considered as multiple items that differ in their properties. With the exception of Porter et al. (2009), in the context of emissions permits auctions, this case has not been studied yet. The present study contributes to a systematic investigation of the multi-item case.

A particular question that arises in the multi-vintage case concerns the auction sequence. Should multiple vintages be sold simultaneously, as in the simultaneous USBA or ECA, or should they be sold sequentially, in a sequence of single-vintage auctions? A prominent conjecture in the market design literature is that simultaneous procedures outperform sequential procedures with respect to allocative efficiency whenever the values of multiple auctioned items are related, either as substitutes or as complements. For example, the different vintages of a pollution permit scheme can be described as partial substitutes, if banking (using a permit later than vintage time stamp) is allowed but borrowing (using it earlier) is restricted.

The advantage of the simultaneous approach is that it allows bidders to shift demand from one vintage to another during the course of the auction. This gives bidders the

[5] The purpose of these early auctions is to reveal abatement costs, to promote price discovery, and to reduce transaction costs, volatility of prices and risks of bidders (Sections 2.2.3 and 4.2, and Betz et al., 2010; Benz and Ehrhart, 2007; Ockenfels, 2009).

flexibility to react to price differences and to adjust their demand accordingly. Through this flexibility, the simultaneous format facilitates more efficient outcomes. On the other hand, a major concern in practice is that multiple simultaneous auctions may be too complex, which may either confuse bidders or deter them from participating in the auction at all. This was one of the reasons why the Virginia NO_x auction was finally implemented as a sequence of clock auctions and not as the recommended simultaneous clock auction (Porter et al., 2009).

When multiple identical items were auctioned sequentially, the earlier items were observed to yield higher prices than the later items (Ashenfelter, 1989; McAfee and Vincent, 1993). This phenomenon is known as the *declining price anomaly* or *afternoon effect*. Ashenfelter reported the phenomenon for auctions of fine wine of identical vintages and products of art sold by traditional auction houses like Sotheby's and Christie's.

Yet, the empirical finding of declining prices in sequential auctions contradicts auction theory under the assumption of risk-neutral bidders, in the case of private values as well as in the case of affiliated values. In the first case, prices should be identical across all auctions. In the case of affiliated values, referring to an unpublished manuscript by Paul Milgrom and Robert Weber, McAfee and Vincent (1993) argued that prices should actually increase due to the information released in the earlier auctions which reduces the so-called winner's curse.

Ashenfelter explained the finding of declining prices with risk-averse bidders who are willing to pay a premium in the earlier auction in order to secure an item. McAfee and Vincent provided a formal model of this concept. Beyond that they showed that the logic of Ashenfelter's explanation rests on the assumption of nondecreasing absolute risk aversion. If this assumption is not fulfilled, McAfee and Vincent predicted inefficient outcomes in sequential auctions.

To sum up, there are theoretic reasons for auctioning multiple vintages simultaneously rather than sequentially. Yet, it is unclear if these theoretic advantages transfer to actual auction situations. Further, higher prices in the early sequential auctions could have a positive effect on auction revenues. In order to explore which of these arguments prevails in real auctions, the present experiment tested the performance of both auction sequences for all auctions types.

4.4 Experiment Design

4.4.1 General Setting and Procedures

The experiment tested the effect of different auction designs and auction sequences on the resulting allocative efficiency, revenues, and price-signals in a multi-item multi-unit environment. From January to March 2010, 54 experimental sessions were conducted at KIT and UNSW. Each session included only one group of bidders with 14 participants. Therefore the total number of independent auction groups equals the number of sessions. For all treatments, two sessions were run at the UNSW, and four sessions were run at the KIT. Participants were university students, recruited from the ASBLab subject pool at UNSW using the online recruitment system Online Recruitment System for Economic Experiments (ORSEE) (Greiner, 2004), and from a corresponding subject pool at the KIT. Sessions at the UNSW were conducted in English, sessions at the KIT in German. Each participant participated only once in the experiment, so all sessions and conditions involve different subjects.

Figure 4.2 displays the treatment structure and the number of independent groups who participated in each of the nine treatments (depicted in the cells).[6] The experiment featured two main treatment axes. First, it compared the Uniform-price Sealed-bid Auction (USBA) with the English Clock Auction (ECA). Second, the experiment compared the sequential auctioning of the two items with the simultaneous auctioning of the items. These treatment axes resulted in four main treatment categories. For each category six independent auction groups, with 14 bidders each, participated in the experiment. Additional treatments served to isolate the potential effects of information revelation in the clock auctions and the effect of secondary markets. Both aspects are particularly relevant with respect to the price discovery performance of the auctions.

[6] The project included treatments that featured pilot runs of the main treatments, single-vintage auctions and auctions with a large number of bidders (Betz et al., 2010). Yet these treatments are not comparable, as they stand outside the systematic analysis. For example, a large group treatment was conducted after the main study, and only for the "best-performing" treatment, in order to test the practical feasibility of the design with a large number of participants. Therefore, these treatments are not reported in the present analysis.

		Sealed-bid	English clock	
			No demand revelation	Demand revelation
Sequential		6 groups	6 groups	6 groups
Simultaneous	No SM	6 groups	6 groups	6 groups
	SM	6 groups	6 groups	6 groups

Figure 4.2: Structure of the treatments.
The figure depicts the main treatment axes, auction sequence (rows) and auction type (columns). Further, the absence or presence of secondary markets is denoted by "No SM" and "SM," respectively. In each treatment (cells) six independent groups participated in the experiment.

The sequence of auctions within one session is summarized in Figure 4.3.[7] All bidders participated in six auctions—two for training and four according to treatment. The training auctions did not involve proxy bids or sealed-bid procedures, but rather a simple clock auction design. After two auctions, the auction design switched to the actual treatment design.

The initial training auctions allowed all bidders to gain the same initial experiences in a minimalistic clock auction setting, which may have been very instructive for the bidders. For instance, Harstad (2000) observed in his second-price auction experiments that subjects who had bid in an English auction before participating in a second-price auction design bid closer to the dominant strategy. Similarly, in the present experiment, it may have facilitated the subjects' comprehension of the basic auction situation to participate in several clock auctions before the sealed-bid auctions, and before the clock auctions with proxy bidding.

Before the first training auction, instructions for the training auction design were distributed in written form and were also read aloud by a research assistant. Questions could be asked throughout the instruction phase and the experiment, and were answered privately. After all questions had been answered, participants completed a short com-

[7] The entries "Shock" and "Discount" in the figure denote characteristics of the induced values tables, and will be explained in Section 4.4.3.

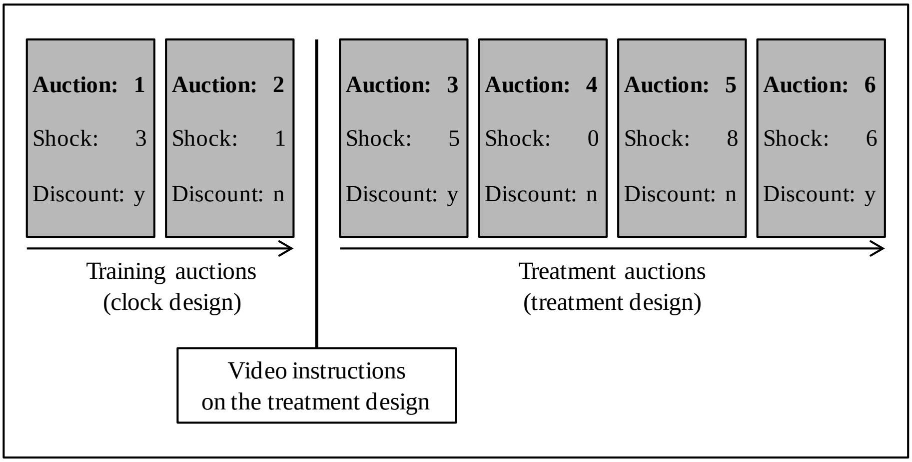

Figure 4.3: Sequence of the auctions in one session.
"Shock" denotes the value shock induced into the values tables. If Item B was discounted, this is denoted with "Discount: y," while the opposite is denoted with "Discount: n."

puterized comprehension test. Then the two training auctions were conducted. During the experiment, no communication with other participants was allowed.

To explain the change in the bid submission procedures after the last training auction, participants were shown a video on the computer screen which was tailored to the relevant treatment, with the audio channeled either through headsets (UNSW) or via loudspeaker (KIT). Participants in the USBA received the additional instructions in written form as well, since they had to submit their bid function in advance, without the opportunity to revise. Then Auctions 3 to 6 were run according to the relevant treatment.

At the end of the experimental session, one of the six auctions was randomly selected for payoff. Then participants were paid privately in cash and left the laboratory. During the experiment we used E$ (experiment dollars) as the currency. For the randomly selected auction, participants were paid their profits/losses from the auction, plus a lump-sum of E$150, which also covered potential losses. The E$ were converted at a publicly known exchange rate of AUD$0.15/E$ at UNSW and €0.10/E$ at the KIT. On average, sessions lasted about 2 hours, and participants earned AUD$31.77 at UNSW and €21.02 at KIT, including an additional fixed show-up fee of AUD$5/€5.[8]

4.4.2 Items and Values Table

In each auction, 100 units of Item A and 80 units of Item B were sold. Item A represented the current vintage, which covered the present year's emissions, while Item B represented the next vintage, which covered the following year's emissions. No bidder was allowed to bid for more than 15 units of Item A and 10 units of Item B. Figure 4.4 compares the resulting numbers of units of items A and B that could be demanded at most with the numbers of units supplied. For both items, the maximum demand clearly exceeded the supply.

In each auction, individual heterogeneous demand functions were induced with the help of individual redemption values for each possible bundle of A and B that could be purchased. The sets of value functions (values structures) differed between sessions within a treatment, but the same six different value structures were implemented in every experimental treatment.

To create the six values structures, marginal value functions for Item A were generated by randomly drawing the height and length of value steps. The marginal values for Item B were either defined as being the same as for Item A (discount factor of 1), or were proportionally discounted by a factor of 0.8. A discount factor smaller than one may represent technology improvements or simple discounting of future profits. The same series of discount factors was used in all sessions of all treatments.

To derive valuations over all A-B-bundles, asymmetric substitutability was modeled on top of the separate marginal value functions. In other words, the two-dimensional values table took into account that Item A units (current vintage) could be used for purpose B (cover next year's emissions), but Item B units (next year's vintage) could not be used for purpose A (to cover the present year's emissions). As a result, the marginal bundle value of one more unit of Item A was always at least as high as the marginal bundle value of one more unit of Item B. Values for A-B-bundles were given to participants

[8] The show-up fee was paid in addition to the above mentioned lump-sum payment, in order to meet the ethics rules at UNSW, which prescribed fixed minimum payments that were not to be affected by losses in the experiment.

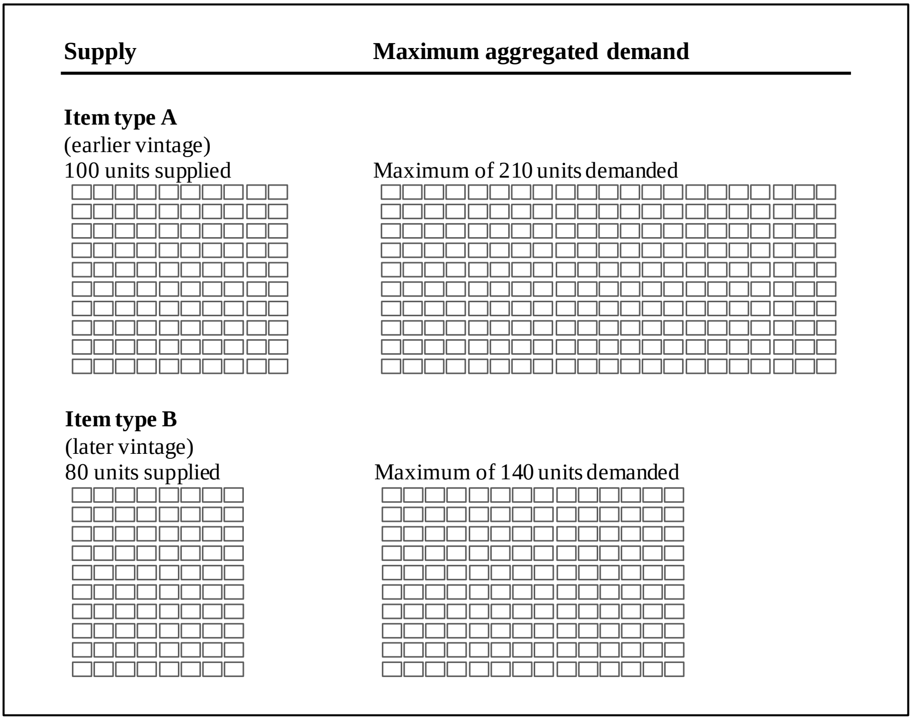

Figure 4.4: Number of units of Items A and B supplied and demanded.

in the form of a two-dimensional values table. An example for the layout of the table as it was distributed in the experiment is given in Table B.1 in the Appendix. In the following example, a simplified (shortened) version will be used for the convenience of the presentation.

Example 4.1 (Presentation of the values table)
(This example was adopted and adapted from Betz et al. (2010), p. 35f. Note that it uses the terms "permit" and "vintage" rather than "unit" and "item," respectively.)

Assume that a bidder is emitting carbon dioxide and would ask for at most 2 permits in the first year and 2 permits in the second year. In the first year, his abatement costs would be $15 for the first unit and $20 for the second unit. Therefore, his valuation for permits usable in the first year is $20 for the first permit and $15 for the second

Table 4.1: Example for a marginal values table (cf. Betz et al., 2010, p. 35).

<table>
<tr><td></td><td>Marginal value Vintage B</td><td colspan="8">Number of Vintage B permits</td></tr>
<tr><td>Marginal value vintage A</td><td></td><td colspan="2">0</td><td colspan="2">1</td><td colspan="2">2</td><td colspan="2">3</td></tr>
<tr><td rowspan="8">Number of Vintage A permits</td><td rowspan="2">0</td><td></td><td>16</td><td></td><td>12</td><td></td><td>0</td><td></td><td>0</td></tr>
<tr><td>20</td><td></td><td>20</td><td></td><td>20</td><td></td><td>20</td><td></td></tr>
<tr><td rowspan="2">1</td><td></td><td>16</td><td></td><td>12</td><td></td><td>0</td><td></td><td>0</td></tr>
<tr><td>16</td><td></td><td>15</td><td></td><td>15</td><td></td><td>15</td><td></td></tr>
<tr><td rowspan="2">2</td><td></td><td>15</td><td></td><td>12</td><td></td><td>0</td><td></td><td>0</td></tr>
<tr><td>15</td><td></td><td>12</td><td></td><td>0</td><td></td><td>0</td><td></td></tr>
<tr><td rowspan="2">3</td><td></td><td>12</td><td></td><td>0</td><td></td><td>0</td><td></td><td>0</td></tr>
<tr><td>12</td><td></td><td>0</td><td></td><td>0</td><td></td><td>0</td><td></td></tr>
</table>

permit. In this example, a discount factor of 0.8 applies, such that his valuations for permits usable in the second year are \$16 for the first permit and \$12 for the second permit. (This discount can be interpreted as lower abatement technology costs in the second year, or general discounting of future profits, see below.) Unlimited banking is assumed; thus permits for Vintage A can be used in Year 1 or in Year 2, while permits for Vintage B can only be used in Year 2.

Table 4.1 tabulates the bidder's corresponding marginal values for permits of Vintage A and Vintage B. For each possible bundle of permits a bidder might already own, the table displays the value of one more Vintage A permit in the lower left corner of a cell, and the value of one more Vintage B permit in the upper right corner of the cell. Consider three examples:

1. If the bidder owns 0 permits of Vintage A and 2 permits of Vintage B (row 0/ column 2 in Table 4.1), his value for one more permit of Vintage B is \$0, as he already covers his maximum need in Year 2, and cannot use the Vintage B permit to cover his emissions in Year 1. One more permit of Vintage A allows him to cover one more unit of emissions in Year 1, therefore his marginal value for one additional unit of a Vintage A permit is \$20.
2. If the bidder owns 1 permit of Vintage A and 0 permits of Vintage B (row 1/ column 0 in Table 4.1), his value for one more permit of Vintage B is \$16, as he would be able to cover one unit of permissions in Year 2 with this permit. The

Table 4.2: Example for a absolute values table (cf. Betz et al., 2010, p. 36).

Absolute value of bundle		Number of Vintage B permits 0	1	2	3	4
Number of Vintage A permits	0	0	16	28	28	28
	1	20	36	48	48	48
	2	36	51	63	63	63
	3	51	63	63	63	63
	4	63	63	63	63	63

value of a second permit of Vintage A is the maximum value at which it can be put into use. If this second Vintage A permit was used to cover emissions in Year 1, then its value would be \$15 (the value of a second unit of emissions in Year 1). However, if the second Vintage A permit was used in Year 2, this would bear a value of \$16. The marginal value of one more Vintage A permit is the maximum of those values, i.e. \$16.

3. Assume the bidder owns two permits of Vintage A and zero permits of Vintage B (row 2/ column 0 in Table 4.1). We know that if the bidder owns two permits of Vintage A, then he will use one of these permits to cover a first unit of emissions in Year 1 (value \$20), and the other permit to cover a first unit of emissions in Year 2 (value \$16). Now, if the bidder receives one more unit of Vintage A, then he will use it to cover a second unit of emissions in Year 1 (a value of \$15). However, if instead the bidder purchased one more unit of Vintage B, he would not use it to cover a second unit of emissions in Year 2 (a value of \$12). Rather he would allocate his permits efficiently, such that the additional Vintage B permit is used to replace the Vintage A permit which previously covered the first unit of emissions in Year 2. This way, the freed-up Vintage A permit can be used where its value is highest: for a second unit of emissions in Year 1. Thus, in this case the marginal value of a first vintage 2 permit is equal to the value of a second unit of emissions in Year 1, \$15.

From Table 4.1 it is easy to derive the absolute value for each possible bundle of Vintage A and Vintage B permits. Table 4.2 displays the results of that transformation.

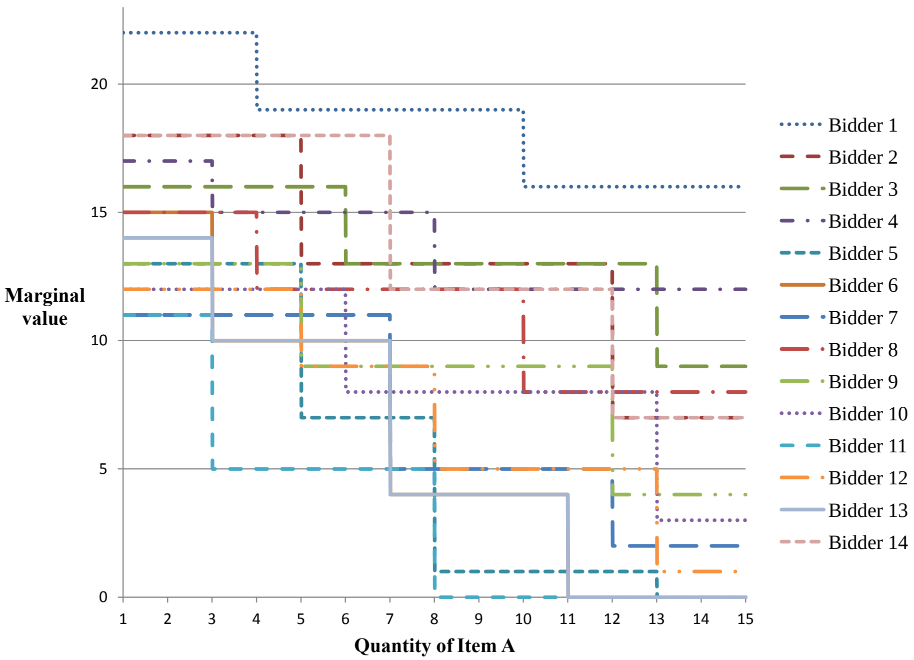

Figure 4.5: Example for one set of value functions (Session 3, Auction 1).

4.4.3 Values Distribution

Heterogeneity of the bidders' value structures was obtained by randomly drawing the slope and the intercept of the value functions (cf. Section 4.4.2). Figure 4.5 shows an exemplary set of 14 value functions that was used in one of the experimental sessions. In this example, the bidders' marginal values of the first unit ranged between 11 and 22 monetary units, and the bidders' number of units with positive marginal values ranged between 8 and 15.

For reasons of experimental control and in order to facilitate data analysis, a stationary replication of the one-shot auctions was employed. Therefore, the same set of value functions was used in all six auctions in a session. So that no bidder received the same value function more than once, the individual functions were rotated after each auction.

This way, from the bidders' perspective, the values tables were different between the auctions, while at the same time the overall market values structure stayed constant.[9]

Further, in order to prevent bidders from focusing on the price of the previous auction, and to further explore the robustness of the auction mechanisms, constant exogenous value function shocks in each auction shifted all values up or downwards. That is, in the marginal values table, the value shock was added to every value, while in the absolute values table, the number of units multiplied with the value shock was added to every value. In theory these constant shocks would only shift the resulting auction prices by the same amount. Therefore, in equilibrium (after controlling for the shock) the shocks would not affect market prices, seller revenues, or bidder profits.

4.4.4 Auction Rules

Bidding in all auctions was restricted to prices between E$1 and E$30 (the maximum marginal value including value shocks). If, at the price of E$1, the aggregate demand had been lower than the supply, the auction would have been considered to have failed. However, in none of the experimental auctions did this happen, and in none of the auctions did the price rise to E$30.

In each session, the first two of the six auctions were implemented as simple clock auctions with no proxy bidding. The auctions started at a price of E$1 and asked for quantity bids at this price. The default bid at the beginning of the auctions—which was set by the software and bid automatically, if the bidders did not change their entries—was the maximum demand of 15 and 10 units of Item A and B, respectively. If the total group demand of an item over all bidders at the last price was higher than the number of units offered, the item price of the following auction round was increased by E$1, and new quantity bids were elicited. Each price step lasted 30 seconds (except the first and second step which lasted 60 and 45 seconds, respectively). If no new quantity bid was submitted within this time, the previous bid was automatically repeated. This procedure continued until, at a given price, the aggregated demand for an item was equal to or lower than its supply. Then the price clock of this item stopped. If aggregate demand

9 The subjects were not informed about this procedure or about the distribution of the values. The instructions stated only that the tables were "different" between different auctions and between different bidders.

increased again (which was possible in the simultaneous auctions due to switching of demand from one item to the other), the price clock started to tick forward again. Once the aggregate demand did not exceed supply for both items at the same time, the auction was over. Auction history tables for each item showed the personal bidding history over previous bidding rounds. In the treatments where aggregate demand was revealed, this demand was also displayed in the tables.

In Auctions 3 to 6 of each session, the actual auction type according to the experimental treatment was implemented. The treatments featured either a USBA, or a (proxy) ECA with or without revelation of aggregate demand—denoted with ECAr and ECAn respectively. In the USBA treatments, the simple change with respect to the introductory clock format was that now a complete bidding plan had to be determined before the auction started. The auction history table of the first two rounds became an "Auction History and Planning Table," and sliders at each future clock price allowed bidders to select a bidding plan for the remainder of the auction. Bidders had five minutes to choose a plan, after which the auction ran automatically according to the bid function submitted, with no opportunity for participants to intervene. Figure 3.5 in Chapter 3 depicts screenshots of the proxy bidding interfaces.

The implementation of the ascending clock auction in treatments ECAn and ECAr allowed for proxy bidding. That is, as with the sealed-bid mechanism, the change between the Training Auctions 1 and 2 and Treatment Auctions 3 to 6 was that bidders could now submit a bidding plan for current and future prices. This plan, however, was not binding and could be revised at any time during the auction for current and future prices. Each price step now lasted 30 seconds (with 180 seconds for the first step).

Designing and implementing auctions (both in the real world and in the laboratory) involves a high level of detail. For this particular experiment additional rules for each type of auction had to be specified, which are partly still a matter of debate in practice, with no unambiguous recommendations from the economic literature. Appendix A addresses the details and reasons for the specific design choices. In sum, in any auction, the total demand of a bidder was not allowed to increase from one price step to the next. Excess demand at the final price was proportionally served, with non-integer fractions of supply being rounded according to the largest remainder method. In sealed-bid auctions, bids were sorted so that the auction would not result in a price reversal, and the price was determined by the lowest accepted bid. In multiple clock auctions, bidders could increase demand for one vintage at a specific price step if they decreased demand for the other vintage by at least the same amount. However, if total demand for one item would drop below supply purely because of switching, it was adjusted ex-post by a proportional reduction of the switch such that a complete allocation of the supply was ensured. Finally, in the sequential auctions, the earlier vintages were auctioned first.

4.4.5 Bidding Strategies

Two important motives, which might affect bidding behavior, are (1) obtaining a desired bundle of items and (2) paying as low a price as possible. With respect to the first motive, bidders seek to obtain the bundle of items that *maximizes their profits* at given prices according to their personal values tables. With respect to the second motive, they seek to keep the prices low, which requires the submission of a lower bid, also known as *bid-shading*. How relatively pronounced these motives are depends on the value schedules and prices (which determine the profits in the case of an award), and on the number of bidders and the distribution of values (which affect the likelihood of submitting a pivotal bid).

In the experiment, only in the ECA with demand revelation did the bidders obtain additional information during the auction. The lower the aggregated demand of an item dropped, the more likely it might appear to the bidders that the price clock of the item would soon stop. Once the excess demand dropped to the demand of an individual bidder, that bidder was able to end the auction unilaterally by decreasing her own bid. Yet, she would not know whether, at the same time, an opposing bidder was decreasing her bid, ending the auction anyway. In the latter case, the first bidder could profit from the fact that her opponent had halted the price clock without increasing her own demand.

In the experimental market with 14 bidders, a single bidder, was unlikely to submit (the only) pivotal bid and thereby determine the final price. Further, the bidders in the experiment knew only their personal value schedules; they did not know the distribution of the opposing bidders' value schedules. Therefore, it seems likely that bidders found it difficult to guess the position of their values table relative to that of the other bidders, which may have further promoted a heuristic bidding approach.

Given the high number of bidders, the small probability of influencing the price and the principle problem of calculating probabilities, a “Walrasian” Straightforward Truthful Bidding (SFTB) strategy would have seemed to be a good heuristical bidding strategy in this case. Using this strategy the bidders simply bid the quantities that maximize their profits at the given price combination, without any further strategic considerations to influence the price. Section 4.6.5 will show that most of the bidders in the experiment followed this strategy.

In the analysis of the experimental results in Section 4.6, the Walrasian benchmark was also employed to normalize the data, and to derive a measure of the theoretically predicted market concentration under the specific values schedules. For each of the six schedules, there was a vector of 14 predicted quantities that corresponded to the number of items allocated to the 14 bidders in an auction. In order to serve as a control variable in the data analysis, the data vector was aggregated to a one-dimensional concentration measure. For reasons of simplicity and comparability, the well-established Gini coefficient was used for the aggregation. The value of the Gini coefficient generally ranges between zero and one. At a value of zero, all bidders receive the same number of units, while at a value of one, a single bidder receives all units of an item. In the experimental design, for both items, the Gini coefficients of the Walrasian allocations ranged between 0.25 (Session 1) and 0.43 (Session 3).[10]

4.5 Hypotheses

Based on the existing literature on the relevant auction designs (cf. with the previous Sections and Chapter 2), the main hypotheses of this experimental study were as follows:

1. Simultaneous auctions yield higher allocative efficiency than sequential auctions.

[10] Detailed tables of the allocations and the respective Gini coefficients are available for download from http://www.sascha-schweitzer.de/download/spectrum.

2. Sealed-bid auctions lead to higher prices and revenues than clock auctions without aggregate demand revelation, which in turn result in higher prices than open clock auctions with demand revelation.
3. Open clock auctions exhibit better price discovery than clock auctions without aggregate demand revelation, which in turn exhibit better price discovery than sealed bid auctions.

According to Hypothesis 1, simultaneous auctions are expected to yield a more efficient allocation than sequential auctions, since bidders can consider bundle values. On the other hand, because open clock auctions may facilitate collusion as well as unilateral demand reduction, Hypothesis 2 predicts lower prices and revenues for open clock auctions with aggregate demand revelation. Note that Hypothesis 2 and Hypothesis 3 are not independent, as they both refer to prices and revenues. However, their meaning is different, as Hypothesis 2 refers to the level of prices and revenues, while Hypothesis 3 refers to the correlation of the induced values with prices and revenues. According to Hypothesis 3, prices should reflect induced value shocks more accurately when using a clock auction with aggregate demand revelation than when using a sealed bid auction.

4.6 Results of the Experiment

Before the presentation of the experimental results in the following sections, some paragraphs will be devoted to a short summary of the data structure and of the transformations and adjustments of the data that were applied in the analysis. All adjustments were conducted in order to increase the comparability of the data, and to eliminate confounding effects between the sessions and the auctions—without changing the primary nature of the data.

In evaluating the performance of auction types in different market environments (as defined by the values schedules, cf. Section 4.4.2), the present analysis followed the existing literature in using the SFTB or "Walrasian equilibrium" as a benchmark. The technical advantage of this normalization was an increase of the comparability between the six sessions. Potential differences in the level of the measured criteria which were purely due to differences between the sessions were minimized by leveling out the theoretical differences (leaving only differences that were due to deviations between theoretical and empirical effects).

For the analysis of the main treatment parameters—auction sequence and auction type—the data was adjusted further, in order to increase comparability. First, subtracting the demand shocks described in Sections 4.4.2 and 4.4.3 served to eliminate theoretical differences between the auctions. Second, restricting attention to auctions 3 to 6 in each session seemed reasonable, since the first two auctions per session did not implement the actual treatment design and were solely intended to allow subjects to become familiar with the auction situation and to learn proper use of the auction software.

In the first step of the statistical analysis, the data was aggregated to the mean values of the independent sessions—fulfilling the independency assumptions of the statistical tests, while ignoring the micro-level information of the individual auctions. As the main treatment parameters are measured on a nominal scale, an Analysis of Variance (ANOVA) with the factors auction *sequence* (sequential vs. simultaneous) and auction *type* (USBA vs. ECA with no demand revelation vs. ECA with demand revelation—denoted with ECAn and ECAr respectively) was employed for the identification of the factors' potential effects.

In the second step of the analysis, session and within-session variables were included. Relevant explanatory variables on the auction level were the time-component of the auction, which captured potential learning effects, and the induced demand shock, which—although theoretically irrelevant—may have empirically influenced the auction results. The first of these variables was measured on an ordinal scale, while the second one required a ratio measurement. An approximative representation of these measures was provided by a linear regression model. In the regression, all nominal variables were dummy coded. Further, the dependence within the sessions was taken into account through the use of robust clustered standard errors on the level of the individual sessions.

For the sake of clarity, the following text will contain only a selection of the most relevant data, statistics and graphical displays. The complete data and the computer program scripts that were used to obtain the results presented are provided under http://www.sascha-schweitzer.de/download/co2. At the same place, interested read-

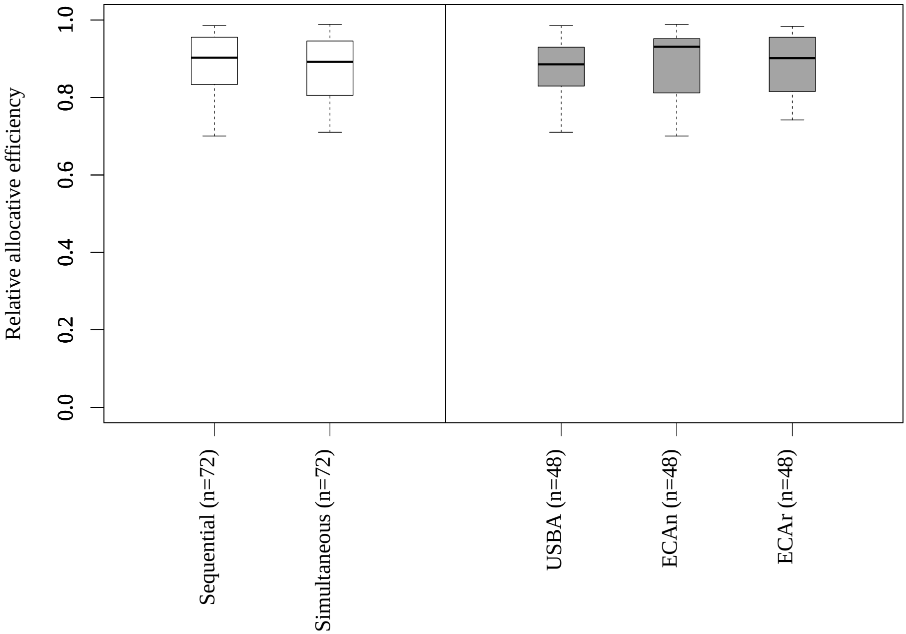

Figure 4.6: Relative allocative efficiency by treatment axes.
(Tukey box plots. The number of observations is denoted by n.)

ers will also find further details and additional materials that may help them to gain further insights into particular details of the results.

4.6.1 Efficiency

In general, relative allocative efficiencies (as defined in Section 2.2.1) in all experimental treatments were very close to each other. The values ranged from 70.0% of the maximum potential social surplus to 98.8%. Figure 4.6 shows the box plots of the relative allocative efficiency by the treatment parameters *auction sequence* and *auction type*. The box plots largely overlap and the interquartile range looks similar along all box plots. An ANOVA showed no effect of the treatment factors auction type (USBA vs. ECAn vs. ECAr),

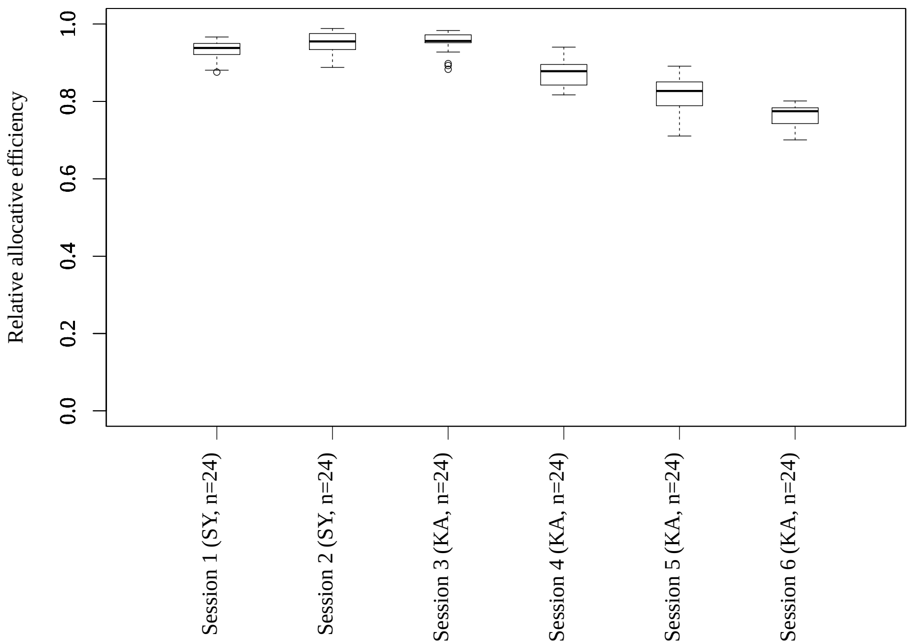

Figure 4.7: Relative allocative efficiency by sessions.
(Tukey box plots. The observations are depicted on the level of individual auction. n denotes the number of observations, SY indicates the sessions conducted in Sydney, and KA indicates the sessions conducted in *Karlsruhe*.)

and auction sequence (sequential vs. simultaneous) on the relative allocative efficiency.[11] Therefore, from the present data, it was not possible to conclude that any of the auction designs was inferior to any other auction design with respect to efficiency.

Complementing the analysis of the aggregated data, the regression analysis (Table 4.3) included the session variables *isSydney* indicating the laboratory where the sessions were conducted (Sydney or Karlsruhe), *SessionNumber* indicating the chronological order of the sessions, and *GiniCoefficient* measuring the market concentration, as well as the within-session variables *AuctionNumber*, *ValueShock* and *isDiscounted*. While none of the within-session variables showed a significant effect on efficiency, the regression revealed significant effects of the session timing and of the Gini coefficient. With respect to

[11] ANOVA: model: F=1.51, p=0.25 (model not significant); auction type: F=0.06, p=0.95; auction sequence: F=0.20, p=0.66; interaction auction type/sequence: F=0.20, p=0.82.

Table 4.3: OLS regressions of relative allocative efficiencies.
(·,*, **, and *** denote significance at the 10%, 5%, 1% and 0.1% level. Robust standard errors are calculated at the independent group level and are given in parentheses.)

	(1): Estimate (standard error)	
isECAn	0.0068	
	(0.0073)	
isECAr	0.0106	
	(0.0065)	
isSequential	0.0118	
	(0.0054)	*
AuctionNumber	-0.0004	
	(0.0025)	
ValueShock	-0.0005	
	(0.0011)	
isDiscounted	0.0001	
	(0.0058)	
isSydney	0.0168	
	(0.0104)	
GiniCoefficient	0.1980	
	(0.0707)	**
SessionNumber	-0.0572	
	(0.0034)	***
Observations	144	
R^2	0.850	
$\overline{R}^2$	0.840	
AIC	-577.8	

the latter—in line with the intuition that more pronounced differences in the valuations of the bidders led to an easier coordination of the allocation—a higher Gini coefficient clearly facilitated efficiency.

Figure 4.7 depicts the effect of the session timing, which consisted in an efficiency decrease from Session 3 to Session 6. The first two sessions, which were conducted in parallel in the large laboratory in Sydney, and the first session in Karlsruhe showed roughly the same efficiency. Yet, the later sessions which were conducted one after another in Karlsruhe (usually within one week on subsequent days) exhibited a strong downwards trend in efficiency. However, as the same value schedules were always employed in the same order, it is not possible to conclude ultimately, whether the decreasing efficiency is due to interactions within the subject pool or caused by the particular value structures.

With respect to the auction sequence, the regression revealed a significant effect of about 1.2% efficiency gains when auctioning sequentially rather than simultaneously. However, this effect should be interpreted cautiously, as it was not revealed by the more conservative ANOVA on the aggregate level of the independent groups. Indeed, 1.2% is small relative to the inter-quartile range of 12.8%, and even smaller relative to the total value range of 28.8%. Therefore, this difference could not be considered economically significant, even if it was statistically significant.

4.6.2 Revenue

The auctions yielded between 60.7% and 109.3% of the revenues that would be predicted by the Walrasian equilibrium, i.e. by efficient prices reflecting marginal costs. On average, revenues were clearly below the predicted values. Figure 4.8 shows the box plots of the relative revenues in the treatment parameters, *auction sequence* and *auction type*. An ANOVA on the aggregated session level did not reveal significant differences in auction revenues between auction types (USBA vs. ECAn vs. ECAr).[12] However, the analysis revealed higher revenues when auctioning sequentially rather than simultaneously.

Again, complementing the above analysis, the regression analysis (Table 4.4) included the session variables *isSydney*, *SessionNumber*, and *GiniCoefficient*, as well as the within-session variables *AuctionNumber*, *ValueShock* and *isDiscounted*. The significant effect of the auction sequence revealed by the ANOVA was confirmed by the regression. The revenue increase when auctioning sequentially rather than simultaneously was estimated to be about 7.4%. Also consistent with the above analysis, the regression on the adjusted data revealed no effects from the auction type.

[12] ANOVA: model: F=3.24, p=0.02; auction type: F=0.194, p=0.83; auction sequence: F=11.52, p<0.01; interaction auction type/sequence: F=2.14, p=0.14.

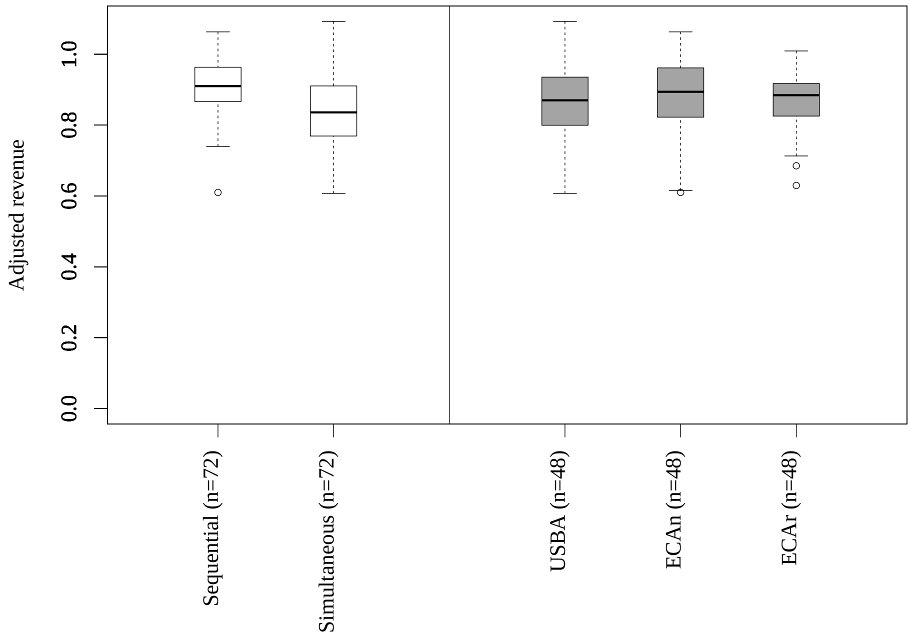

Figure 4.8: Adjusted revenues by treatment axes.
(Tukey box plots. The number of observations is denoted by n.)

In contrast to the pronounced session effect on relative allocative efficiency, the regression on the relative revenues revealed no significant session effect. This speaks against the conjecture that the efficiency losses reported in the previous section stemmed from collusive behavior within the subject pool.[13] Collusive behavior would imply decreasing revenues in the later sessions.

With respect to the within-session variables, the regression on the adjusted data showed some pronounced effects. In particular, a significant effect was detected from the value shocks. As the adjusted data was corrected for the value shocks predicted by theory, this effect should not have occurred, given that bidders were expected to behave as predicted. Instead, the auction revenues did not completely reflect the value shocks.

[13] Note that although "smart" collusion should not have led to efficiency decreases, not knowing the above findings on auction revenues, one could have speculated that uncoordinated forms of collusion, or unilateral demand reductions were responsible for the observed efficiency decreases.

Table 4.4: OLS regressions of relative (1) and unadjusted (2) revenues.
(·,*, **, and *** denote significance at the 10%, 5%, 1% and 0.1% level. Robust standard errors are calculated at the independent group level and are given in parentheses.)

	(1): Adjusted Estimate (standard error)		(2): Unadjusted Estimate (standard error)	
isECAn	0.0165		36.2500	
	(0.0291)		(64.6624)	
isECAr	0.0062		11.6667	
	(0.0239)		(52.4271)	
isSequential	0.0741		167.2222	
	(0.0214)	***	(47.0663)	***
AuctionNumber	0.0101		21.7391	
	(0.0052)	·	(10.9861)	*
ValueShock	-0.0101		155.8937	
	(0.0025)	***	(6.0375)	***
isDiscounted	0.0050		-184.8925	
	(0.0122)		(28.3460)	***
isSydney	0.0108		576.6631	
	(0.0382)		(90.8854)	***
GiniCoefficient	0.0921		2857.2498	
	(0.2625)		(614.9053)	***
SessionNumber	0.0175		176.9107	
	(0.0120)		(27.1445)	***
Observations	144		144	
R^2	0.254		0.867	
$\overline{R}^2$	0.204		0.858	
AIC	-280.9		1945.3	

The unadjusted data (without correction for value shocks) provided insights into how the revenue actually reacted to value shocks. Regressions (2) on this original data demonstrated that value shocks did have a significant effect in the way predicted by theory: A value increase of one monetary unit should result in revenue increasing by 180 monetary units (the number of items multiplied by the monetary increase). The actually estimated slope was 155.89, meaning that roughly 87% of the value increase was reflected in the revenue.

As in all auctions, all units of both items were sold successfully; the revenue data completely mirrored the combined price data. Section 4.6.3 on prices and price signals will provide details on this underlying data and may also help to make clear the composition of the revenue data.

4.6.3 Price Signals

Figure 4.9 shows the box plots of the relative prices of items A and B in the *auction sequence* and *auction type* treatment parameters. Consistent with the results for allocative efficiency and revenues, the ANOVA on the independent session level revealed no trends in the prices of Item A and B with respect to the auction type.[14]

However, comparing simultaneous and sequential auctions, a significantly positive effect on the price of the item auctioned first (Item A) was observed when the two items were auctioned sequentially rather than simultaneously. This result was robust across the auction types, and consistent with what was observed for revenues. No such consistent effects were observed for Item B prices, indicating that the differences in overall revenues were driven mainly by more aggressive bidding in the first auction when auctioning sequentially.

An examination of price variances within demand structures indicated that price volatility was lower in the ECA with demand revelation than in the USBA, but significantly so only for prices of Item A in the simultaneous auctions. As expected, this effect was not observed for the ECA without demand revelation. The lowest overall variances were found for the sequential auction in the ECA with demand revelation.

In the price regressions (Table 4.5), the estimated coefficient for the binary dummy parameter *isSequential* indicated that the price of Item A was almost 11% higher (and thereby closer to the Walrasian benchmark) if it was auctioned first rather than simultaneously with Item B, while no significant effect on the price of Item B was revealed.

[14] ANOVA price Item A: mode: F=2.48, p=0.07; auction type: F=0.39, p=0.68; auction sequence: F=20.85, $p<10^{-4}$; interaction auction type/sequence: F=0.16, p=0.86.
ANOVA price Item B: model: F=1.19, p=0.40 (model not significant); auction type: F=0.02, p=0.98; auction sequence: F=1.64, p=0.21; interaction auction type/sequence: F=7.11, $p<0.01$.

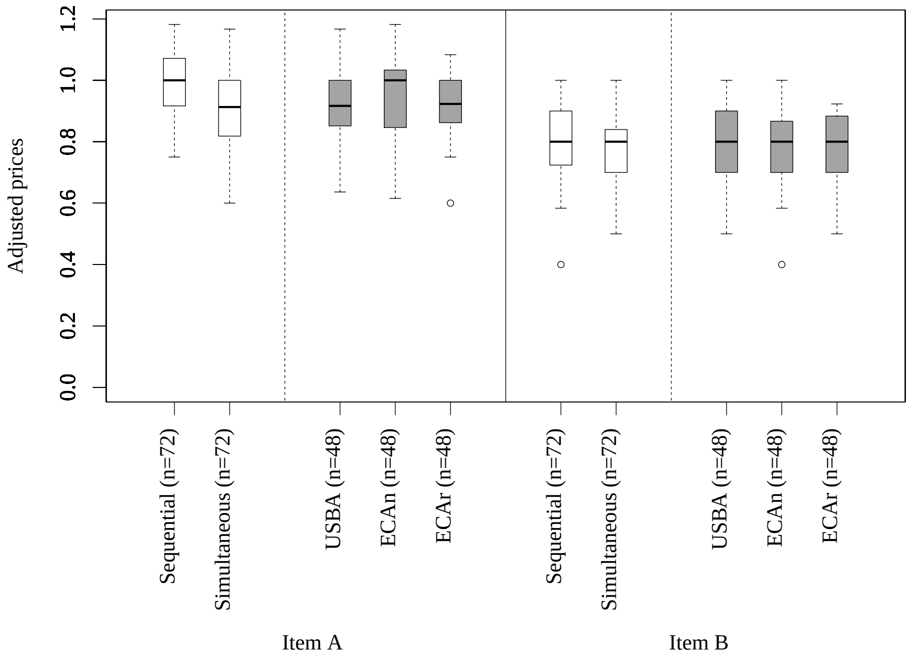

Figure 4.9: Adjusted prices by treatment axes.
(Tukey box plots. The number of observations is denoted by n.)

If the price signals generated by the auctions were “good” price signals, the prices should have reflected the value shocks. In this context, the adjustment of the data for the value shocks played a role in the interpretation of the effects. For the adjusted data (which was corrected for the value shocks), under perfect price discovery, the value shock variable should show no effect on the prices. Theoretically, an increase of the value should just shift the price upwards by the same absolute amount, and after deducting the shock from the resulting prices (as was done by adjusting the data and calculating relative prices), no effect should remain.

Hinting at potential imperfections in the price discovery performance of the auctions, the shock variable turned out to matter for the adjusted prices. In particular, the higher the demand shock of an auction in a session, the lower were the adjusted prices for items A and B. This observed effect implied that rather than increasing their bids by

Table 4.5: OLS regressions of relative adjusted (1, 2) and unadjusted (3, 4) prices.
(·,*, **, and *** denote significance at the 10%, 5%, 1% and 0.1% level. Robust standard errors are calculated at the independent group level and are given in parentheses.)

	(1): A adj. Estimate (st. error)		(2): B adj. Estimate (st. error)		(3): A unadj. Estimate (st. error)		(4): B unadj. Estimate (st. error)	
isECAn	0.0248		0.0054		0.31		0.06	
	(0.0277)		(0.0366)		(0.35)		(0.44)	
isECAr	0.0077		0.0047		0.08		0.04	
	(0.0243)		(0.0289)		(0.31)		(0.34)	
isSequential	0.1068		0.0301		1.36		0.39	
	(0.0215)	***	(0.0261)		(0.27)	***	(0.31)	
AuctionNumber	0.0049		0.0177		0.06		0.19	
	(0.0064)		(0.0074)	*	(0.08)		(0.08)	*
ValueShock	-0.0098		-0.0105		0.87		0.86	
	(0.0027)	***	(0.0030)	***	(0.04)	***	(0.04)	***
isDiscounted	-0.0146		0.0181		-0.59		-1.57	
	(0.0149)		(0.0185)		(0.17)	***	(0.24)	***
isSydney	-0.0088		0.0358		3.31		3.07	
	(0.0372)		(0.0481)		(0.52)	***	(0.61)	***
GiniCoefficient	0.0146		0.2086		16.48		15.11	
	(0.2872)		(0.3035)		(3.84)	***	(3.82)	***
SessionNumber	0.0135		0.0234		1.03		0.92	
	(0.0108)		(0.0163)		(0.14)	***	(0.20)	***
Observations	144		144		144		144	
R^2	0.330		0.105		0.850		0.808	
$\overline{R}^2$	0.285		0.045		0.840		0.795	
AIC	-255.2		-208.4		475.1		512.4	

the same absolute amount as item values were increased, bidders discounted the increase in their bidding.

To what extent price discovery occurred becomes more transparent when looking at the unadjusted data. Under perfect price discovery, there should be a significant effect from the value shock and the coefficient for this variable should equal 1. The regression on the

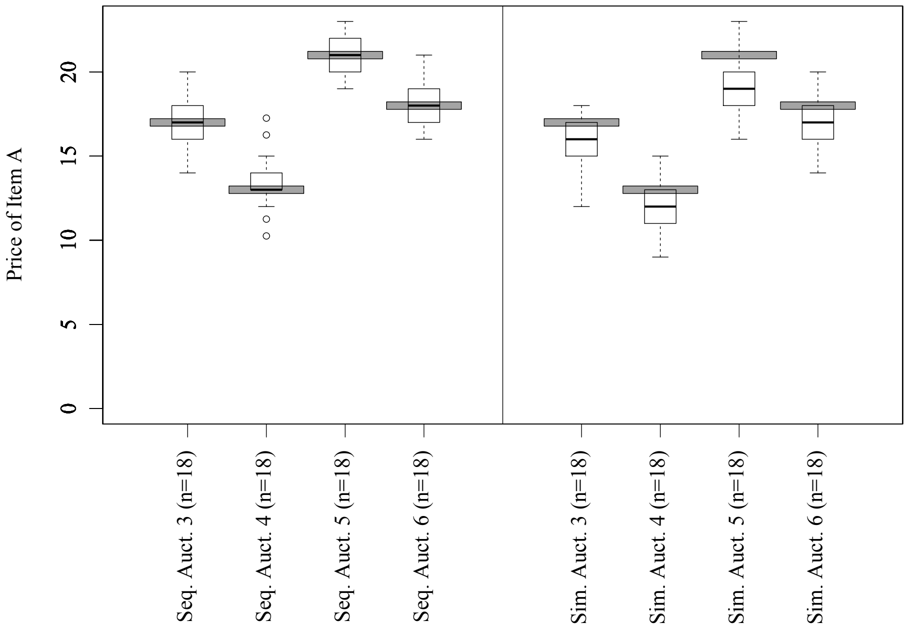

Figure 4.10: Prices of Item A by auction and auction sequence.
(The Tukey box plots represent the observed price data, while the grey bars indicate the Walrasian benchmark. The number of observations is denoted by n.)

unadjusted data revealed a significant positive effect, meaning that prices in principle reacted to value shocks in the desired way. The estimated slope of this reaction is 0.87 for Item A and 0.86 for Item B. Therefore, most of the value shock was mirrored in the price (with a lag of 13–14%).

Figures 4.10 and 4.11 illustrate the price discovery performance, clustered by the treatment parameters auction sequence and auction type. It is interesting to note that the visible differences between the simultaneous and the sequential treatments were not due to interactions (which were not significant in the regressions and would actually decrease the quality of the model in terms of the Akaike Information Criterion (AIC) and $\overline{R}^2$). Instead, the price adoption itself was very similar across the treatments, while the whole graph itself was shifted by a constant offset.

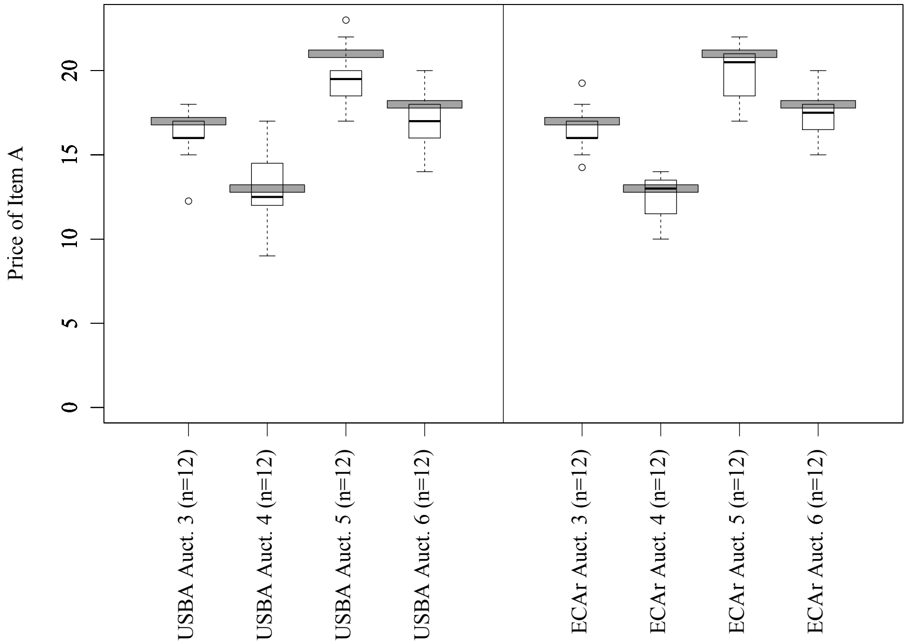

Figure 4.11: Prices of Item A by auction and auction type.
(The Tukey box plots represent the observed price data, while the grey bars indicate the Walrasian benchmark. The number of observations is denoted by n.)

4.6.4 Secondary Markets

Under the presence of secondary markets in the simultaneous auction treatments, the principle results showed no difference from those presented above. Table 4.6 shows the regressions on the adjusted data from Tables 4.3, 4.4 and 4.5 when the three secondary market treatments are included. All estimated effects of the secondary markets were negative—on efficiency as well as on revenues, on prices of Item A and on prices of Item B. However, these findings were (weakly) significant only for revenues and for the prices of Item B.

It is interesting to note that efficient allocations in the primary auctions were not a pre-requisite for overall efficiency, as the bidders could realize any mutually beneficial

Table 4.6: OLS regressions with secondary market treatments.
(·,*, **, and *** denote significance at the 10%, 5%, 1% and 0.1% level. Robust standard errors are calculated at the independent group level and are given in parentheses.)

	(1): Eff. Est. (st. error)		(2): Rev. Est. (st. error)		(3): Pr. A Est. (st. error)		(4): Pr. B Est. (st. error)	
isECAn	0.0065		0.0249		0.0265		0.0228	
	(0.0068)		(0.0264)		(0.0239)		(0.0330)	
isECAr	0.0073		0.0177		0.0146		0.0229	
	(0.0058)		(0.0204)		(0.0192)		(0.0256)	
isSequential	0.0118		0.0741		0.1068		0.0301	
	(0.0056)	*	(0.0215)	***	(0.0216)	***	(0.0262)	
AuctionNumber	0.0014		0.0116		0.0091		0.0153	
	(0.0021)		(0.0047)	*	(0.0053)	·	(0.0065)	*
ValueShock	-0.0006		-0.0122		-0.0113		-0.0134	
	(0.0008)		(0.0024)	***	(0.0026)	***	(0.0029)	***
isDiscounted	0.0038		0.0230		-0.0005		0.0421	
	(0.0049)		(0.0111)	*	(0.0120)		(0.0161)	**
isSydney	0.0047		-0.0170		-0.0384		0.0102	
	(0.0102)		(0.0365)		(0.0347)		(0.0435)	
GiniCoefficient	0.1708		0.0897		0.0260		0.1788	
	(0.0655)	**	(0.2355)		(0.2389)		(0.2720)	
SessionNumber	-0.0576		0.0111		0.0073		0.0164	
	(0.0031)	***	(0.0104)		(0.0094)		(0.0135)	
hasSecondMarket	-0.0038		-0.0425		-0.0363		-0.0502	
	(0.0065)		(0.0251)	·	(0.0238)		(0.0295)	·
Observations	216		216		216		216	
R^2	0.825		0.296		0.326		0.162	
$\overline{R}^2$	0.817		0.261		0.358		0.122	
AIC	-854.6		-377.0		-366.7		-276.9	

trades on the secondary markets. Despite this option, the primary markets did not suffer a significant loss of efficiency, but rather efficient allocations had already been obtained on the primary markets. This indicates that bidders did not regard the goods as exchange goods for later trade, but rather focused on their private values to guide their bidding.

With respect to prices and revenues, under the presence of secondary markets, a (weakly) significant decrease of between 4% and 5% occurred. Yet, although the level of revenues and prices was slightly lower in the secondary market treatments, the estimated correlation coefficients of value shocks and prices did not change significantly, indicating that the price discovery function of the auctions stayed intact in this situation.

All in all, the secondary markets seemed to have no noteworthy impact on the primary markets. However, as the influence of secondary markets was investigated only for the simultaneous treatments, it would be interesting to see if the price and revenue decrease under secondary markets would transfer to sequential auctions.

4.6.5 Bidding Behavior

The previous analysis focused on the aggregate results of efficiency, revenue and prices. This section seeks to explain the observed effects by investigating the underlying bidding behavior. For this purpose, the following section will provide several visual displays and corresponding explanations to make clear and understandable what has happened in the auctions on the micro-level. The focus of the analysis will be on the comparison of sequential and simultaneous auctions, which is the only treatment parameter that showed consistent significant effects with respect to all measures on the aggregate level. Further, as the aggregate effect was mainly driven by the first item, the analysis will focus on Item A.

Benchmarks and Data Adjustment

Before presenting the results on bidding behavior, it may be worthwhile to spend the first paragraphs of this section explaining how the adjustment of the individual bidding data differs from the aggregate case. As with the aggregated data (which was normalized by the Walrasian equilibrium benchmark) the individual data needed to be adjusted in order to obtain comparability. Comparability was a complex issue on the individual data level, because the differences in the value schedules, auction designs and specific price developments imply different bids in the theoretical benchmark.

In contrast to the Walrasian benchmark used for the aggregated results, the benchmark for individual bidding behavior depended on the particular price combination that was valid when the bid was submitted. For the critical bids at the end of an auction, these prices could be different for different auctions, which made it necessary to correct for these differences in order to obtain comparable data (as these differences stemmed from the aggregate market situation and were not part of the individual bidding behavior).

The baseline of the comparison was a SFTB strategy (cf. Section 4.4.5). In the SFTB strategy the bidders bid the quantities that maximize their profits at a given price combination. The bids are called truthful and straightforward, because the bidders do not make any further strategic moves—such as, for example, shading their bids to influence the price or to coordinate with other bidders. These theoretic benchmark bids served to normalize the data. Yet, the result of this optimization was not necessarily unique, since several combinations of A and B could be optimal. Therefore, the benchmark took on the shape of a corridor—defining an upper and a lower value—rather than a single benchmark value.

A further issue of comparability between the treatments was raised by the information available to the bidders in the sequential vs. the simultaneous treatments. While the bidders in the simultaneous auctions knew the current prices of both items, bidders in the sequential auctions needed to rely on their expectations for the future auction development. Since the bidders' beliefs on future prices and quantities were unknown, the liberal benchmark corridor used for this analysis permited the whole spectrum of valid assumptions.[15] The highest number of units of an item should have been purchased if a bidder expected to obtain no units of the other item at the end of the auction. By the same token, the lowest number of units should have been purchased if the bidder expected to obtain the full amount of the other item (limited by the quantity cap). In order to maintain comparability, the same benchmark was used for the simultaneous auctions, although more information was available to the bidders in that case.

Bidding Behavior and Bidder Types

Figure 4.12 shows three examples of typical benchmark corridors of Item A. Further, the figure depicts the bidding behavior of three corresponding bidders. The bidder in

[15] Alternative benchmarks were investigated and, in principle, they yielded the same results.

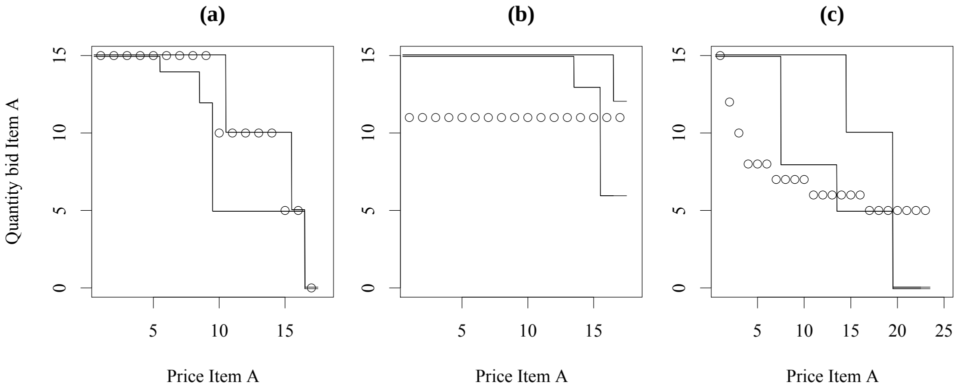

Figure 4.12: Exemplary benchmark corridors and bids observed in the experiment for Item A.
The upper and lower lines indicate the upper and lower bounds of the benchmark corridor, respectively. The circles indicate observed bids.
(a): Sequential ECAr, Session 4, Auction 6, Bidder 3; (b): Sequential ECAr, Session 4, Auction 6, Bidder 4; (c): Sequential ECAr, Session 2, Auction 5, Bidder 3.

part (a) bid perfectly within the benchmark corridor. The bidder in part (b) lowered her bid early in the auction, but submitted a bid within the benchmark corridor in the critical last auction round. This kind of ideal behavior was observed quite often, and for Item A (Item B) more than 50% (more than 60%) of all bids in the final auction round lay within the benchmark corridor. Only a minority of all bids resembled the example in part (c), where the bidder failed to meet the benchmark corridor with her final bid.

Figure 4.13 gives a graphical overview of the percentage of Item A and B bids within, below and above the benchmark corridor in the last auction round. Exact percentage values and further details on the nature of the deviations from the benchmark corridor are provided in Figure B.1 in the Appendix.[16]

[16] Since the exact shape of the benchmark corridor depended on the particular development of the item's price, the corridors differed slightly. In order to make this difference transparent, Figure B.1 in the appendix adds the mean width of the benchmark corridor in parentheses. Although the average benchmark width was slightly higher for the simultaneous treatments, the percentage of bids in the corridor was higher in the sequential treatments. Note, too, that although the benchmark corridor for the simultaneous treatments was inflated in order to maintain comparability, there were still fewer bids in this corridor. Therefore, it is clear that the choice of the benchmark could not be responsible for the difference in the results. Rather, a tighter benchmark would make the difference even more pronounced.

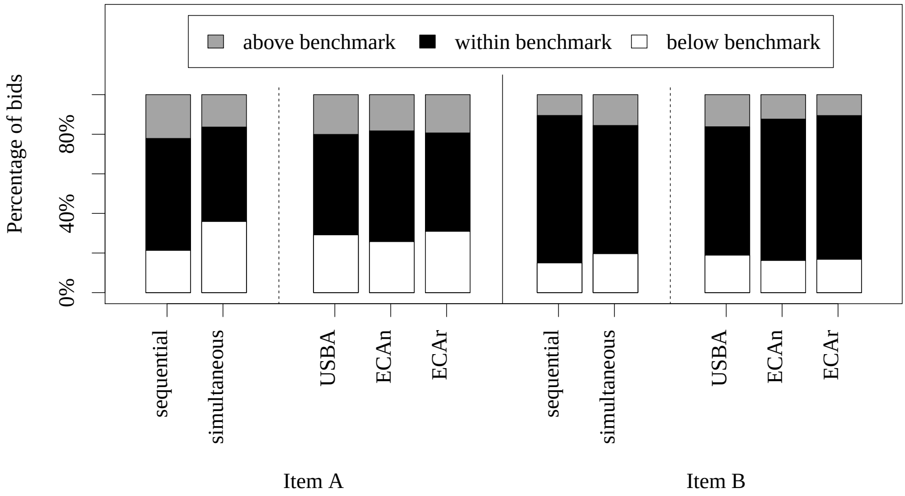

Figure 4.13: Percentage of bids in the benchmark corridor by treatment axes. The lower part of the bars indicates bids for fewer units than in the benchmark corridor, the middle part of the bars indicates bids for a number of units within the benchmark corridor and on the corridor's bounds, and the upper part of the bars indicate bids for more units than in the benchmark corridor.

For the sequential treatments, in the case of Item A, the proportion of bids within the benchmark corridor was higher than for the simultaneous treatments—a difference of about nine percentage-points. While 36% of all bids in the simultaneous auctions lay below the benchmark corridor, the same was true for only 21% of all bids in the sequential auctions. By the same token, more bids lay above the benchmark corridor in the simultaneous than in the sequential auctions. Even more strikingly, the ratio of bids below and above the benchmark corridor was almost one to one in the sequential treatments, while in the simultaneous treatments more than twice as many bids were below the benchmark than above it.

An ANOVA on the data aggregated to the level of independent sessions confirmed that the auction sequence had a significant effect on the bid/benchmark position, while the analysis revealed no effects from auction type and session.[17] The effect was revealed

[17] ANOVA on percentage of bids for Item A within the benchmark: model: F=3.38; p=0.02; auction type: F=2.26, p=0.12; auction sequence: F=11.76, p<0.01; interaction auction type/sequence: F=0.32, p=0.73.

for the percentage of bids within the benchmark corridor as well as for the ratio of bids below the benchmark corridor. The percentage of bids above the benchmark corridor was very volatile between the bidder groups, which is why the test could not reveal an effect for this measure for the given number of observations.

While the analysis to this point considered all bids without attributing them to individual bidders, Figure 4.14 gives an overview of the individual bidders' deviations (in quantity units) from the benchmark corridor for Item A. The bidders were sorted by their mean deviation and two black vertical lines indicate three bidder types. The bidders on the left side of the first line bid below the benchmark corridor, the bidders between the lines bid within the benchmark corridor, and the bidders on the right side of the lines bid above the benchmark corridor (on average). Clearly, most bidders in the sequential auctions bid within or above the benchmark corridor, while a majority of the bidders in the simultaneous auctions bid below the corridor.

About 30% of all bidders showed a somewhat erratic behavior by changing between bids below and above the benchmark corridor. This share of "erratic" bidders was surprisingly stable across all treatments, indicating that—in contrast to most other measures—erratic behavior did not depend on the treatment configuration. It also suggests that confusion was not higher or lower in any of the treatments and was probably not the cause of the observed effects.

While the previous analysis focused on bidding on Item A, Figure 4.15 provides an inkling of how the bivariate bidding for both items looked. Before knowing the actual results, one intuitive conjecture could be that—for psychological reasons—bidders who shaded their bids for one item were inclined to compensate by bidding on a higher quantity of the other item. An alternative and equally intuitive conjecture could be that bidders were either over- or under-bidding types, which applied to both items in the auction in the same way.

The second conjecture turned out to be true. The bivariate plots of deviation for Item A and B depicted in Figure 4.15 show some pronounced patterns. Negative de-

ANOVA on the percentage of the bids for Item A below the benchmark: model: F=4.91, p<0.01; auction type: F=0.97, p=0.39; auction sequence: F=22.10, $p<10^{-4}$; interaction auction type/sequence: F=0.24, p=0.79.
ANOVA on the percentage of the bids for Item A above the benchmark: model: F=1.20, p=0.33 (model not significant); auction type: F=0.15, p=0.86; auction sequence: F=4.69, p=0.04; interaction auction type/sequence: F=0.51, p=0.60.

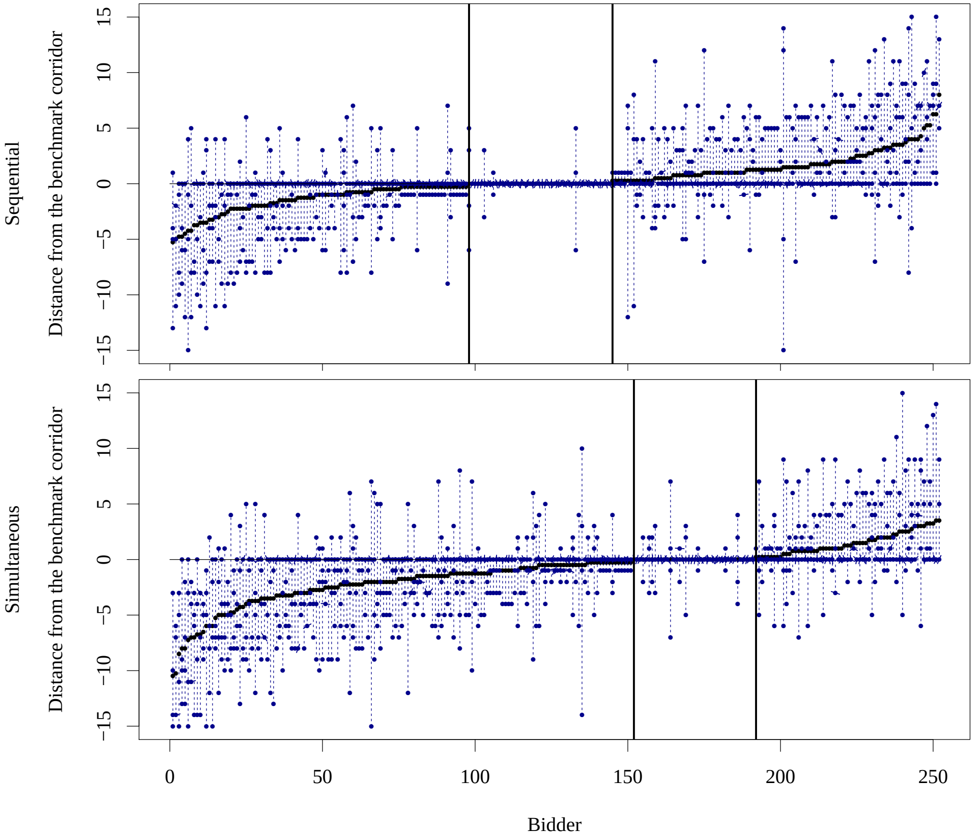

Figure 4.14: Bidders clustered by mean distance from the benchmark corridor and by auction sequence.
For each bidder the four final bids in the treatment specific Auctions 3 to 6 are depicted by the blue dots and connected with a dotted vertical line for visual convenience. The black dots indicate the mean values of a bidder's bids.

viations from the benchmark for Item A went along with negative deviations from the benchmark for Item B.[18] Therefore, bidders have engaged in bid shading as well as in overbidding in a consistent way.

[18] In all 36 groups, the number of deviations into the same direction (over-/underbidding) was higher than the number of deviations into opposing directions (compensating).
Sign test on the number of groups in which the frequency of over-/underbidding was higher than the frequency of compensating: s=36, p<10^{-10}.
There were no treatment effects with respect to the ratio of over-/underbidding to compensating.

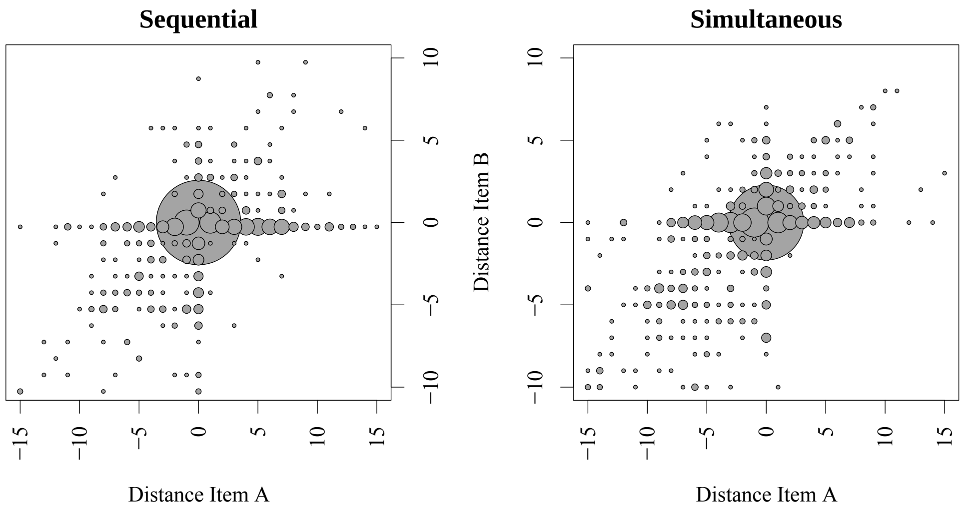

Figure 4.15: Bivariate bid distance from the benchmark corridor for Item A and B. The areas of the circles indicate the number of observations at the coordinates of the center of the circle. The areas are comparable between both plots. The total number of observations represented in each plot is $n_1 = n_2 = 1008$.

The differences between the simultaneous and sequential auctions were as pronounced in the bivariate case as they were in the univariate case. In principle, the same effects reoccurred. For instance, the number of bids that were within the benchmark corridor for both items at once (the big circle in the center of the graphs) was higher for the sequential auctions.[19] Also, the plot in the sequential case is more symmetrical, due to the more balanced distribution of over- and underbidding in comparison to the simultaneous case.

4.6.6 Summary

The results of the experiment gave no evidence that the simultaneous auctioning of two vintages yielded higher efficiency than a sequential procedure. Quite to the contrary,

ANOVA: model: F=0.52, p=0.76 (model not significant); auction type: F=0.60, p=0.56; auction sequence: F=0.23, p=0.63; interaction auction sequence/type: F=0.59, p=0.56.

[19] ANOVA on the percentage of bivariate bids within the benchmark for both items per group: model: F=3.34, p=0.02; auction type: F=1.34, p=0.28; auction sequence: F=13.91, $p<10^{-3}$; interaction auction type/sequence: F=0.06, p=0.94.

the sequential auction tended to slightly more efficient allocations. Thus, Hypothesis 1 had to be rejected.

The analysis did not reveal significantly stronger bid-shading in the clock auctions than in a sealed bid auction. In general, the USBA, the ECA without revelation of excess demand, and the ECA with revelation of excess demand all performed rather similar with respect to efficiency, auction revenues and price discovery. Therefore, there was no support for Hypothesis 2.

With respect to price discovery, all auction designs performed well, as more than 80% of the induced value shocks were reflected in the prices. However, the sequential auctions clearly yielded higher auction revenues and better price signals (closer to Walrasian equilibrium prices). Yet, as no significant differences were revealed between the three auction types USBA, ECAn, and ECAr, there was no support for Hypothesis 3.

The pronounced effects of the auction sequence on auction revenues and prices were driven by the bid-shading behavior for Item A. While in the simultaneous auctions, systematic bid-shading was observed for both items alike, in the sequential auctions there were no indication for bid-shading for Item A.

5 Study 2: A Spectrum Rights Application

5.1 Background

> *"The spectrum sale is more complicated than anything in auction theory. No theorem exists—or can be expected to develop—that specifies the optimal auction form."*
>
> (McAfee and McMillan, 1996, p. 171)

A leading role in the advancement of new combinatorial auction types is taken by the sale of radio spectrum rights. Often cited as one of the breakthrough applications of auction theory (e.g. McAfee and McMillan, 1996; Klemperer, 2002b; Kagel and Levin, 2002a), spectrum auctions gained a high public visibility. In the wake of the new economy, the worldwide auctions of 3G radio spectrum rights alone raised about 100 billion US$ (Klemperer, 2004). More than just a means of revenue generation, spectrum auctions are of high general economic relevance. In particular, they influence the course of the telecommunications industry, which is one of the key industries of the current innovation cycle (Freeman and Louçã, 2002; Freeman, 2009).

In 1959, Coase introduced the idea of a spectrum auction. More than three decades later, spectrum auctions were established in the Western world. The first spectrum auction was conducted by the New Zealand government in 1989,[1] the first one employing a Simultaneous Ascending Auction (SAA) was conducted by the U.S. regulator

[1] The New Zealand auction employed a sealed-bid, second price type of auction design (Mueller, 1993).

Federal Communications Commission (FCC) in 1994,[2] and the first European SAA was conducted by the German Federal Ministry of Post and Telecommunications in 1996.[3] These auction events heralded the ongoing prevalence of auctions for the sale of spectrum rights. Since then, variations of the SAA have dominated the field of spectrum auctions.

The present experimental study compares two prominent auction designs for the sale of radio spectrum rights in a controlled lab environment with respect to efficiency, revenues, and price signals. Chapters 1 and 2 discussed the relevance of these criteria. The latter criterion was primarily discussed by scholars (e.g. McMillan, 1994, also see Section 2.2.3). Regulators tended rather to emphasize the criteria of efficiency and revenue generation. For instance, the Statutory Guidelines for FCC Auctions listed the goals of "ensuring efficient use of the spectrum, promoting economic opportunity and competition, avoiding excessive concentration of licenses, preventing the unjust enrichment of any party, and fostering the rapid deployment of new services, as well as recovering for the public a portion of the value of the spectrum" (Congressional Budget Office, 2000, p. 117).

Other countries likewise regarded efficiency as the primary goal of spectrum auctions. For instance, the German Telecommunications Act (Bundesamt für Justiz, 2004) mentioned efficiency several times (§2, §21, §28, etc.), and prescribed auctioning as the obligatory default mechanism for awarding spectrum rights (§61). Note that in the present study, other criteria related to the sale of radio spectrum—for example, the encouragement of competition—were not included, either because they were not directly related to the choice of an auction type, or because their inclusion would have exceeded the scope of a single study.

Although apparently, the SAA has served the auctioneers' economic and political goals well enough to establish itself over the last decades as the main device for spectrum sales around the world, the design also suffers from some weaknesses—such as susceptibility to collusion and insufficient accommodation of interdependencies (e.g. Cramton, 2009a, for further details on the SAA and its shortcomings also compare with Section 2.4.2). For example, a typical feature of spectrum sales is the presence of complementarities,

[2] The auction followed a proposal by McMillan (1994). Paul Milgrom, Robert Wilson and Preston McAfee developed the first full-fledged SAA design. The very idea of conducting multiple ascending auctions simultaneously was proposed in Vickrey (1976).

[3] See Keuter and Nett (1997).

as providers need to acquire a certain minimum amount of spectrum in order to provide attractive services. For this reason—in contrast to the sale of emissions permits (Chapter 4)—sequential auctioning of spectrum rights is not common practice and was rejected early in the academic debate (e.g. McMillan, 1994). Although the SAA allows for simultaneous bidding on multiple items, it does not guarantee bidders will acquire desired bundles, exposing them to the risk of buying unwanted subsets (see Sections 2.1 and 2.4.2). In order to tackle problems like this, in the recent two decades, researchers and practitioners have aimed to modify and improve the traditional SAA. They have also designed entirely new, more advanced auction types.

The present study compares the SAA with one of its most likely successors, the Package-clock Auction (PCA), by the means of a laboratory experiment. The PCA has gained considerable traction in field applications. For example, it was implemented in the Austrian spectrum auction 2010 for the auctioning of 240 MHz in the 2.6 GHz band used for the mobile broadband standard Long Term Evolution (LTE).[4] In 2012, the Swiss regulator employed the PCA for the sale of spectrum in the 800 MHz, 900 MHz, 1.8 GHz, 2.1 GHz, and 2.6 GHz bands. According to the British regulator Ofcom, the PCA will also be used for the UK spectrum auction, and similar proposals have been made in other European countries, such as Ireland and Denmark. For further details on the PCA's development, its theoretical advantages, and potential disadvantages see Section 2.4.3.

Nevertheless, in recent auction events that exhibited typical features addressed by combinatorial auctions like the PCA, not all regulators replaced the SAA by one of these newer auction types. For example, shortly before the Austrian LTE auction, in the very same year, the German regulatory authorities auctioned off an even larger amount of spectrum for mobile broadband communication. Besides spectrum in the 2.6 GHz band, the German offer included spectrum in the existing 1.8 and 2.1 GHz bands and a highly attractive chunk of spectrum in the 0.8 GHz band, which had been freed from its former use for analog TV. As the goods for sale were more complicated, it seems that a combinatorial auction might have been even more advisable than in the Austrian case.[5]

[4] Fourteen paired blocks of 2x5 MHz and ten unpaired blocks of 5 MHz were sold.
[5] Indeed, in the Swiss case, which featured essentially the same goods as the German case, the PCA was employed.

In the comments on the proposal for the German spectrum auction, Deutsche Telekom AG, the incumbent telecommunications service provider, recommended the PCA as a "theoretically and practically tested" alternative to the SAA (translated from the German original Deutsche Telekom, 2009, p. 2). However, due to concerns about the complexity and lack of experience with the PCA, the German regulatory agency refused to adopt the new auction type (Bundesnetzagentur, 2009, p. 124). Instead, a classical SAA was conducted. The regulator named the lack of practical experience as a main reason for not choosing the PCA (ibid.). As discussed in Section 2.4.3, the PCA might indeed suffer from potential disadvantages, even from a theoretical perspective. The current study contributes to the discussion of the PCA by empirically testing the performance of this auction type against the benchmark of the more traditional SAA.

A particular focus of the current study was the comparison of the SAA with the PCA with respect to their price discovery performance. As argued in Section 2.2.3, price signals are especially relevant in the presence of uncertainty. Indeed, in the context of spectrum auctions, there is a high degree of uncertainty. Many of the high revenue auctions (such as the European 3G auctions) introduced new technologies to the market and sometimes created entirely new markets. Yet, by definition, the market development in a new area is uncertain. The technological development, the customer demand and also the speed and costs of these developments can only be estimated roughly. In contrast to the emissions permits sale presented in Study 1, radio spectrum rights purchases involve higher stakes, as the available radio spectrum is scarce, the license prices are often high and there exists no liquid secondary market where licenses could be resold. Therefore, uncertainty might play an even more pronounced role in a spectrum rights auction than in an emissions permits auction.

Both auction types, the SAA as well as the PCA, seek to address uncertainty by their dynamic nature. Both formats feature bidding in multiple rounds with increasing prices that can be observed by all bidders. Often, the preliminary allocation of the items can also be observed. The information gained during the auction helps bidders to determine the value of the spectrum. Cramton (2009a) suggested that bidders could gather "collective market insights, which can be revealed in a dynamic auction process" (p. 49). The present study seeks to verify Cramton's proposition in a specific spectrum auction application. For a further discussion of uncertainty in auctions in general see Section 2.1, and in the context of spectrum auctions, in particular Section 5.2.

In a way, the present study also provides an example of how far experimenters can go in bringing complex situations to the lab, and explores the limits of this approach. The experiment situation was complicated by the combinatorial nature of the auctioned goods, by the presence of uncertainty and by the elaborate auction rules. In order to tackle the complex market situation of the present study, it incorporated the experience of the earlier Study 1 (Chapter 4) and the experimental methodology introduced in Chapter 3.

5.2 Price Signals in Spectrum Auctions

> *"In the case of spectrum auctions, there is much uncertainty about what things are worth."*
>
> (Cramton, 2009a, p. 48)

In the course of an ascending auction, the auctioneer repeatedly calculates and publishes prices, preliminary allocations, and related information. This process allows the bidders to observe and process the published information. As Cramton (2009a) has put it, in an iterative auction, bidders can gather "collective market insights, which can be revealed in a dynamic auction process" (p. 49). Bidders can adopt the estimation of their individual and the market value according to the information revealed.

Price signals are particularly relevant in situations where bidders are uncertain about the actual value of the items at auction. Clearly, participants in a spectrum auction typically face a high degree of uncertainty, because the future development of technology, as well as the adoption of the products by the consumers and the development of the market environment are (to some extent) uncertain.[6] In the case of the European UMTS auctions in 2000 and 2001—which coincided with the peak of the New Economy hype—the market for mobile broadband internet was virtually non-existent before the auction

[6] Less relevant is the influence of secondary markets, as resale is often excluded by the regulator (as in the German case), and as the usage of spectrum rights is closely connected with the physical installation of the technical infrastructure.

event. Even crucial technological components, for instance handsets, were still at a very early stage of their development.

The uncertain development of future telecommunication markets and technology is a primary reason for the use of auctions for the allocation of radio spectrum. For example, the facilitation of price discovery has been one of the design requirements for spectrum auctions since the first FCC auction conducted in 1994 (McMillan, 1994). To allow bidders to gather information during the auction process, spectrum auctions are typically conducted in an ascending, dynamic process rather than as a one-shot event.

A rough, but publicly available proxy of the value of radio spectrum is provided by expert estimations of the expected auction revenue in the preparation of an auction event. However, note that revenues are not identical to bidders' valuations, but tend to be lower bounds for the respective values. Before the German spectrum auction in 2010, the revenue estimations published in the media ranged between €2.5 billion and €8 billion. The lowest estimation known to the author was given by the consultancy Arthur D. Little,[7] while the highest number was announced by KPMG.[8] Remarkably, the midpoint of these two extremes is pretty close to the actual auction revenue of roughly €4.5 billion.

The uncertain value components outlined above are often identical or similar for all firms in the market. If this is the case, they are also called *Common Value (CV) components* (Section 2.1). However, the individual overall valuations also depend on a firm's market share, its technology and other factors specific to the firm. In this text the individual differences between valuations (although not perfectly separable from the CV components) are called *Independent Private Values (IPV) components* (Section 2.1). Since both value components are of high relevance in the context of a spectrum auction, neither a pure CV model nor a pure IPV model represents the spectrum situation well. This notion was shared by Kagel and Levin (2002a) who remarked that "Spectrum licenses typically involve both common-value and private-value elements" (p. 65). Note that the presence of IPV components is also a necessary condition for evaluating the

[7] As reported in the *Handelsblatt* on December 7, 2009, http://www.handelsblatt.com/unternehmen/it-medien/breitbandversorgung-auktion-von-rundfunkfrequenzen-droht-debakel/3320504.html, copy available from the author.

[8] As reported in the *Wall Street Journal* on April 20, 2010, not available online, copy available from the author.

relative allocative efficiency of the auctions in the experiment, since under a pure CV model it would not matter to which bidder the goods are allocated.

Despite being employed mainly for their price discovery potential, in laboratory experiments, ascending spectrum auction designs have been investigated mostly under the pure IPV assumption (e.g. Jehiel and Moldovanu (2001); Seifert and Ehrhart (2005), also see Section 2.1). The only exception known to the author is Abbink et al. (2005) who experimentally compared two hybrid forms of an English and a sealed-bid auction, on the one hand,[9] with a pure English auction, on the other. In contrast to Abbink et al.'s study, the present study deals with the currently particularly relevant SAA and PCA, and also investigates the price-discovery performance of the auction designs and the bidders' abilities to estimate an uncertain value component (Section 5.3.4).

5.3 Experiment Design

5.3.1 General Setting and Procedures

The experiment compared the SAA with the PCA in a controlled laboratory environment. In each experimental session, only one auction design was implemented in a between-subject design. Overall, 96 individuals participated in the experiment. For organizational reasons, the experiment was conducted in eight sessions, featuring twelve participants each. The participants in each session were divided into three independent groups of four bidders.[10] Therefore, each session resulted in three independent observations and the eight sessions resulted in $8 \cdot 3 = 24$ independent groups.

Each group of bidders participated in seven consecutive auctions. The sequence of auctions within one session is depicted in Figure 5.1. The first four auctions were conducted in a setting with independent private valuations, while in the last three auctions a CV component was introduced, and the bidders' estimation of the CV component was explicitly elicited.

[9] One auction featured a discriminatory-price rule, the other featured a uniform-price rule.

[10] The groups were formed after the comprehension test (see Section 5.3.2). As the bidders always stayed in the same group, any dependencies between groups could be due only to the bidders' collective participation in the comprehension test and their physical presence in the laboratory.

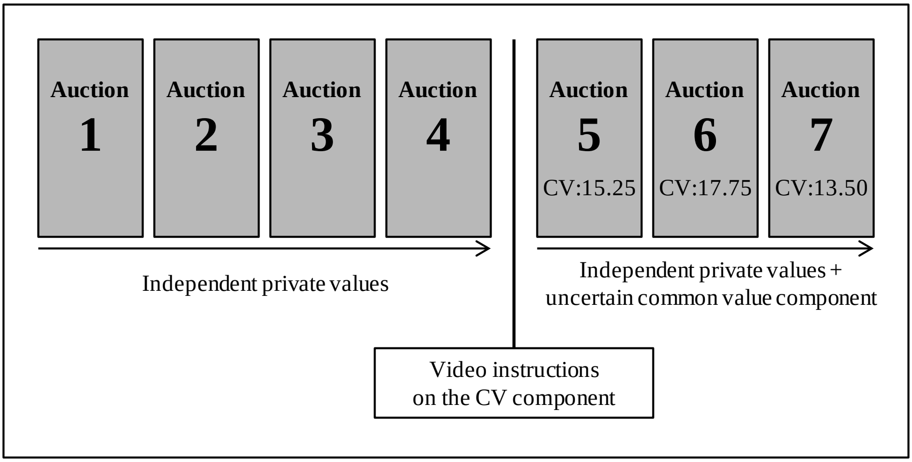

Figure 5.1: Sequence of the auctions in one session.

The focus of the analysis was on the comparison of the auction designs with an uncertain CV component, rather than on the effect of the CV component itself. In order to make the experiment feasible, the CV component was introduced only in the second half of the experiment. By segmenting the learning into two stages, cognitive load was reduced to a manageable level (cf. Chapter 3). Very likely (and supported by pilot runs), the subjects would find it easier to process the additional complexity of the CV scenario after becoming familiar with the basic IPV setting.

All experimental sessions were conducted in February and March 2011 at the Institute of Information Systems and Management (IISM) economics laboratory in Karlsruhe, Germany. Subjects were recruited randomly from a Karlsruhe Institute of Technology (KIT) subject pool using the Online Recruitment System for Economic Experiments (ORSEE by Greiner, 2004).[11] Sessions lasted about three hours in the PCA treatments and four hours in the SAA treatments.[12] Subjects earned on average €38.06 in the PCA

During the comprehension test, bidders were physically isolated by divider walls, so that there was no interaction of any kind.

[11] Readers of Study 1 may be confused, as the subjects in the first study were recruited from the same subject pool, but without the use of Online Recruitment System for Economic Experiments (ORSEE). Indeed, ORSEE was introduced in Karlsruhe after Study 1, and before Study 2.

[12] The relatively long session time was necessary in order to conduct the video instructions, the comprehension test, and the auction in a single fully controlled session. This was an intentional

and €46.58 in the SAA treatments, including the €20.00 payment for participation in the video instructions and in the comprehension test.

In a remarkable aside, after describing the strategic options and pitfalls in the SAA treatment of their spectrum auction experiment, Kagel et al. (2010) stated in the textual instructions: “What should you do? If we knew that we would not have to run the experiment” (Kagel et al., 2010, p. 3). A potential reason for this kind of statement could have been to prevent the subjects’ confusion, in case they could not find a robust strategy by themselves. In the light of the findings of cognitive research presented in Chapter 3, however, the instructions of the present experiment abstained from similar statements. According to cognitive research, each additional statement can increase the subjects’ confusion, and increase the extraneous cognitive load unnecessarily, rather than reducing confusion. In general, the instructions of the present experiment provided only the relevant information in the form of multimedia instruction, and in a neutral framing.

5.3.2 Comprehension Groups

The distribution of bidders into groups was based on the results of the comprehension test that followed each part of the video instructions (cf. Section 3.3.2). In order to prevent strategizing during the comprehension test, the bidders were not informed of this procedure. The experiment software ranked all bidders according to the number of their correct answers in the first try, the number of their correct answers in the second try, and the time they took to complete the test, applying a lexicographical order. A bidder with more correct answers in the first try was always assigned a higher rank than a bidder with fewer correct answers. In case of ties, the number of correct answers in the second try became relevant, and in the case of further ties, the completion time became relevant.

decision to avoid a multi-session design with intermediate loss of control when subjects leave the laboratory between sessions. It seems that initial concerns about fatigue were not realized, as the subjects became agitated rather than tired during the unusually interactive experiment. Actually, some subjects even remarked that the experiment was more interesting or exciting than other experiments they had participated in before.

For each Bidder i, the experiment software calculated an individual comprehension score $\widetilde{h_i}$. Given the parameters of the experiment, the following aggregation function returned a score that reflected the lexicographical order defined above:

$$\widetilde{h_i} = 1000 \cdot ans_{(1),i} + 100 \cdot ans_{(2),i} + \left(1 - \frac{time_i}{\max_j time_j}\right) \tag{5.1}$$

with $ans_{(1),i}$ denoting the number of answers Bidder i got right at the first try, $ans_{(2),i}$ denoting the number of answers Bidder i got right at the second try, and $time_i$ denoting the completion time of the test for Bidder i.

After evaluating the bidders' comprehension, the software ranked the bidders according to their scores. As discussed in further detail in Section 3.3.2, the clustering of the bidders by their comprehension score served to increase control on the effect of the subjects' comprehension. The four bidders with the highest score participated in Group 1, the four bidders with the lowest score participated in Group 3, and the remaining four bidders participated in Group 2.

Further, in order to obtain comparability between the treatments, a transformation of the comprehension score was used in the analysis. For two reasons, the comprehension score $\widetilde{h_i}$ was not directly comparable. First, the number of questions differed because the SAA and the PCA did not have the same number of training modules. Second, the questions themselves differed due to different auction rules. Therefore, for the analysis in Section 5.5, a binary measure of comprehension level h_i was calculated.[13] For all bidders whose comprehension score $\widetilde{h_i}$ was equal to or greater than the mean comprehension score of all 48 bidders who participated in the treatment, comprehension level h_i equaled one. For all other bidders, h_i equaled zero. The same categorization was applied to the individual groups, based on the mean comprehension score of all bidders in the respective group.

[13] Although a measurement in finer steps would have been possible, a binary measure seemed reasonable after inspection of the data. Roughly two thirds of all bidders yielded a high number of correct answers in the first try, between 35 and 40. The other third of the bidders showed a broad dispersion of between 15 and 35 correct answers in the first try. The binary measure served to reflect this apparent dichotomy into "good" and "bad."

5.3.3 Items and Values Table

Spectrum auctions typically feature multiple items and multiple units of each item. The experiment implemented the simplest case of a multi-item auction, a *two-item auction*. The two items represented two spectrum bands and were called Item A and Item B (in line with the neutral framing of the experiment). The multi-unit demand observed in real spectrum auctions was simplified to a demand of two units of each item in the experiment. Typically, in spectrum auctions, at least two bidders are awarded considerable quantities of spectrum blocks, but the supply does usually not suffice to provide all bidders with the full quantity of spectrum blocks that they desire. The structure of demand and supply in the experiment is illustrated in Figure 5.2.

The relation of demand to supply was chosen in analogy to the 2.6 GHz spectrum band in the German and in the Austrian spectrum auctions. In order to establish a realistic level of scarcity in the experiment, the supply was set to seven units of Item A and four units of Item B, and the maximum number of units that could be demanded by all bidders together was eight units for each item. Item A represented the paired spectrum, which was offered in fourteen blocks. A technically sound service required around four blocks. Therefore, the resulting demand-to-supply ratio was about eight to seven. Item B represented the unpaired spectrum, which was offered in ten blocks and required about five blocks for a technically sound service, implying a demand-to-supply ratio of around four to two.

Besides simplifying the demand schedules, the restriction of demand to two units per item and bidder in the experiment can also be seen as a representation of decreasing marginal values, when a certain number of spectrum blocks is reached. When exceeding the *technically feasible bandwidth*, additional spectrum blocks contribute no additional utility. Another parallel to real spectrum auctions in the current experiment is a *spectrum cap* often imposed in spectrum auctions. Thus, the design choice of restricting demand to two units per item and bidder simplified the value schedule, while at the same time, it emphasized some of the characteristics of actual applications.

Unfortunately, the concise valuations of the companies bidding for radio spectrum were (and are) not fully known—and, thus, could not be used in the experiment. Rather, it was desirable to design the valuation schemes as simple as possible without giving up

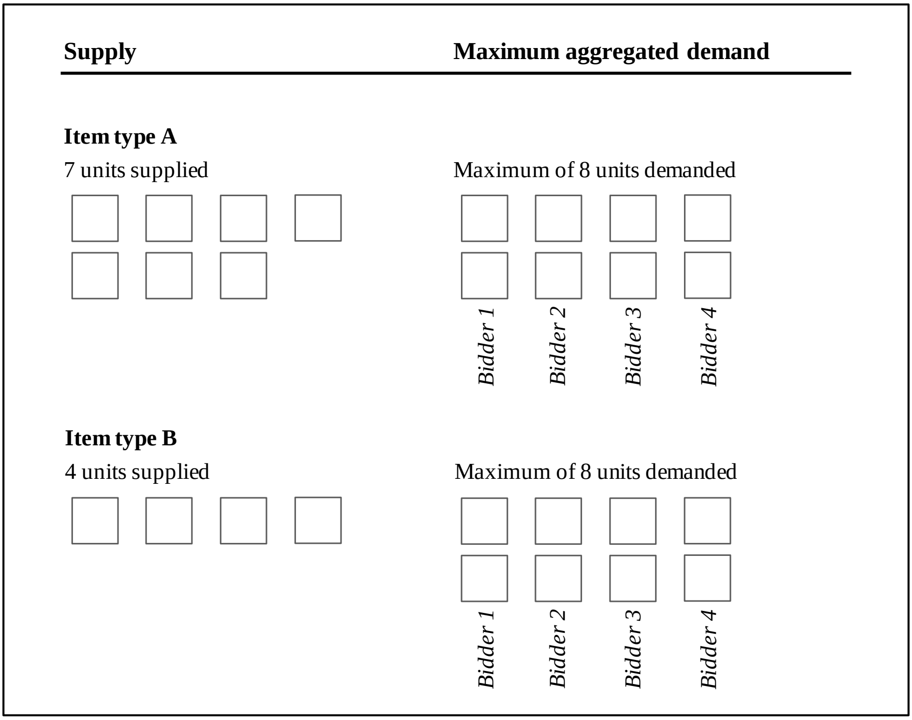

Figure 5.2: Number of units of Items A and B supplied and demanded.
The blocks on the left hand represent the units available in one auction. The blocks on the right hand represent the units that can be demanded by all bidders together. Note that each bidder can bid for a maximum of two units.

the essential characteristics of the real-world example, which will be explained in the following paragraphs.[14]

Radio spectrum is typically auctioned in blocks of several MHz. The blocks within the same spectrum band are of a strongly complementary nature. For physical and technological reasons, a single block cannot be used efficiently. Therefore, additional blocks add disproportionably to the value of the spectrum acquired—up to a certain maximum number of blocks. For instance, for LTE, the scalable channel bandwidths—which can be used for a single user and which determine the peak uplink and downlink rates—are 1.4, 3, 5, 10, 15, and 20 MHz (Agilent, 2009, p. 4). In contrast, on the

[14] Cf. Chapter 3 for a discussion of the experimental methodology in complex market situations.

level of spectrum bands, the items are substitutes rather than complements, as separate spectrum bands that are available for mobile communications cannot be combined to obtain a higher bandwidth. However, the bands can be used in a similar way and, thus, (imperfectly) substitute for each other. For example, in Germany, two of the four GSM operators—the market leaders Deutsche Telekom and Vodafone—mainly use the 900 MHz spectrum band, while the two smaller operators O_2 and E-Plus mainly use the 1800 Mhz band. Although there are some technical differences in the capacity and the reach of these bands, all operators offer roughly the same GSM services.

For a meaningful comparison of spectrum auction formats, it was necessary to model the above interdependencies between units and items. Not only was this an essential feature of actual radio spectrum auctions, but since the advantages of a combinatorial auction can be observed only in the context of a combinatorial problem, it was also a technical necessity for testing the PCA. To model the interdependencies of blocks and bands, the value of two units of the same item was chosen to be super-additive, while the value of two units of different items was sub-additive.

The values were presented to the subjects in the form of a two-dimensional 3x3 matrix, which was called *basic values table*, and is depicted in Table 5.1. The nature of the values table was explained to the subjects in a three-dimensional animated video.[15] All subjects in the experiment received the same basic values table and were informed about this.

5.3.4 Values Distribution and Uncertainty

A firm's valuation for a spectrum block is influenced by multiple factors, such as its market share, its technology, and its historical spectrum endowment. Thus, the valuations typically differ from firm to firm. In the German mobile communications market, the largest firm in terms of subscribed customers is Vodafone with a yearly revenue of €9.3 billion and a customer base of 37.6 million customers, while the smallest player in this market is O_2 with a yearly revenue of €5.0 billion and a customer base of 18.4 million customers.[16]

[15] See Section 3.3 for details on the training concept, Figure 3.2 for screen captures of the values table, and http://www.sascha-schweitzer.de/download/spectrum for the complete instruction video.

[16] Revenue data from:
http://www.vodafone.de/unternehmen/umsatz.html, year of 2010/2011
http://www.telefonica.de/ext/portal/online/22/index, year of 2011

Table 5.1: Basic values table.
The cells of the table represent the value of the respective package of A- and B-items in monetary units. A similar graphical layout as in this display was used in the instruction video for the experiment (cf. Section 3.3.1).

		Quantity item A		
		0	1	2
Quantity item B	0	0	10	40
	1	3	12	41
	2	12	18	44

The market shares are likely to be correlated with the companies' valuations of a spectrum block. Due to their larger customer base and existing infrastructure, larger companies might gain a higher profit from a given quantity of spectrum. Therefore, the asymmetry of company sizes implies a similar asymmetry of valuations for the spectrum.[17] The real-world companies' sizes—as indicated by their revenues—served as a proxy for modeling the bidders' valuations in the experiment.

Roughly in line with the revenue data presented above, the size or signal s_i of a Bidder i was drawn independently for all bidders from a uniform distribution from $\{10, 11, ..., 19, 20\}$. For each auction in the experiment, a new company size was drawn

Customer data from:
http://www.bundesnetzagentur.de/cln_1931/DE/Sachgebiete/Telekommunikation /Marktbeobachtung/Mobilfunkteilnehmer/Mobilfunkteilnehmer_Basepage.html, 4^{th} quarter of 2011
Archived screen shots of the web site are available from the author.

[17] The diversity of valuations is an essential feature of most auctions and also determines upper and lower bounds for the auction performance. The larger the spread between bidders' valuations of items in the auction, the higher are the possible gains from an efficient allocation.

and communicated to the bidders at the beginning of the auction.[18] This procedure and the distribution of the signals were common knowledge.[19]

A company's (bidder's) size determined its final values table. In order to obtain the final values $v_i(a,b)$, every cell $v_i^b(a,b)$ in the basic value table (Table 5.1) was multiplied by s_i

$$v_i(a,b) = v_i^b(a,b) \cdot s_i. \tag{5.2}$$

By the linear transformation (5.2), the relative values and the complementary and substitutive characteristics of the items were kept identical for all bidders; but the levels of the valuations varied, reflecting the bidders' sizes. On their bidding screen, the bidders saw only their individual final values table and their private signal s_i.

The first four auctions of each experimental session employed the independent private values model described in the previous paragraphs. After Auction 4, an additional instruction video was shown to the subjects. The video introduced an extension that enhanced the valuation model by an uncertain CV component. This extension—with the purpose of investigating the information discovery performance of tested auction designs—stayed valid during the last three auctions.

The uncertain CV value component was introduced in addition to the IPV structure, and its implementation was based on Klemperer's (1998) wallet game. Again, the basic values table (Table 5.1) was multiplied by a factor. However, in the modified auction, the factor was s'_i, instead of s_i

$$v_i(a,b) = v_i^b(a,b) \cdot s'_i. \tag{5.3}$$

The factor s'_i did include the additional CV component and was calculated by the formula

$$s'_i = \underbrace{s_i}_{\text{IPV}} + \underbrace{\frac{1}{n}\sum_{j \in N} s_j}_{\text{CV}}. \tag{5.4}$$

[18] For the sake of a neutral framing, in the experiment, the number representing the company size was called *multiplicator*.

[19] With respect to external validity, an argument in favor of informing the bidders about the distribution of the signals is that, in real-world spectrum auctions, bidders can typically roughly judge their relative strength, rather than being completely unaware of their relative position (which would correspond to a model of ambiguity).

Bidder (i)	# Units A	# Units B	Bidder Surplus
(1)	2	2	$s_{(1)} \cdot 44$
(2)	2	0	$s_{(2)} \cdot 40$
(3)	2	0	$s_{(3)} \cdot 40$
(4)	1	2	$s_{(4)} \cdot 18$

Table 5.2: Welfare maximizing allocation. (i) denotes the bidder with the i^{th} highest signal $s_{(i)}$.

The values model of equation (5.4) combines a private values component with an uncertain common value component. As in equation (5.2), the individual values differed in the first term s_i on the right hand side of the equation. Now, however, the second term on the right hand side (the sum) was identical for all bidders in an auction. The exact value of this sum depended on the other bidders' signals which were unknown to the individual bidders.

The basic values table (Table 5.1) and the vector of the bidders' private signals $s = (s_1, \ldots, s_4)$ were designed in such a way that they always led to the same principle constellation, under all realizations of s (for the strategic implications, see Section 5.3.6). Therefore, in the welfare maximizing allocation (Table 5.2), which was derived from the values tables, the bidder with the highest signal would always obtain two units of both items, the bidders with the second highest and third highest signals would each obtain two units of Item A and zero units of Item B, and the bidder with the lowest signal would obtain one unit of Item A and two units of Item B. This design was intended to reduce the variance of strategic situations that could occur during the experiment, in order to keep the auctions and sessions comparable.[20]

Another major feature of the experimental design was the provision of an *estimation slider* to the bidders (Figure 5.3). The slider was a UI element that allowed bidders to select a value from $\{10, 11, ..., 19, 20\}$ that represented their estimation of the CV component. The value of the slider set by the bidder was also used for the calculation of the final values table and the preliminary calculation of profits displayed by the software.

[20] The reasoning behind this is similar to the motivation of the stationary replication of the one-shot design employed in Study 1, as described in Section 4.4.3. Note that there was a trade-off between generality, control, and feasibility, and it seemed advisable to put the main focus on control and feasibility.

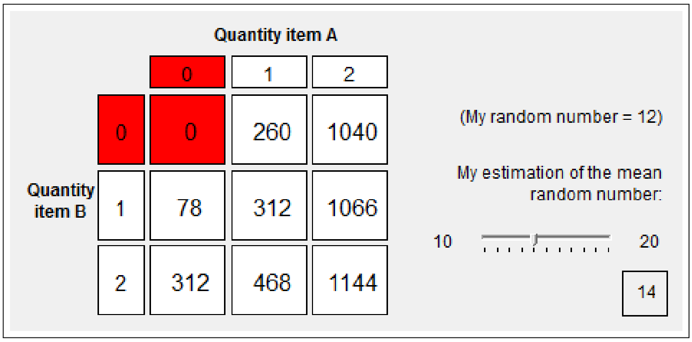

Figure 5.3: Screen capture of the slider for estimating the uncertain CV component. (Translated from the German original.)

In all values settings, the software screen displayed only one values table—in the IPV setting representing final values, in the CV component setting representing estimated values. The slider offered the subjects a tool for supporting their decisions on submitting bids.

For the analysis of the experimental results, the slider also generated helpful data for the analysis of the subjects' estimation behavior. To the author's knowledge, this data is the most immediate data on the value discovery process for this type of auction available so far. Still, as with any design element, the slider itself was not free of pitfalls as it had the potential to affect the subjects' behavior. For instance, subjects might have become more aware of the process of estimation, and this required the calculation of a number, which would not have been required without the existence of the slider. Although certainly interesting of itself, the investigation of the slider's influence on bidding behavior was not a part of this study. Hence, the same slider was used in all treatments in order to maintain comparability.

A graphic example of the way the slider was integrated into the software screen is provided by Figure D.1 in the Appendix. The purpose and use of the slider was explained to the bidders in detail in the training video introducing the CV component.[21] In addition to the elicitation of their value estimate during the experiment, bidders were also asked about the formation of their estimate in a survey after the experiment.

[21] http://www.sascha-schweitzer.de/download/spectrum/saa/video_4.

5.3.5 Auction Rules

General descriptions of the auction designs in the experiment are provided in Chapter 2. The following section details the specific auction rules.

The Simultaneous Ascending Auction

The SAA employed the following rules:

- *Stopping rule:* The bidding phase ended with the round in which there was no new bid on or withdrawal of any of the items.
- *Minimum bid increment:* In order to speed up the bidding process, the minimum bid for all units of an item increased by at least one minimum bid increment in each auction round (as long as there had been at least one bid on one unit for that item in the previous auction round). By this procedure, the timing of the SAA became more similar to the PCA, ensuring that the auctions would not run longer than feasible in a laboratory experiment. The minimum bid increments are given in Appendix C.
- *Activity rule:* For reasons of simplicity, a strict activity rule was used that did not allow bidders to increase the total number of units they bid for.[22]
- *Bid information:* The highest bidders were published after each round. Bidders were identified only by a number that did not give any hint about the name or the seat of the participant in the experiment.
- *Bid withdrawal:* Analogously to the German spectrum auction in 2010, bid withdrawals were allowed. However, withdrawn units were reallocated only when the withdrawn bid was overbid. Otherwise the original bidder had to pay the bid price without receiving the object.
- *Tie-breaking rule:* Ties were solved through a random draw.
- *Click-box bidding:* A click box with four predefined bid values for each unit was used. In addition to the minimum bid, for Item A, voluntary increments of 10, 50

[22] There have been several different versions installed by the FCC. In some auctions the bidders were in possession of a certain number of waivers that could be used in a round like a "time-out" in which they were not required to submit a bid.

and 100 Money Units (MU) were allowed. For Item B, the voluntary increments of 5, 10 and 50 MU were allowed.

The Package Clock Auction

The PCA rules used in the experiment were identical with those of Cramton's (2009b) proposal as summarized in Section 2.4.3.

The auction started with the *clock stage*. For every item a clock announced the current price for one unit. After each round the prices increased for items in excess demand. The increments of the clock price increase are given in Appendix C.

In Cramton's (2009b) proposal, the *generic assignment* of abstract lots was followed by the *specific assignment* of the particular frequency lots. In the present experiment, however, where the items were simplified, this procedure was rendered unnecessary and was not implemented.

5.3.6 Bidding Strategies

In both auction designs discussed in this study, equilibrium strategies are not generally known (cf. Chapter 2). However, a basic approach to understanding the auction situation of the experiment, and to anticipate potential bidding strategies of the subjects in the experiment, is the analysis of Straightforward Truthful Bidding (SFTB) in the context of the specific configuration of the markets in the experiment.

Under SFTB, the bidders bid for those items that maximize their utility at the current prices. Profit calculation is performed under the assumption that all units a bidder bids for are allocated to the bidder at the bid price. In every single round of an ascending auction, it is assumed that bidders are shortsighted, that they will not anticipate future developments, nor act strategically. When prices rise at the end of the auction, SFTB implies that the bidders bid up to their true marginal valuations and stop bidding when prices exceed their valuations.

Table 5.3 summarizes some metrics that are helpful for calculating SFTB bids. In the upper left part, the basic values structure from Section 5.3.3 is repeated. In the upper right part, the marginal values for Item A, and in the lower left part, the marginal values

<table>
<tr><td colspan="2">basic value structure</td><td colspan="3">item A</td><td colspan="3">marginal values A</td></tr>
<tr><td></td><td></td><td>0</td><td>1</td><td>2</td><td>1^{st}</td><td>2^{nd}</td><td>mean</td></tr>
<tr><td rowspan="3">item B</td><td>0</td><td>0</td><td>10</td><td>40</td><td>10</td><td>30</td><td>20</td></tr>
<tr><td>1</td><td>3</td><td>12</td><td>41</td><td>9</td><td>29</td><td>19</td></tr>
<tr><td>2</td><td>12</td><td>18</td><td>44</td><td>6</td><td>26</td><td>16</td></tr>
<tr><td rowspan="3">mar. val. B</td><td>1^{st}</td><td>3</td><td>2</td><td>1</td><td></td><td></td><td></td></tr>
<tr><td>2^{nd}</td><td>9</td><td>6</td><td>3</td><td></td><td></td><td></td></tr>
<tr><td>mean</td><td>6</td><td>4</td><td>2</td><td></td><td></td><td></td></tr>
</table>

Table 5.3: Marginal and mean marginal values.

for Item B are listed. The *mean marginal values* for Item A are given in the very last column, and the mean marginal values for Item B are given in the very last row. Note that the actual values for Bidder i were calculated by multiplying her table with i's signal s_i or s_i', respectively (Section 5.3.4).

In the following analysis, in both auction designs, prices for all units of one item are assumed to be equal. Indeed, in the clock stage of the PCA, prices for all units of an item are identical by construction. Also, in the SAA the prices tend to equalize, since rational bidders tend to bid on the unit with the lowest price. In the experiment, the price equalization in the SAA was further fostered by increasing the minimum bid, which enforced an average increase of one bid increment per auction round for all units (Section 5.3.5).

Also, note that the SFTB strategy in the following analysis can only be an "approximate SFTB strategy." There is a large difference between the marginal values of the first and the second unit of an item, but because the prices for all units of a given item are assumed to be equal, bidders cannot express those two different marginal values for two individual units. If bidders desire to "bid up to their values," the best they can do is bid up to their total values of the bundle, splitting their bid equally between the two units. However, if at some point in the auction it becomes more favorable (and thus straight forward and truthful) for a bidder to bid for only one unit of an item at a lower price, the bidder will not be able to express this bid, as the activity rules in both the SAA and the clock stage of the PCA do not allow for decreasing bids. Therefore, it is not obvious what SFTB means in the given situation of the experiment.

In the following analysis, a SFTB approach for the given experiment situation will be outlined. The bidders' signals are $s_{(1)} \geq s_{(2)} \geq s_{(3)} \geq s_{(4)}$, and (i) denotes the bidder with the i^{th} highest signal $s_{(i)}$. In the opening round of the SAA, and the PCA alike, the bidders bid on two units of both items, since this is the profit-maximizing bundle at the (low) opening prices. In the following auction rounds, the bidders continue to increase their bids until certain price points are reached. These price points are defined by the bidders' indifference between whether they keep to the last bid or choose between reducing demand on one of the items, reducing demand on both of the items, or switching from one item to the other.

In the SAA, the first price points of interest are $p_A = 26s_{(4)}$ and $p_B = 2s_{(4)}$, at which a reduction of demand for either Item A or Item B becomes relevant. For Item A, bidders cannot decrease their demand by more than one unit, as there is a total supply of seven units, while the opposing bidders can demand a maximum of six units, leaving one unit that no opposing bidder will overbid on. Therefore, the marginal value of the second unit of Item A determines the price at which bidders should reduce their demand for Item A from two units to one. For Item B, on the other hand, it is possible to reduce demand on the bundle of two units; and the exit price, at which bidders reduce their demand to zero units, is determined by the mean marginal value of two units of Item B. Which of the price points is reached first depends on the increment configuration, on the signa $s_{(4)}$, and on the competition for an item. In the increment configuration of the experiment and SFTB, it will always be the second case—$p_B = 2s_{(4)}$—being reached first, since the prices for Item A increase slightly more slowly than for Item B. In the following, both cases will be presented.

In the first case, when $p_A = 26s_{(4)}$ is reached first, Bidder (4) abstains from bidding on the second unit of Item A. From then on, p_A comes to a halt, while p_B is still increasing. When p_B reaches bidder (3)'s mean marginal value for Item B of $2s_{(3)}$, she abstains from bidding on Item B. Price p_B increases further, until it reaches Bidder (2)'s mean marginal value for Item B of $2s_{(2)}$. After that auction round, Bidder (2) abstains from bidding on Item B and the auction ends. The resulting allocation is given in Table 5.4.

In the second case, when $p_B = 2s_{(4)}$ is reached first, Bidder (4) abstains from bidding on both units of Item B. Since all bidders keep on bidding on two units of Item A and three bidders keep on bidding on two units of Item B, the prices of both items increase

(i)	# A	Price A	# B	Price B	Bundle Value	Profit
(1)	2	$26s_{(4)}$	2	$2s_{(2)}$	$44s_{(1)}$	$44s_{(1)} - 4s_{(2)} - 52s_{(4)}$
(2)	2	$26s_{(4)}$	0	0	$40s_{(2)}$	$40s_{(2)} - 52s_{(4)}$
(3)	2	$26s_{(4)}$	0	0	$40s_{(3)}$	$40s_{(3)} - 52s_{(4)}$
(4)	1	$26s_{(4)}$	2	$2s_{(2)}$	$18s_{(4)}$	$-4s_{(2)} + 8s_{(4)}$

Table 5.4: Allocation SFTB strategy SAA in Case 1.

further, until p_B is $2s_{(3)}$ and Bidder (3) abstains from bidding on Item B, bringing p_B to a halt.[23] In the following rounds, only p_A increases until it is $30s_{(4)}$ forcing Bidder (4) to stop bidding on the second unit of Item A. With that, the auction ends and the units are allocated as presented in Table 5.5.

(i)	# A	Price A	# B	Price B	Bundle Value	Profit
(1)	2	$30s_{(4)}$	2	$2s_{(3)}$	$44s_{(1)}$	$44s_{(1)} - 4s_{(3)} - 60s_{(4)}$
(2)	2	$30s_{(4)}$	2	$2s_{(3)}$	$44s_{(2)}$	$44s_{(2)} - 4s_{(3)} - 60s_{(4)}$
(3)	2	$30s_{(4)}$	0	0	$40s_{(3)}$	$40s_{(3)} - 60s_{(4)}$
(4)	1	$30s_{(4)}$	0	0	$3s_{(4)}$	$-27s_{(4)}$

Table 5.5: Allocation SFTB strategy SAA in Case 2.

As a comparison with Table 5.2 confirms, in the first case, the SFTB SAA allocation is efficient. But in the second case (which is the relevant case under the bid increments in the experiment), the SFTB allocation is not efficient. Bidder (4) has a higher valuation for the bundle of two units of Item B than Bidder (2). In both cases, Bidder (4) falls prey to the exposure problem (Section 2.1) and receives a single unit of Item A. Depending on the specific signal configuration, the other bidders may also face severe losses. For example, in Case 2, even Bidder (1) (who has got the highest signal) could suffer a loss of up to -400 monetary units. Therefore, using hindsight, most (if not all) of the bidders would not have participated in the auction at all, if their only option was SFTB.

As demonstrated, SFTB is not a very good bidding strategy in the experiment. With respect to Item A an alternative strategy—in particular, for the weakest bidder, who

[23] Due to the relative speed of the price increases of p_A and p_B, this price point of Item B is reached before p_A reaches $30s_{(4)}$.

will end up with only one unit of Item A—would be strategy σ: "Bid only on one unit of Item A, up to the marginal value of a single unit. Also, truthfully bid on two units of Item B." The resulting allocation, if the weakest Bidder (4) applies strategy σ while the opposing bidders keep to the SFTB strategy, is presented in Table 5.6.

(i)	# A	Price A	# B	Price B	Bundle Value	Profit
(1)	2	d_A	2	$2s_{(2)}$	$44s_{(1)}$	$-2d_A + 44s_{(1)} - 4s_{(2)}$
(2)	2	d_A	0	0	$40s_{(2)}$	$-2d_A + 40s_{(2)}$
(3)	2	d_A	0	0	$40s_{(3)}$	$-2d_A + 40s_{(3)}$
(4)	1	d_A	2	$2s_{(2)}$	$18s_{(4)}$	$-d_A - 4s_{(2)+18s_{(4)}}$

Table 5.6: Allocation alternative strategy SAA. The minimum bid for Item A is denoted by d_A.

In the new situation, the prices for Item A equal the minimum bid, improving all bidders to a profitable situation. In this example, with the weakest Bidder (4) applying strategy σ, the allocation is efficient and identical to the allocation in Case 1. More generally, ex-post, all situations in which three bidders bid truthfully on two units of Item A, one bidder bids only on one unit of Item A, and all bidders bid truthfully on two units of Item B constitute an equilibrium of the auction game. No bidder can improve herself by deviating from her strategy: With respect to Item A, if the bidder who bids according to strategy σ were to deviate by bidding on two units of Item A, she would end up in the less favorable situation of Case 1 or 2. If, on the other hand, any of the other bidders deviated by bidding on fewer units of Item A, they would obtain a less valuable bundle, without affecting the price. With respect to Item B, a bidder who abstained from bidding on both units would lose her chance to obtain these units, and would therefore not profit from the price effect of her demand reduction. On the other hand, a bidder who abstained from only one unit of Item B, would be outbid by the opposing bidders, as the marginal value of one unit is always clearly lower than the mean value of two units.

In the clock stage of the PCA, the first price points of interest are $p_A = 16s_{(4)}$ and $p_B = 2s_{(4)}$. Which of the price points is reached first depends on the increment configuration, on the signal $s_{(4)}$, and on the competition for an item. As in the SAA, the prices of Item A increase slightly more slowly than the prices of Item B when all bidders bid according to SFTB (under the increment configuration of the experiment). Again, in the following, both cases will be presented.

If $p_A = 16s_{(4)}$ is reached first, Bidder (4) reduces her quantity of Item A to zero. From then on, p_A comes to a halt, while p_B is still increasing. When p_B reaches the price of $p_A - 28s_{(4)}$, Bidder (4) is indifferent between continuing to bid on two units of Item B or switching his demand to two units of Item A. From then on, Bidder (4) begins switching between the two items causing both prices to increase at a constant relation of $p_B = p_A - 28s_{(4)}$. At $p_B = 2s_{(3)}$ Bidder (3) stops bidding on Item B and at $p_B = 2s_{(2)}$ Bidder (2) also stops bidding on Item B. From then on the price of Item B does not increase anymore, Bidder (4) settles with two units of Item B and the clock stage ends. The resulting preliminary allocation is given in Table 5.7.

(i)	# A	Price A	# B	Price B	Bundle Value	Preliminary Profit
(1)	2	$2s_{(2)} + 28s_{(4)}$	2	$2s_{(2)}$	$44s_{(1)}$	$44s_{(1)} - 8s_{(2)} - 56s_{(4)}$
(2)	2	$2s_{(2)} + 28s_{(4)}$	0	0	$40s_{(2)}$	$36s_{(2)} - 56s_{(4)}$
(3)	2	$2s_{(2)} + 28s_{(4)}$	0	0	$40s_{(3)}$	$36s_{(3)} - 56s_{(4)}$
(4)	0	0	2	$2s_{(2)}$	$12s_{(4)}$	$-4s_{(2)} + 12s_{(4)}$

Table 5.7: Clock stage allocation SFTB strategy PCA.

In the second case, when $p_B = 2s_{(4)}$ is reached first, Bidder (4) reduces her quantity of Item B to zero. From then on, p_B comes to a halt, while p_A is still increasing. When p_A reaches the price of $p_B + 28s_{(4)}$, Bidder (4) is indifferent between continuing to bid on two units of Item A or switching his demand to two units of Item B. From then on, the auction takes the same course as in Case 1. Bidder (4) begins switching between the two items, causing both prices to increase at a constant relation of $p_B = p_A - 28s_{(4)}$. At $p_B = 2s_{(3)}$ Bidder (3) stops bidding on Item B and at $p_B = 2s_{(2)}$ Bidder (2) also stops bidding on Item B. After that, the price of Item B stops increasing. Bidder (4) settles with two units of Item B and the clock stage ends. The resulting allocation is identical to case one as presented in Table 5.7.

After the clock stage, there is one orphaned unit of Item A left. However, in the supplementary stage that follows the clock stage, the bidders bid their true bundle value for each of the eight bundles. This allows Bidder (4) to express her valuation for a bundle containing the orphaned unit of Item A. The final allocation is identical for both cases and can be found in Table 5.8.

A comparison with Table 5.2 confirms that the allocation is efficient. Furthermore, SFTB is an equilibrium strategy in the PCA.

(i)	# A	# B	Bundle Price	Bundle Value	Profit
(1)	2	2	$4s_{(2)} + 4s_{(3)} + 22s_{(4)}$	$44s_{(1)}$	$44s_{(1)} - 4s_{(2)} - 4s_{(3)} - 22s_{(4)}$
(2)	2	0	$4s_{(3)} + 22s_{(4)}$	$40s_{(2)}$	$40s_{(2)} - 4s_{(3)} - 22s_{(4)}$
(3)	2	0	$4s_{(2)} + 22s_{(4)}$	$40s_{(3)}$	$-4s_{(2)} + 40s_{(3)} - 22s_{(4)}$
(4)	1	2	$4s_{(2)}$	$18s_{(4)}$	$-4s_{(2)} + 18s_{(4)}$

Table 5.8: Final allocation SFTB strategy PCA.

In order to get an idea of the strategic implications of the CV component in the auction designs, this situation was analyzed in several simulations. These simulations were conducted under the assumption of Straightforward Truthful Bidding (SFTB), and they modeled the exact situation of the experiment, employing the same auction algorithms as were used in the experiment software. The code and results are provided at http://www.sascha-schweitzer.de/download/spectrum. As well as the auction results under SFTB, deviations from SFTB were considered. However, as it turned out to be a problem of high computational complexity, the search for equilibrium strategies could not be accomplished within the time frame and scope of this work.

Summing up the findings of these simulations, there were two major effects. First, the electronic agents' profits were higher when they continuously updated their estimations of the CV component and adjusted their bids accordingly. Second, the agents' own behavior influenced the opposing agents' estimations of the CV component and their behavior. When an agent submitted lower bids, the estimations of the opposing bidders were lower as well, and the auctions resulted in lower prices. This increased the agents' incentives to submit low bids.

5.4 Hypotheses

Roughly speaking, from a theoretical perspective (Chapter 2), the PCA should be superior to the SAA. This expectation was even stronger in the experiment situation, which strongly favored the PCA, letting the said auction design play out its strengths by imposing a pronounced exposure risk (Section 5.3).

Therefore, the main hypotheses with respect to the evaluation criteria efficiency, revenue and price signals were as follows:

1. The PCA yields a higher allocative efficiency than the SAA.
2. The PCA leads to higher prices and revenues than the SAA.
3. The PCA exhibits a better price discovery performance than the SAA.

If the bidders can express interdependencies between the items in combinatorial bids and thus avoid the exposure problem, Hypothesis 1 predicts that the PCA will yield a more efficient allocation than the SAA. Further, if bidders fear and seek to avoid the exposure risk and if collusion is facilitated by the SAA's rich opportunities for interaction, the SAA should lead to lower prices (and revenues) than the PCA, as stated in Hypothesis 2. According to Hypothesis 3, prices (and revenues) should reflect the induced valuations and the CV component more accurately when using the PCA, which possesses a SFTB equilibrium. Note that Hyptheses 2 and 3 are not independent of each other, as they both refer to prices. However, they aim at two different aspects of the prices. Hypothesis 2 refers to the price level, while Hypothesis 3 refers to the correlation of the induced values with the prices.

5.5 Results of the Experiment

5.5.1 Efficiency

Figure 5.4 gives an overview of the social surplus and the relative allocative efficiency in Study 2, arranged by treatment and auction number (for detailed data see Table D.1 in the appendix). Similar to the findings in Study 1, allocative efficiencies in both experimental treatments were very close to each other. The mean relative efficiency was

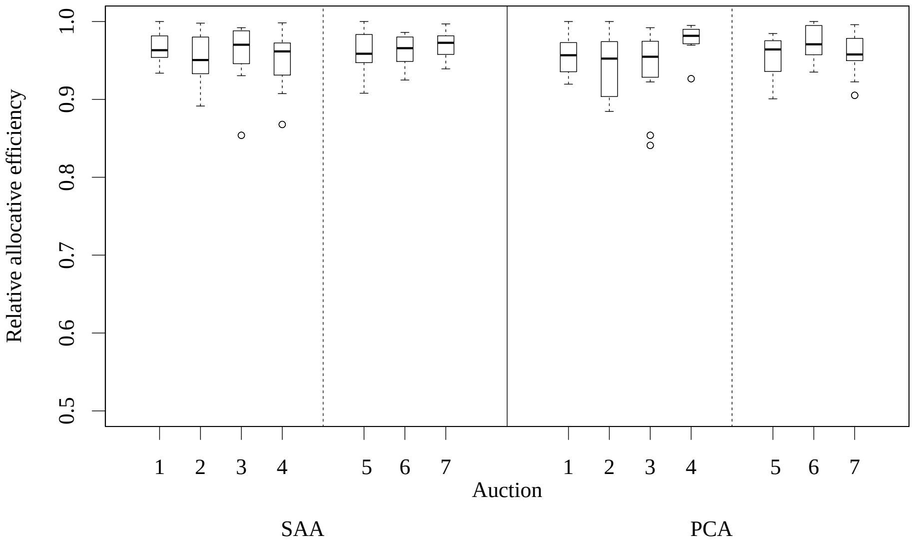

Figure 5.4: Relative allocative efficiencies by treatment and auction.

96.0% in the SAA and 95.8% in the PCA, ranging from 85.4% to 100% in the SAA and from 84.1% to 100% in the PCA. In the SAA, six out of 84 auctions, and in the PCA five out of 84 auctions were efficient in the sense that their relative allocative efficiency equaled 100%. In the SAA, the standard deviation of the relative allocative efficiency was 2.9%, and in the PCA, the standard deviation was 3.2%. To sum up, efficiency values were very close to each other.

The impression that there were no strong differences in efficiency between treatments was also supported by a non-parametric Mann-Whitney U test on the level of the independent groups, which did not indicate significant differences.[24] Also, a regression analysis on the auction-level data did not yield a significant model,[25] implying that neither the auction number nor the presence of a common-value component, nor indeed the comprehension score showed significant effects on efficiency.

[24] Mann-Whitney U: n=24, W=85, p-value=0.48.

[25] Ordinary Least Squares (OLS) regression: F-statistic=1.63 on 4 and 163 degrees of freedom, p-value=0.17.

Given that the structure of the values induced in the present experiment was constructed to give the PCA a clear advantage, the similarity in the efficiency values appeared as a surprise. The PCA had two advantages (cf. Section 5.3.6). First, in the SAA, the induced values inflicted a strong exposure problem that did not affect the PCA. Second, at the end of the auction, one bidder was supposed to switch to a larger package, which was possible only in the PCA. While in the SAA, the bidders handled the first issue better than expected (cf. the discussion of prices in Section 5.5.3), the second advantage did not play out for the PCA, either. In the PCA, bidders did not bid sufficiently sincerely on the low value packages, which in theory should have been allocated optimally only in the PCA.

The efficiency values were not only very close to each other; inefficiencies also arose from the same sources in both treatments. The main sources of inefficiencies were allocations to bidders with low valuations and the allocation of single units instead of bundles. Again, when suboptimal allocations were observed, they were suboptimal in a similar way in both auction designs. Beforehand, the experimenters had been concerned about the option of bid withdrawals in the SAA, as they can facilitate inefficient orphaned units (units not sold). Still, these orphaned units accounted only for a small part of the inefficiencies. Surprisingly, in the PCA orphans could be observed almost as often as in the SAA.

A reason for the unexpected occurrence of orphaned units in the PCA was that the bidders tended to bid only on a subset of the available bundles, and in some cases, there was no combination of bundles that included all units for sale. Even those bidders who bid on all bundles, often entered very low numbers for low value bundles. A potential explanation of this behavior may be that bidders were reluctant to buy any low-value bundles, unless they could really make “a good bargain.”

Although the measure of relative allocative efficiency is helpful for comparing two auction designs, with respect to a single auction, a number above 90% does not say a lot, as long as there is no benchmark to compare it with. One possible benchmark is the worst possible allocation of units (without orphaning any unit). Reassuringly, the observed efficiency was generally greater than the worst-case benchmark.

At the first glance, the results on efficiency may seem odd. However, these results are consistent with the findings on efficiency in Study 1 (Chapter 4), and also with other studies on complex auctions—such as Holt et al. (2007) and Porter et al. (2009)—which report very similar efficiency values across treatments, while they observe significantly different revenues and prices. A potential reason for these observations may be that the efficiency results strongly depend on the variance of the bidding behavior, while revenues and prices mostly depend on the level of the bids. It seems that the choice of auction type affects the behavior of most bidders roughly in the same way, but it contributes rather little to the dispersion of the bids.

5.5.2 Revenue

Figure 5.5 depicts the revenues in the experiment arranged by auction and treatment. In the SAA, the revenues lay between 92 and 5099 MU, and in the PCA, the revenues ranged between 0 and 3345 MU, averaging 1304.51 and 704.39 MU respectively for SAA and PCA. A Mann-Whitney U test on the data aggregated to the level of the independent groups confirmed the significance of the revenue differences between the treatments.[26] As the analysis of prices in Section 5.5.3 did not reveal significant differences between the mean session prices, the lower revenues in the PCA must have stemmed from the Closest-to-Vickrey (CtV) pricing rule, which caused a considerable gap between the clock prices in the first auction stage and the final prices in the second auction stage.

Although the mean revenues per session did not differ, the visual impression of Figure 5.5 suggested that there might have been learning effects which differed between the two auction designs. In order to first gain a better understanding of the effects within the single treatments, two separate analyses for the SAA and the PCA were conducted before performing an overall analysis of the complete data set.

For the SAA, the regression of revenues in Table 5.9 revealed a (weakly) significant positive effect of the auction number and a significant negative effect of the groups' comprehension level. In stark contrast, for the PCA, no significant effects of these variables were revealed, and the coefficient of comprehension even had the opposite sign relative to the SAA. These findings suggested that good comprehension and learning led to lower revenues in the SAA, while they did not affect revenues in the PCA. A potential explanation for these results is that experience and a good understanding of

[26] Mann-Whitney U: n=24, W=123, p-value<0.003.

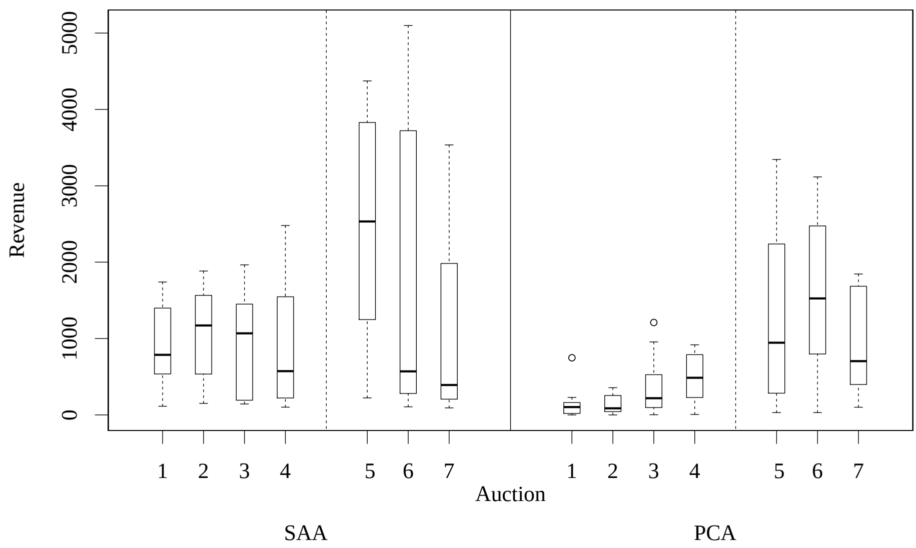

Figure 5.5: Revenues by treatment and auction.

the auction situation helped the bidders to avoid the exposure trap in the SAA, which was not relevant in the PCA. From this perspective, understanding and experience may be more crucial in the SAA than in the PCA.

For the PCA, the regression showed a significant positive correlation between the mean signal $\overline{s}$ and the revenues. This effect could be explained by the price discovery performance of the PCA which will be discussed in Section 5.5.3. As in most auctions, all units of both items were sold successfully, and the revenue data mostly mirrored the price data. The investigation of this underlying data was helpful when it came to understanding the composition of the revenue data. For detailed explanations, please refer to Section 5.5.3.

For both the SAA and the PCA, the separate regressions revealed a strong, significant effect produced by the CV component. In the last three auctions, revenues were generally

Table 5.9: Results from OLS regressions of revenues by auction design.
(·,*, **, and *** denote significance at the 10%, 5%, 1% and 0.1% level. Robust standard errors were calculated at the independent group level and are given in parentheses.)

		(1): SAA Estimate (standard error)		(2): PCA Estimate (standard error)	
Auction Number	a	-301.92 (174.23)	·	-56.83 (61.20)	
Comprehen. is high	h	-639.29 (240.15)	**	276.82 (224.46)	
Mean Signal	$\overline{s}$	123.89 (124.79)		119.53 (52.17)	*
has CV Component	c	1629.82 (509.62)	**	928.31 (254.29)	***
Observations		168		168	
R^2		0.23		0.42	
$\overline{R}^2$		0.19		0.39	
AIC		1,425		1,333	

higher, reflecting the presence of the additional common value component, as the bidders' valuations were on average twice as high in the CV auctions.[27]

The separate analysis of the two auction types in Table 5.9 provided relevant information for the formulation of a regression model for a combined regression of both treatments in Table 5.10. In the separate regressions, the effects of the independent variables seemed to be different and partly opposite across the auction types. In particular, the coefficients of a high comprehension level h were opposed across the auction types (though only one of the effects was significant). The effect of the auction number a was significant for the SAA but not for the PCA, and for the effect of the mean signal $\overline{s}$ the opposite was true. This suggested an interaction between auction type t and the other variables.

[27] The reason for the difference in the values level was a design decision to keep the same distribution of signals over all auctions, without applying a normalization factor, thus avoiding any unnecessary increase in the subjects' cognitive load.

Table 5.10 shows the regression on the combined data set of both treatments. To accommodate diverging effects, interaction terms with t were included in the combined model. In Model (1), all interactions between auction type t and each of the other variables were included (Table 5.10). The Akaike Information Criterion (AIC) as well as the adjusted $\overline{R}^2$ were slightly higher in Model (2) than in Model (1) (Akaike, 1974). Both model specifications returned similar results with consistently lower p-values in Model (2). All in all, Model (2) seemed superior to Model (1) in explaining the data.

The opposing effects of the comprehension level between the two treatments that was revealed in the separate regression was confirmed, as the regression revealed a significant interaction between auction type and comprehension level. On the other hand, with respect to the diverging effects of the auction number, there was only weak statistical evidence for a treatment interaction.

5.5.3 Price Signals

For the PCA, the item prices after the clock stage in each auction were investigated.[28] In order to operate on comparable data sets, the 7+4 prices in each SAA were aggregated by taking the respective mean values for Item A and B. This way, both analyses were conducted on the same level of depth. Checks for robustness with different aggregations (maximum, minimum, median) were performed and are provided in the Appendix. As it turned out, the principle results were robust against the aggregation method.

A Mann-Whitney U test of the price data at the level of the independent groups did not reveal systematic differences between the treatments, neither for Item A nor for Item B.[29] Yet the visual impression given by Figures 5.6 and 5.7 suggested that, at the level of individual auctions, there were pronounced differences, and opposing trends in the price development over the subsequent auctions. The statistical analysis at the

[28] Comparing prices between the two auction designs was a somewhat delicate task, since the SAA and the PCA designs represented fundamentally different mechanisms. In the SAA, there were seven individual prices for the units of Item A and four individual prices for the units of Item B. These prices were final prices that were paid by the respective winning bidders. In contrast, in the PCA, there was one clock price for Item A and one clock price for Item B at the end of the first stage of the auction. The final prices, however, were only determined after the supplementary stage and referred to bundles instead of individual units.

[29] Mann-Whitney U on Item A prices: W=67, p-value = 0.80; Mann-Whitney U on Item A prices: W=45, p-value=0.13.

Table 5.10: Results from OLS regressions of SAA and PCA revenues.
(·,*, **, and *** denote significance at the 10%, 5%, 1% and 0.1% level. Robust standard errors were calculated at the independent group level and are given in parentheses.)

		(1): Estimate (standard error)		(2): Estimate (standard error)	
Treatment		-1751.90		-1502.03	
is PCA	t	(1350.81)		(248.47)	***
Auction		-301.92		-225.31	
Number	a	(170.92)	·	(95.23)	*
Comprehen.		-639.29		-639.29	
is high	h	(235.58)	**	(234.10)	**
Mean		123.89		121.71	
Signal	$\overline{s}$	(122.41)		(65.93)	·
has CV		1629.82		1279.07	
Component	c	(499.92)	**	(287.48)	***
Interaction		245.08		91.88	
t and a		(181.15)		(46.86)	·
Interaction		916.11		916.11	
t and c		(322.46)	**	(320.44)	**
Interaction		-4.36			
t and $\overline{s}$		(132.68)			
Interaction		-701.51			
t and CV		(558.70)			
Observations		168		168	
R^2		0.34		0.34	
$\overline{R}^2$		0.30		0.31	
AIC		2,779		2,777	

level of individual auctions showed pronounced effects.[30] As in the previous Section on auction revenues, before the overall comparison two separate analyses for the SAA and the PCA were conducted. Again, this stepwise procedure helped make the interactions that played a prominent role more comprehensible.

[30] As the time trends were opposed to each other, on average there was no difference. An analysis at the level of independent groups could not reveal such effects. However, the regressions in Table 5.12 pointed to a significant interaction between the auction design and auction number.

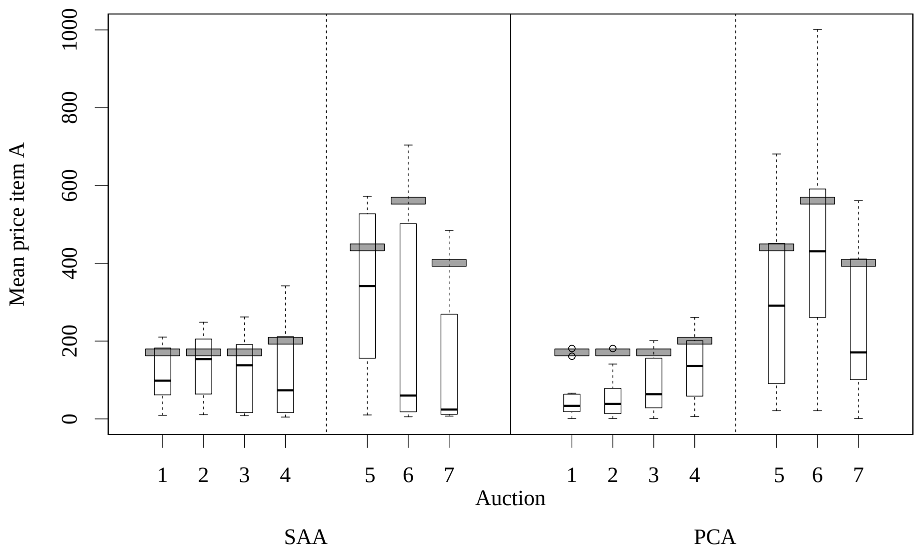

Figure 5.6: Prices Item A by treatment and auction.

Prices in the SAA ranged between 1 MU and 738 MU for Item A and between 1 MU and 94 MU for Item B. The mean price was 169 MU for Item A and 30 MU for Item B, with standard deviations of 175 MU and 17 MU respectively.[31] Within a single auction, prices of the units differed considerably, in particular for Item A. This was mainly due to single high bids, which may have been submitted with the purpose of signalling or deterring other bidders.

The regression in Table 5.11 revealed a strong, significant effect from the CV component. In the last three auctions prices were generally higher, reflecting the presence of the additional common value component (cf. Section 5.5.2). The regression further showed a significant negative impact from the auction number on the prices for both items. The later the auction within the sequence in one session, the lower the price. This tendency could be attributed to learning as well as to fatigue. However, the subjects' feedback after the experiment and the following results on the effect of the comprehension level pointed to learning as the primary reason. For Item A, the regression revealed a significant negative effect of the comprehension level h. This supports the conclusion

[31] A table containing all SAA prices is available in Appendix D.

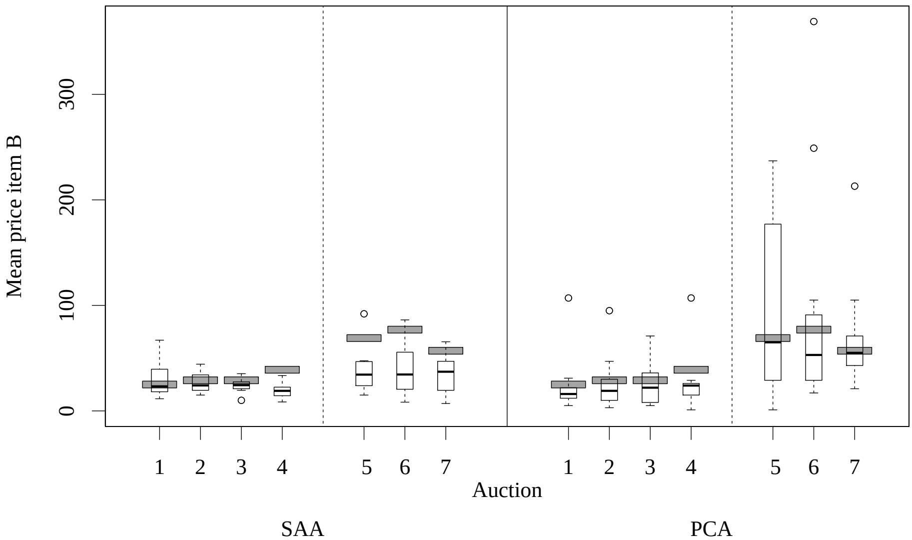

Figure 5.7: Prices Item B by treatment and auction.

that comprehension and learning were driving prices lower in the SAA. Bidders learned to coordinate on a low price level and to avoid the exposure trap early in the auction. For Item B, the comprehension effect was not significant, yet the regression coefficient was still negative.

In the SAA the regression did not reveal a significant effect of the mean signal $\overline{s}$ (equaling the CV component in the last three auctions). There seemed to be no correlation of mean price and mean value. These results cast some doubt on the price discovery performance of the SAA.

Prices in the PCA ranged between 1 MU and 1001 MU for Item A and between 1 MU and 369 MU for Item B. The mean price was 185 MU for Item A and 52 MU for Item B, with standard deviations of 204 MU and 65 MU respectively.[32] In contrast to the SAA, by definition, there was no dispersion of item prices within the single auctions.

In contrast to the SAA, the regression of PCA prices in Table 5.11 showed a positive correlation between the mean signal $\overline{s}$ and the item prices. However, this effect was

[32] A table containing all PCA prices is available in Appendix D.

Table 5.11: Results from OLS regressions of prices by auction design.
(·,*, **, and *** denote significance at the 10%, 5%, 1% and 0.1% level. Robust standard errors were calculated at the independent group level and are given in parentheses.)

		SAA				PCA			
		mean A		mean B		price A		price B	
Auction		-41.3		-3.2		-13.5		-7.4	
Number	a	(24.5)	*	(1.5)	**	(12.5)		(5.1)	
Comprehen.		-88.8		-4.4		42.7		14.6	
is high	h	(31.6)	***	(7.3)		(62.7)		(23.2)	
Mean		17.6		0.1		32.1		4.6	
Signal	$\overline{s}$	(17.8)		(0.8)		(10.7)	***	(4.2)	
has CV		219.6		23.1		219.1		77.7	
Component	c	(71.3)	***	(7.4)	***	(43.5)	***	(24.7)	***
Observations		84		84		84		84	
R^2		0.21		0.18		0.42		0.25	
$\overline{R}^2$		0.17		0.14		0.39		0.21	

significant only for the more valuable Item A. In terms of price-discovery performance, this was a favorable result for the PCA.

The regression coefficient for a high comprehension level h in the PCA was positive, in stark contrast to the significantly negative effect in the SAA. However, in the isolated PCA regression, the effect was not significant. Nevertheless, it seemed plausible that better comprehension lead to bidding closer to the equilibrium strategy, resulting in higher prices.

Again, the separate analysis of the two auction types provided relevant information for the formulation of a regression model for a combined regression of both treatments. The effects of the comprehension level, the auction number, and the mean signal seemed to be different and partly opposite across the auction types. Therefore, in Model Configuration (1) for Item A and Item B, all interactions between auction type t and each of the other variables were included (Table 5.12). For both items the AIC as well as the adjusted $\overline{R}^2$ were slightly higher in Model (2) than in Model (1).[33] For Item A, both model specifications returned similar results with consistently lower p-values in Model (2). For Item B, after the AIC minimization some of the original independent variables were omitted and no additional effects were identified. At the same time, for Item B, the unadjusted R was lower in the second model. To sum up, for Item A, Model (2) was superior to Model (1) in explaining the data, while the choice between the two models for Item B was less clear cut, with intuition voting in favor of Model (1).

The resulting regression of prices over both auction formats in Table 5.12 supported the findings of the separate analyses. For Item A, the regression revealed significant effects from all conditional independent variables. The negative effect of auction number a indicated that prices decreased over time in the SAA, while according to the interaction $t{:}a$, in the PCA, the effect decreased. Similarly, a high comprehension level h went along with a negative effect in the SAA, but decreased or even became positive in the interaction $t{:}h$ with the PCA. For the mean signal $\overline{s}$ the effect was generally positive. The stronger price discovery effect of the PCA suggested by the separate regressions could not be identified in the interaction $t{:}\overline{s}$ (although the coefficient in Model (1) was consistent with the findings of the separate analyses). The presence of a CV component c had a strong positive effect on auction prices, in line with the results of the separate regressions.

For Item B, the only significant effect revealed in Models (1) and (2) was the strong positive effect of the CV component (which had to be expected by definition). In the PCA, this effect was even stronger. Additionally, in Model (1), the regression revealed a significant negative effect from auction number a. In contrast to the prices for Item A, for Item B the decrease of prices over time seemed to be equally pronounced in SAA and PCA.

To sum up, the findings of the combined regression support the proposition that learning as well as good comprehension were correlated with lower prices in the SAA, but with higher prices in the PCA. While experienced bidders learned to avoid the exposure trap in the SAA, experienced bidders in the PCA—who did not need to care

33 For comparison, the regression tables without interaction terms are given in Appendix D. With the treatment interaction terms omitted, the explained variance decreased from 33% to 26% for Item A and from 29% to 21% for Item B. For Item A the regression did not reveal the effect of auction format f and comprehension level h (which was directed in opposite directions from one auction type to the next).

Table 5.12: Results from OLS regressions of SAA and PCA prices.
(·,*, **, and *** denote significance at the 10%, 5%, 1% and 0.1% level. Robust standard errors were calculated at the independent group level and are given in parentheses.)

		mean A (1)		mean A (2)		mean B (1)		mean B (2)	
Treatment		-379.0		-210.2		-59.3		-10.5	
is PCA	t	(207.5)	**	(40.0)	***	(38.5)		(12.3)	
Auction		-41.3		-46.1		-3.2		-	
Number	a	(24.0)	**	(14.0)	***	(1.5)	**	-	
Comprehen.		-88.8		-88.8		-4.4		-4.4	
is high	h	(31.0)	***	(30.8)	***	(7.2)		(7.1)	
Mean		17.6		24.9		0.1		-	
Signal	$\overline{s}$	(17.5)		(10.3)	**	(0.8)		-	
has CV		219.6		219.4		23.1		12.4	
Component	c	(69.9)	***	(40.7)	***	(7.2)	***	(4.2)	***
Interaction		27.8		37.3		-4.3		-	
t and a		(27.0)		(11.7)	***	(5.2)		-	
Interaction		131.6		131.6		18.9		18.9	
t and c		(68.9)	*	(68.5)	*	(23.9)		(23.6)	
Interaction		14.5		-		4.4		-	
t and $\overline{s}$		(20.4)		-		(4.2)		-	
Interaction		-0.5		-		54.5		49.1	
t and CV		(81.9)		-		(25.3)	**	(15.8)	***
Observations		168		168		168		168	
R^2		0.33		0.33		0.29		0.27	
$\overline{R}^2$		0.29		0.30		0.24		0.25	
AIC		2,192		2,189		1,744		1,740	

about exposure risks—learned to bid closer to the profit maximizing equilibrium strategy. With respect to price discovery, the difference between the auction types observed in the previous analysis did not show up significantly in the interaction term (although the interaction coefficients at least pointed in the "right" direction).

5.5.4 Value Discovery

An important element of the experiment was the presence of an uncertain common value component which could be estimated by the bidders at any time during the auction.[34] The estimation slider offered values between 10 and 20 with a preset value of 10. During the course of a session, 89 out of the 96 bidders in the study (or about 93%) made use of the estimation slider. On average, the values estimated at the end of an auction were 1.85 units lower than the actual values of the CV component. In 74 of 288 occasions (or 26 %), the value was guessed correctly.

The numbers reported above differed across the two auction types. Only 29 correct estimations were observed in the SAA, compared with 45 correct estimations in the PCA. Correspondingly, the mean distance of the estimate to the actual value of the CV component was -2.25 units in the SAA, compared with only -1.56 units in the PCA. However, there was virtually no difference with respect to the adoption of the slider by the bidders. Forty-four bidders in the SAA and 45 bidders in the PCA actively estimated the CV component.

Table 5.13 gives the results of the regression of the estimation error defined as the difference between the actual value of the CV component and the estimated value of a bidder at the end of an auction. In addition to the signed difference, the unsigned absolute value of the difference was included in the right-hand part of the table. Also, for both response variables, a regression model (2) minimizing the AIC was included in the table (Akaike, 1974).

The strongest effects—which were identified at a significant level in all models—were the effect of the actual CV component represented by the mean signal $\overline{s}$, and the effect of

[34] A potential problem was that, in addition to their actual estimation, the bidders also expressed their risk aversion through the slider. Although the regressions controlled for the risk aversion measures of the the survey after the experiment, for future experiments it may be advisable to introduce two separate sliders (which, however, on the downside would complicate the user interface).

Table 5.13: Results from OLS regressions of CV component estimates.
(·,*, **, and *** denote significance at the 10%, 5%, 1% and 0.1% level. Robust standard errors were calculated at the independent group level and are given in parentheses. Bidders with non-monotone risk preferences have been omitted, reducing the number of observations from 288 to 267.)

		Signed (1)		Signed (2)		Absolute (1)		Absolute (2)	
Treatment		0.617		0.617		-0.485		-0.436	
is PCA	t	(0.370)	*	(0.369)	*	(0.259)	*	(0.216)	**
Auction		0.074		-		0.273		0.273	
Number	a	(0.143)		-		(0.085)	***	(0.085)	***
Comprehen.		0.705		0.705		-0.272		-	
is high	h	(0.414)	*	(0.413)	*	(0.310)		-	
Mean		-0.890		-0.904		0.596		0.596	
Signal	$\overline{s}$	(0.053)	***	(0.054)	***	(0.065)	***	(0.065)	***
Risk		-0.181		-0.181		0.050		-	
Index	r	(0.098)	*	(0.098)	*	(0.090)		-	
Observations		267		267		267		267	
R^2		0.39		0.39		0.27		0.26	
$\overline{R}^2$		0.37		0.38		0.25		0.25	
AIC		1,164		1,162		1,045		1,043	

the auction type t. Other effects revealed by the regression were a positive effect of a high comprehension level h and a negative effect of a high risk-aversion index r on absolute estimation errors. The later two effects were not revealed for absolute estimation errors. This indicated that the effect was relevant for the height of the estimation, but not so much for the actual exactness.

The significant effect of $\overline{s}$ meant that the higher the actual CV component, the larger the absolute estimation error. This was due to the fact that bidders generally tended to give low value estimations. Some bidders always bid a low, fixed value independent of the information they acquired during the auction. Therefore, estimations for high CV components were generally farther away from the real value. Also, since the bulk of the estimation errors was negative, the signs of the effects changed when moving from signed to absolute values.

A particularly interesting effect was the negative impact of auction type t on the absolute estimation error. If the auction was conducted in the form of a PCA, estimations were closer to the real value. This was in line with the possibly superior price discovery features of the PCA suggested in Section 2.4.3. The relationship between the CV component and the price was stronger in the PCA than in the SAA. The improved price discovery seemed to carry on to improved value discovery.

5.5.5 Summary

The results presented above did not point to a general superiority of the PCA over the SAA. In the PCA, the subjects did not make full use of the opportunity to bid on all valid bundles, and in the SAA, subjects were able to handle the potential problems surprisingly well, provided that they were sufficiently experienced.

Although the market environment induced a pronounced exposure risk—a situation with a clear theoretical advantage for the PCA—no significant differences in relative allocative efficiency could be observed between the SAA and PCA. Thus, there was no support for Hypothesis 1.

With respect to absolute prices and revenues, the session averages did not differ significantly. Yet, for those bidders with a good understanding of the auctions, the prices in the SAA were lower. Furthermore, the prices tended to decrease in the sequence of the auctions in a session, probably due to learning effects. This trend was in line with Hypothesis 2.

With respect to the quality of price and information discovery, the PCA did play out its advantages. For Item A, the clock stage prices of the PCA reflected the mean valuation and the CV component better than SAA prices did. Apparently, this advantage carried on to the bidders' value estimation performance in the two auction designs, as more accurate estimates were observed in the PCA. These results favored Hypothesis 3.

6 Conclusion

6.1 Efficiency, Revenue, and Price Signals in Multi-item Auction Applications

Table 6.1 provides an overview of the findings of Studies 1 and 2 with respect to the performance criteria, efficiency, revenue, and price signals. One surprising finding was that there was no indication in either study of a difference in the allocative efficiency of the auction designs. But at the same time, the auction designs did differ significantly with respect to revenues and price signals.

Prices and revenues reflect the level of the bids. However, allocative efficiency does not depend as much on the level of the bids as on the position of the bids relative to each other. If all bids are multiplied by the same factor—possibly due to different behavior caused by differences in the auction situation and time—the allocation does not change. Only a change in the relative order of the bids can cause a reduction in efficiency. It seems that, across the different auction situations modeled in the experiment, which facilitated different general tendencies of all bidders, the spectrum of the behavior remained similar. Klemperer (2002b) seemed to anticipate the weakness of the connection between auction design and efficiency when he argued that parameters other than auction design should be taken into account in order to obtain efficient results. He emphasized the role of competition and incentives to participate in the auction, as well as the design of the items. Study 1 supported Klemperer's advice, as the value structure indeed seemed to affect efficiency. Therefore, the configuration of the items on sale and the encouragement of bidder participation may be worthwhile further investigation.

Although in complex situations, the auction design may have only a small impact on efficiency, it seems to affect other parameters more strongly. In the experiment,

Table 6.1: Overview of the experimental results.

	Study 1		Study 2
Efficiency	Sequential $\sim$ Simultaneous	USBA $\sim$ ECA	SAA $\sim$ PCA
Revenue	Sequential $\succ$ Simultaneous	USBA $\sim$ ECA	SAA $\succ$ PCA
Price signals	Sequential $\succ$ Simultaneous	USBA $\prec$ ECA	SAA $\prec$ PCA

changes in the quality of the price signals and the revenues yielded by the auctions were dependent on the auction design. In Study 1, sequential auctioning led to significantly higher prices and revenues. In Study 2, the use of a combinatorial auction design led to lower revenues, but also to a better correlation of price signals and the bidders' valuations. These findings may help auctioneers in their choice of an auction design.

In both studies the theory-based predictions and expectations were not completely fulfilled. In Study 1, the theoretically inferior sequential auctioning of two items led to higher revenues, and no evidence was found for higher efficiency when auctioning simultaneously. In Study 2, the theoretically superior Package-clock Auction (PCA) was observed to better reflect the bidders' values. However, even in a situation designed specifically to give an advantage to the new combinatorial auction design, the new design was not able to beat the inferior design with respect to auction efficiency. In Study 1, the bidders' risk aversion may be a plausible explanation for the disparity in the auction results and the predictions of the theoretical benchmark. Intuitively speaking, the bidders' fear that they might not obtain units in the second auction may have incentivized them to bid more sincerely in the first. In Study 2, on the other hand, the most likely reason for unpredicted efficiency losses of the PCA was the bidders' apparent laziness in the selection of bundles.

From the two specific examples presented in this thesis, it is not possible to draw general conclusions. However, the studies showed that the obvious is not always true and complex auction situations may lead to unexpected outcomes. Thus, before implementing a specific complex auction design, it may be very insightful to conduct a testbed experiment, in order to check for any unanticipated effects. One challenge of future research will be to establish standards that increase control and also comparability across the various testbed experiments reported.

6.2 Advancement of the Experimental Methodology

Chapter 3 showed how the insights of cognitive research and the recent advances in computer software can be employed in order to increase control in economic laboratory experiments. In this context, control refers not only to the outer, visible elements of an experiment, but also to the perception and understanding of the experiment situation by the experiment subjects. Studies 1 and 2 provided examples of how the proposed instruments were used to conduct testbed experiments of large-scale auction applications in the laboratory. The feedback of pilot subjects and actual participants in both studies indicated that, in principle, the experiment concept did work.

There are some indications that elements of the proposed experiment concept have already established themselves in the experimental community. For instance, at the Institute of Information Systems and Management (IISM), after the present studies were conducted and presented at the institute, several experimenters started to record the instruction texts and play them to their experiment subjects, instead of having them read out by human instructors. At the Technische Universität München, a group of researchers in the field of combinatorial auctions, started to employ video instructions in their auction experiments, after they had participated in a demonstration of the present studies in mid-2010. Besides these direct consequences of the present work, it seems plausible that the progress in several related fields (computer science, consumer electronics, psychology) will naturally lead to development in line with the proposals made here.

There may be two major hurdles for the introduction of the new instruments: the missing evaluation of the instruments, and the effort associated with their technical implementation. The first question, the evaluation of the new instruments, appears to be the most prominent one. Yet, a systematic evaluation of the proposed instruments may face some serious methodological challenges. In particular, it will be necessary to define precisely the nature of a good experimental result. Is a result better if the subjects understand the experiment situation better, if more of the variance of the data can be explained, or if the observed behavior is closer to the theoretic predictions? Some of the answers may be less obvious than they seem at first glance. From an evaluation perspective, failures in the model and other factors could question the validity of a methodological comparison. Internal validity, subject comprehension, and a high coefficient of determination are important elements. However, the issue of evaluating the basic elements of the present proposal has already been tackled in theoretical and empirical studies in the field of cognitive research (Section 3.2), and experimental economics can benefit from the employment of those findings.

In practice, the effort required for implementing the proposed instruments may have a strong impact on their adoption by the community of experimental economists. The preparation of the animated video instructions in Study 2 required several months in which one PhD-student invested most of his working time into the design and implementation of the experiment software and the videos. While the experiment software itself exceeded the complexity of many traditional examples, requiring an increased time to develop, the videos consumed a much greater share of time. The making of the experiments required knowledge in several fields, such as graphics, sounds, animation, and cognitive research. Also, the fine-tuning of the cognitive concepts of the videos and details like the timing of the sound tracks consumed a considerable amount of time.

In order to broadly use the methods presented in this thesis, the community of experimental economists would need a toolbox-like system (similar to z-Tree for the programming element in experiments) that reduces the effort involved in learning and implementing the new techniques. This toolbox could offer complete pre-defined instruction videos for standard market situations and economic games. Because the fluid nature of research disagrees with static solutions, these pre-defined standard elements would need to be technically open and easily extendable or modifiable. The development of a standardized solution that fulfills these requirements could be achieved in a research project, and might contribute to the increasing success of experimental economics.

A Micro Rules Study 1

The following description of the micro rules has been adopted from Betz et al. (2010).

A.1 Single-item Multi-unit Auctions

Clock auction

In this section the general format of a single-item clock auction is introduced. Consider an auction situation in which s units of an item are auctioned. The quantity s of available units is also called the *supply*. There are n bidders participating in the auction, and the set of bidders is denoted by

$$N = \{1, 2, \ldots, n\}.$$

To simplify the later description, the notions of a *marginal bid*, a *bid schedule*, and a *bidder's demand* at a particular price, as well as the *demand function* of a bidder are introduced. A marginal bid (p, q) is characterized by a price p and a quantity q. It indicates the willingness of the respective bidder to acquire up to q units of the item if the price is not larger than p. In the auction, a bidder does not submit a single marginal bid, but defines a *bid schedule* (the bid schedule is also referred to as a *bidding plan*) which consists of a set of l_i marginal bids. Thus, the bid schedule (bidding plan) of a bidder $i \in N$ is given by the set

$$B_i = \{(p_{i,1}, q_{i,1}), (p_{i,2}, q_{i,2}), \ldots, (p_{i,l_i}, q_{i,l_i})\}.$$

The joint set of bid schedules of all bidders constitute the aggregate bid schedule

$$B = \bigcup_{i \in N} B_i.$$

The demand of a bidder $i \in N$ at a price p is denoted by $d_i(p)$ and refers to the *total quantity* the bidder seeks to buy at this price. The demand can be calculated from the bidder's marginal bid schedule. The bidder's *demand function*, which maps any price p to his demand at this price, is given by

$$d_i(p) = \sum_{(p_{i,k}, q_{i,k}) \in B_i | p_{i,k} \geq p} q_{i,k}$$

(k just serves as an index to enumerate the bidder's marginal bids).

The *aggregate demand* of all bidders at a particular price is the sum of the bidders' demand at that price. Thus, the aggregate demand function $D(p)$ is given by

$$D(p) = \sum_{i \in N} d_i(p).$$

Auction Clock

In a clock auction, a so-called *auction clock* shows the current price at all times. The clock starts at a reserve price p_0 and bidders respond by specifying their demand $d(p_0)$ at this price. The reserve price constitutes the lowest possible price. If the aggregate demand at the reserve is smaller than the supply, the supply is not completely allocated.

If, however, the aggregate demand exceeds supply, the clock ticks forward by increasing the current price and, again, bidders respond by specifying their demand at the new price. This process continues as long as aggregate demand exceeds supply.

Formally: The price increase from round t to the next round $t+1$ is given by an increment $\Delta > 0$, i.e. $p_{t+1} = p_t + \Delta$.

To speed up the auction, the increment can also be set dynamically. In large scale auctions it is typical that the increment is set as a percentage of the current price, and the percentage decreases over time. In the experiment, the increment was always one monetary unit.

Activity Rule

In a clock auction, bidders may not increase their demand as the price of the clock rises.

Formally: A bidder who demands $d(p_t)$ at a price p_t may not demand more than $d(p_t)$ in the further course of the auction, i.e. $d(p_{t'}) \leq d(p_t) \;\; \forall \;\; t' \geq t$.

This activity rule is typical for multi-unit auctions. In the (non-clock) simultaneous multiple-round ascending auction, the number $d(p_t)$ is usually called a bidder's *bidding rights*. In any round a bidder cannot submit more bids (bid on more items) than he has bidding rights, and if he submits fewer bids than he has bidding rights, the bidding rights are reduced accordingly.

Stopping (or Closing) Rule

A clock auction lasts as long as aggregate demand exceeds supply.

Formally: The auction lasts as long as $D(p_t) > s$ and stops if $D(p_t) \leq s$.

Pricing

The lowest price of a winning bid, also referred to as Lowest Accepted Bid (LAB), determines the closing price of the auction. The closing price is the price that all bidders have to pay for all units of the item they receive.

Formally: The closing price p^* of the auction is given by $p^* = \min_{D(p) \geq s} p$ or the reserve price p_0 if $p_0 > p^*$.[1] Note that under the above LAB rule, the closing price is either the last or the second-to-last price shown by the auction clock. If at the end of the auction aggregate demand exactly equals supply, then the price of the item is set to the last price of the clock. If, however, in the last round aggregate demand is smaller than the supply, then the price of the item is set to the second-to-last price of the clock.

[1] In the experiment, an auction that ended with $D(p) < s$ was considered as failed. However, this never occurred.

Allocation of Goods

If, at the end of the auction, aggregate demand equals supply, all bidders receive exactly the amount of their demand at the closing price. If the closing price of the auction is set to the second-to-last price, bidders receive their demand at the last price of the clock, and in addition a share of the residual supply in proportion to their unfulfilled residual demand at the closing price.

Formally: If in the last round t^* the total demand exactly equals supply ($D(p_{t^*}) = s$), then each bidder i receives the quantity $d_i(p_{t^*})$ she has requested in her last bid. If, alternatively, total demand in the last round t^* is lower than the supply ($D(p_{t^*}) < s$), the final price p^* is set to the price of the second-to-last round $t^* - 1$ ($p^* := p_{t^*-1}$). In this case $D(p_{t^*}) < s$, but $D(p^*) > s$, i.e. the demand at the closing price is larger than the supply and, thus, bids must be rationed.

Again, all bidders are awarded the quantity $d_i(p_{t^*})$ they have demanded in their last bid. In addition, the residual supply $s - \sum_i d_i(p_{t^*})$ is allocated to the bidders in equal proportions to the residual demand with respect to the bids $d_i(p_{t^*} - 1)$ in the second-to-last round. This means that a particular bidder j receives, in addition to $d_j(p_{t^*})$ units, an amount given by

$$(d_j(p_{t^*-1}) - d_j(p_{t^*}))\,\frac{s - \sum_i d_i(p_{t^*})}{\sum_i d_i(p_{t^*-1}) - \sum_i d_i(p_{t^*})}$$

If the above formula resulted in fractions smaller than one unit, in the experiment, the largest remainder method was used (also known as Hare-Niemeyer rule which is commonly applied in proportional representation voting).

Information Revelation

If at the end of each round t, the aggregate demand $D(p_t)$ is revealed to all bidders, the auction is referred to as an *open clock auction*.

Proxy Bidding

In a clock auction with proxy bidding, a bidder can instruct the computer to bid on his behalf rather than responding to each current price individually. The bidding rules for the computer are called proxy bids and represent a bidder's demand function (or schedule of marginal bids, depending on the interface; a complete proxy bid schedule is identical to a bid in a sealed-bid auction). At any price of the clock, the computer will automatically—in the name of the bidder—demand the respective quantity that is determined by the bidder's proxy bids.

During the course of the auction, bidders can update their proxy bids insofar as the demand at the current or a future clock price is affected, i.e. a bidder can change his demand function for the current and all higher prices.

Proxy bidding does not impact the pricing or allocation rule. The formulae given above for the calculation of the closing price and the allocation of goods also hold in a clock auction with proxy bidding.

Sealed-bid Auctions

Technically, clock and sealed-bid auctions are very similar. Both the price determination and the computation of the allocation can be performed by the same algorithm. In a sealed bid auction, each bidder submits a non-increasing demand function.[2] The system then calculates the marginal bids as well as the aggregated demand function $D(p)$, i.e.

$$D(p) = \sum_{i \in N} d_i(p).$$

Pricing and the allocation of items is analogous to the clock auctions described above.

[2] If the user interface is based on marginal bids, the bidders' demand functions are calculated by the software.

A.2 Multi-item Multi-unit Auctions

Consider an auction in which m different items are auctioned. The set of items is denoted by

$$M = \{1, 2, \ldots, m\}.$$

Of each item $j \in M$, a real-valued quantity s^j (supply)[3] is being auctioned. The totally available quantities of all items are given by a vector

$$s = (s^1, s^2, \ldots, s^m).$$

The bid schedule of a bidder $i \in N$ for item $j \in M$ is given by the set

$$B_i^j = \left\{ \left(p_{i,1}^j, q_{i,1}^j\right), \left(p_{i,2}^j, q_{i,2}^j\right), \ldots, \left(p_{i,l_i^j}^j, q_{i,l_i^j}^j\right) \right\}.$$

The demand of a bidder $i \in N$ for item $j \in M$ at a price p is denoted by $d_i^j(p)$ and refers to the total quantity the bidder intends to buy at this price. The bidder's *demand function*, which maps any price p to his demand at this price, is given by

$$d_i^j(p) = \sum_{\left(p_{i,k}^j, q_{i,k}^j\right) \in B_i^j | p_{i,k}^j \geq p} q_{i,k}^j.$$

Sealed-bid Auctions

The extension of a single-item multi-unit sealed-bid auction to multi-item multi-unit applications is straight forward. Each bidder submits a non-increasing demand function (or a schedule of marginal bids) for each item $j \in M$. The auctions for the items are considered independently and each auction is evaluated individually. Thus, in terms of algorithms for the pricing and the allocation of goods, there is no difference to single-item multi-unit auctions.

[3] In the CPRS context this is the amount of available permits of a particular vintage.

Bid Sorting with Sealed-bid Auctions

In the experiments, a modified version of Holt et al. (2007, addendum) bid sorting algorithm was applied. The revised version avoids not only price reversals, but also allocation reversals. The modified algorithm works as follows: If an independent evaluation of the auctions would result in an inverted price structure, a fraction of the demand for the less valuable item is shifted to the more valuable item. The quantity of the shift is calculated such that the resulting auction prices of the two items are equal. Bidders who had bid for the less valuable item (i.e. the later vintage) will be awarded the more valuable item (i.e. the earlier vintage), in accordance to their proportional share of the shift. Fractions of the minimum contract size are resolved by a random approach or the Hare-Niemeyer rule.

Open Clock Auctions

In a multi-item extension of the clock auction, several items are auctioned simultaneously. Thus, there is a separate clock for each item. Bidding for all clocks proceeds in synchronized rounds. At the end of each round, the aggregate demand for each item is determined and all clocks at which aggregate demand is larger than supply tick to the next current price. Clocks at which the aggregate demand does not exceed supply keep their price for the next round.

The advantage of the simultaneous approach is that it allows bidders to shift demand from one vintage to another during the course of the auction. This gives bidders the flexibility to react to price differences and to adjust their demand accordingly. By this flexibility, the simultaneous format facilitates efficient outcomes. Note, however, that switches of demand from one item to the other imply that a bidder increases his demand at this item. Thus, the activity rule needs to be refined: In a multi-item clock auction (suited for the case of auctioning emissions permits) the total demand of a bidder over all items is computed in each round. The activity rule requires that the total demand of a bidder may not increase from round to round.

Some more details have to be considered: The postulate of efficiency requires that for every vintage the following holds: if at any time during the auction (i.e. in at least one auction round) the demand for a vintage meets or exceeds the supply of this vintage, the supply of this vintage must completely be sold in the auction. Moreover, no bidder must receive more permits than the activity rule allows, i.e. her total demand at the closing price of the auction, either the last or penultimate prices.[4] As a consequence, demand switches have to be restricted in a certain way. Several solutions are possible. For the experiment we designed and implemented a rule that fulfills the above requirements. The rule is described in the following section.

Ex-post Adjustment of Demand Switches

Consider two different vintages A and B with a supply of $s = \left(s^A, s^B\right)$. Let $D^A(p_t)$ and $D^B(p_t)$ denote the aggregate demand for A and for B in round $t = 1, 2, \ldots$. From the second round on, bidders may switch (parts of) their demand from one vintage to the other, where $x_i(t)$ denotes bidder i's planned demand switch from A to B and $y_i(t)$ his planned demand switch from B to A in round $t = 2, 3, \ldots$. Note that $x_i(t) > 0$ induces $y_i(t) = 0$ and vice versa. The planned aggregated demand switch from A to B over all bidders in round t is then given by $X(t) = \sum_{i \in N} x_i(t)$ and from B to A by $Y(t) = \sum_{i \in N} y_i(t)$, respectively.

In the first step of the ex-post adjustment rule, $X(t)$ and $Y(t)$ are offset against each other by calculating the planned net demand switch from A to B

$$Z^{AB}(t) = \max\left\{0, X(t) - Y(t)\right\}$$

as well as from B to A

$$Z^{BA}(t) = \max\left\{0, Y(t) - X(t)\right\}.$$

Note that $Z^{AB}(t) > 0$ induces $Z^{BA}(t) = 0$ and vice versa. In case of $X(t) = Y(t)$, which implies $Z^{AB}(t) = Z^{BA}(t) = 0$, the demand switches do not need to be ex-post adjusted. Only if one planned net switch amount is positive, an ex-post adjustment of the larger demand switch may become necessary. For the following, let us assume $Z^{AB}(t) > 0$, i.e. the planned total demand switch from A to B is larger than the planned switch in the opposite direction.

[4] The latter is particularly crucial if bidders have a limited budget.

In the second step, the ex-post reduction amount $R^{AB}(t)$ for the planned switches from A to B has to be calculated:

$$R^{AB}(t) = \max\left\{0, \min\left\{Z^{AB}(t), s^A - (D^A(t-1) - Z^{AB}(t))\right\}\right\}.$$

The reduction amount $R^{AB}(t)$ is given by the minimum of the net demand switch $Z^{AB}(t)$ and the (virtual) excess supply $s^A - (D^A(t-1) - Z^{AB}(t))$, which is caused by the planned net demand switch $Z^{AB}(t)$ from A to B. Only if $R^{AB}(t) > 0$, an ex-post adjustment of the planned demand switches becomes necessary. Note that in case of $s^A \geq D^A(t-1)$ the ex post reduction amount $R^{AB}(t)$ is equal to the planned net demand switch $Z^{AB}(t)$. That is, if an excess supply of A already existed in the previous round $t-1$, the total demand for A is not allowed to be reduced by demand switches from A to B in round t.

In the last step, if $R^{AB}(t) > 0$, the individual demand switches have to be ex-post adjusted by proportional reductions of bidders' planned demand switches. That is, instead of her planned switch $x_i(t)$, bidder i's demand switch from A to B is ex-post reduced to

$$x_i^r(t) = x_i(t) \cdot (1 - R^{AB}(t)/X(t)).$$

Hence, the adjusted total demand switch $X^r(t)$ from A to B is given by

$$X^r(t) = \sum_i x_i^r(t) = X(t) - R^{AB}(t),$$

i.e. the planned total demand switch $X(t)$ is ex-post reduced by $R^{AB}(t)$.

In the example above, $X(t) = x_i(t) = 10$ and $Y(t) = 0$, which leads to $Z^{AB}(t) = 10$ and $Z^{BA}(t) = 0$. Applying the ex-post adjustment rule, we get

$$R^{AB}(t) = \max\{0, \min\{10, 100 - (105 - 10)\}\} = 5.$$

That is, the aggregated planned demand switch from A to B has to be ex-post reduced by 5 units. Since only bidder i intends to shift demand from A to B, it is only his planned switch which is reduced by the adjustment, i.e.

$$x_i^r(t) = 10 \cdot (1 - 5/10) = 5.$$

That is, bidder i's planned demand switch of 10 units is ex-post reduced to 5 units. Therefore, the actual aggregated demand for A in round t is equal to the supply of this vintage, i.e. $D^A(t) = s^A = 100$. If the auction ends with this constellation, bidder i receives 10 units of A at the price $p^A(t)$ and 5 units of B if, as before, the total demand for B is assumed to be completely fulfilled. Hence, bidder i receives exactly the number of allowances he demanded at the selling prices, namely 15 units.

Note that the necessity for ex-post adjustments of demand switches has to be checked before pure demand reductions for the vintages are considered. Let us illustrate this by extending the example above. As before, in round t, bidder i intends to shift 10 units of his demand from A to B. Moreover, assume that he additionally intends to reduce his demand for A to zero units. Thus, in round t, bidder i plans to demand 10 units of B only. We now notionally separate between demand shift and pure demand reduction and firstly take demand switches into account. Then, without considering bidder i's demand reduction for A, the situation is same as in the example above. Therefore, the ex-post adjustment of bidder i's demand switch has to be the same too, i.e. instead of shifting $x_i(t) = 10$, he is only allowed to shift $x_i^r(t) = 5$ units from A to B. By additionally taking his demand reduction of 5 units into account, bidder i then demands 5 units of A and 5 units of B. As a consequence, the aggregate demand for A in round t yields $D^A(t) = 95 < s^A = 100$. Thus, if the auction ends with this constellation, the excess supply of 5 units of A in round t has to be proportionally allocated to the bidders (with respect to their demand reduction for A in round t) who have generated the excess supply. Since only bidder i reduces his demand for A, the total excess demand has to be allocated to him. That is, he receives, as before, 10 units of A but now at the price $p^A(t-1)$, because this was the last round in which the demand for A meets or exceeds the supply of this vintage.

B Additional Tables and Figures Study 1

Seat No. X **Bundle values** **Auction X**

Value (E$)		Quantity Item B										
		0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Quantity Item A	**0**	0	22	44	66	88	107	126	145	164	183	201
	1	27	49	71	93	115	134	153	172	191	210	228
	2	54	76	98	120	142	161	180	199	218	237	255
	3	81	103	125	147	169	188	207	226	245	264	282
	4	108	130	152	174	196	215	234	253	272	291	309
	5	132	154	176	198	220	239	258	277	296	315	333
	6	156	178	200	222	244	263	282	301	320	339	357
	7	180	202	224	246	268	287	306	325	344	363	381
	8	204	226	248	270	292	311	330	349	368	387	405
	9	228	250	272	294	316	335	354	373	392	411	429
	10	250	272	294	316	338	357	376	395	414	433	451
	11	272	294	316	338	360	379	398	417	436	455	473
	12	294	316	338	360	382	401	420	439	458	477	495
	13	316	338	360	382	401	420	439	458	477	495	513
	14	338	360	382	401	420	439	458	477	495	513	531
	15	360	382	401	420	439	458	477	495	513	531	548

Table B.1: Exemplary table of aggregated values as handed out at the beginning of each auction.

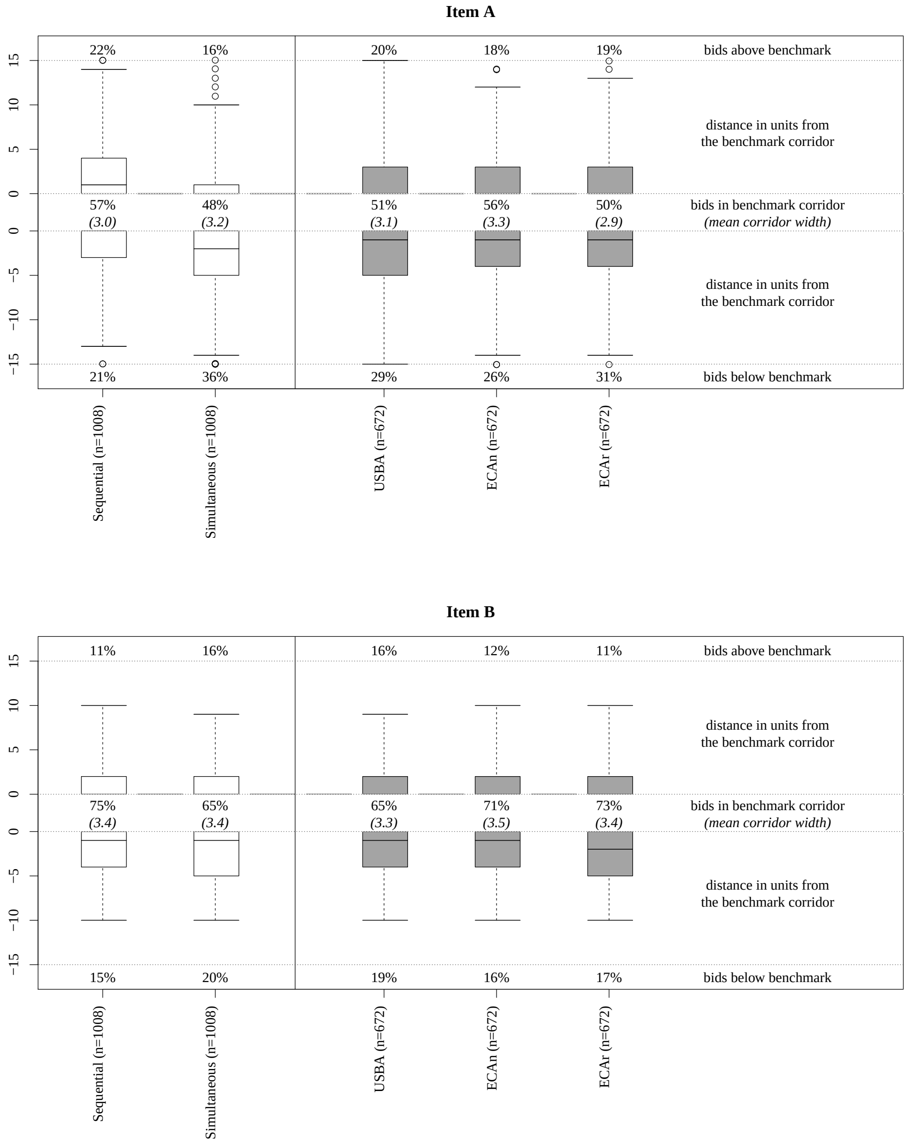

Figure B.1: Bid positions relative to the benchmark corridor in the last auction round. (For the sake of a detailed view of the actual deviations, zero-deviations are not included in the Tukey box plots. The number of observations is denoted by n.)

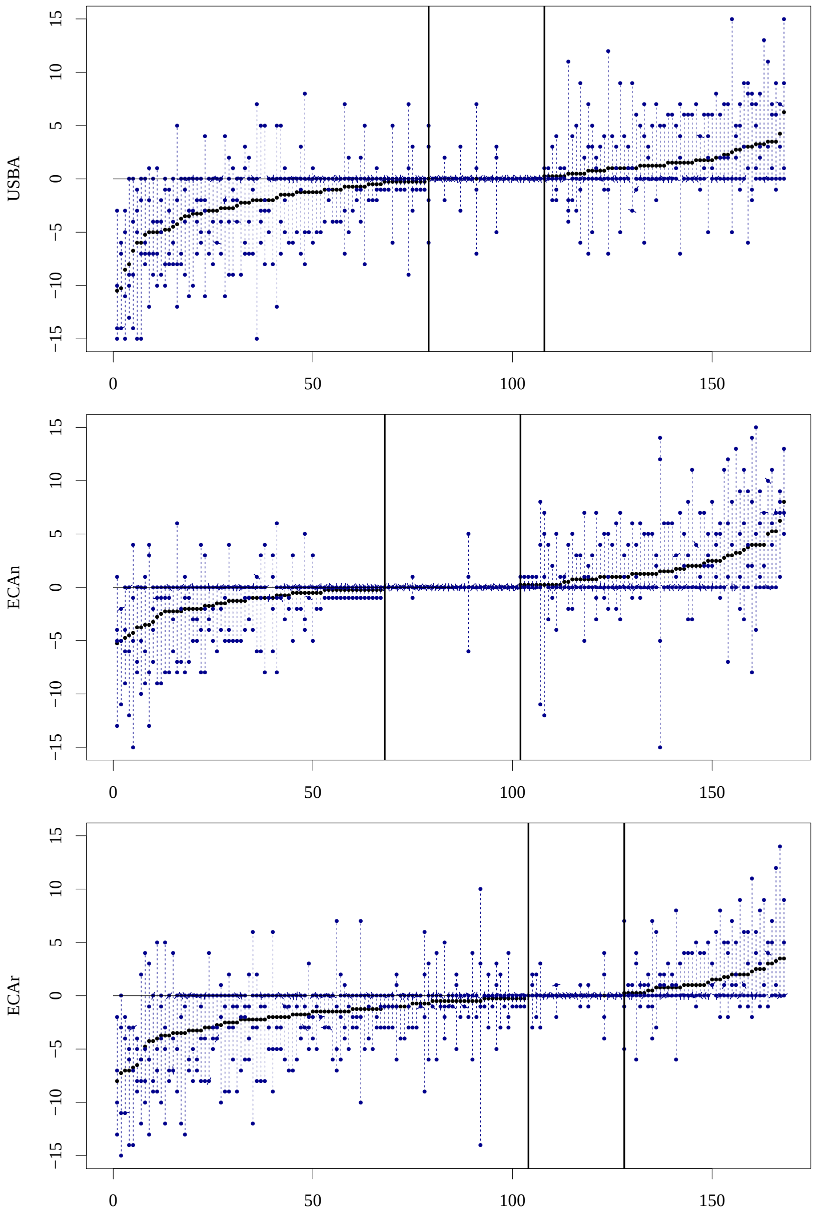

Figure B.2: Bidders clustered by mean distance from the benchmark corridor and by auction type.

The horizontal axis represents individual bidders sorted by the mean distance of their bids from the benchmark corridor. For each bidder the four final bids in the treatment specific Auctions 3 to 6 are depicted by the blue dots and connected with a dotted vertical line for visual convenience. In addition, the black dots indicate the mean values of a bidder's bids.

C Bid increments Study 2

C.1 Simultaneous Ascending Auction

For Item A the minimum bid increments were:

- 5 Money Units (MU) (10 MU) at clock prices smaller than 100 MU (200 MU) in the auctions without (with) a Common Value (CV) component
- 10 MU (20 MU) at clock prices from 100 to 149 MU (200 to 299 MU) in the auctions without (with) a CV component
- 2 MU (4 MU) at clock prices from 150 to 399 MU (300 to 799 MU) in the auctions without (with) a CV component
- 100 MU (200 MU) at clock prices greater than or equal to 400 MU (800 MU) in the auctions without (with) a CV component.

For Item B the minimum bid increments were:

- 2 MU (4 MU) at clock prices smaller than 40 MU (80 MU) in the auctions without (with) a CV component
- 6 MU (12 MU) at clock prices from 40 to 119 MU (80 to 239 MU) in the auctions without (with) a CV component
- 60 MU (120 MU) at clock prices greater than or equal to 120 MU (240 MU) in the auctions without (with) a CV component.

C.2 Package-clock Auction

For Item A, the clock increments were:

- 5 MU (10 MU) at clock prices smaller than 100 MU (200 MU) in the auctions without (with) a CV component
- 10 MU (20 MU) at clock prices from 100 to 399 MU (200 to 799 MU) in the auctions without (with) a CV component
- 100 MU (200 MU) at clock prices greater than or equal to 400 MU (800 MU) in the auctions without (with) a CV component.

For Item B, the clock increments were:

- 2 MU (4 MU) at clock prices smaller than 40 MU (80 MU) in the auctions without (with) a CV component
- 6 MU (12 MU) at clock prices from 40 to 119 MU (80 to 239 MU) in the auctions without (with) a CV component
- 60 MU (120 MU) at clock prices greater than or equal to 120 MU (240 MU) in the auctions without (with) a CV component.

C.3 Explanation

The increments in both auction designs were chosen such that the auction speed was maximized, while at the same time allowing bidders to bid according to a Straightforward Truthful Bidding (SFTB) benchmark strategy. Therefore, the price increase slightly slowed down at relevant price points. As the values in the auctions featuring a CV component were higher than in the auctions under pure Independent Private Values (IPV), the increments were also higher in the CV auctions. Subjects were not informed of this procedure, but they were told that the auctioneer would determine the increments. In the feedback forms, no subject made any remarks on the bid increments.

D Additional Tables and Figures Study 2

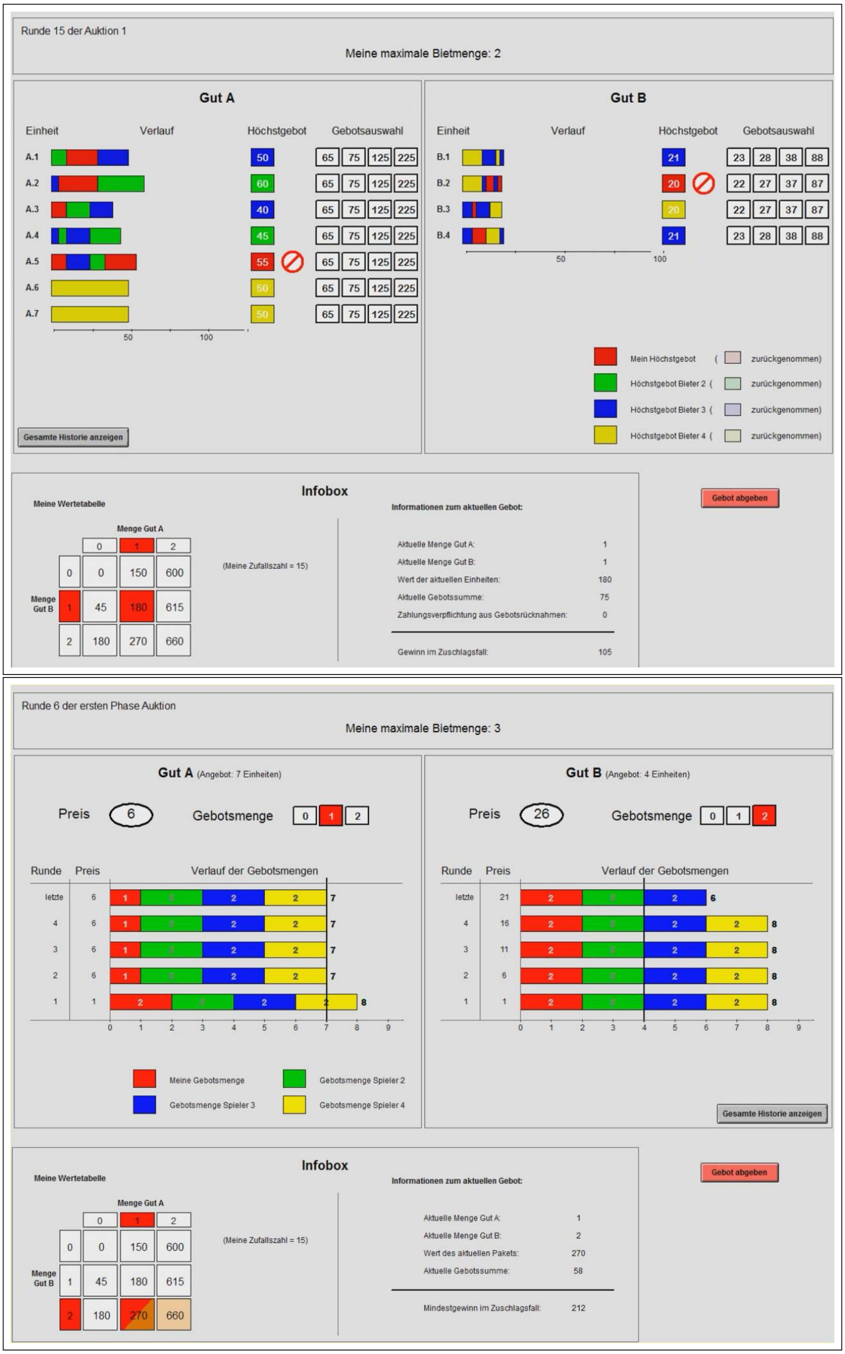

Figure D.1: Screen shots of the experiment software (top: SAA, bottom: clock stage PCA).

Table D.1: Social surplus and relative allocative efficiency.
The first number of each cell gives the social surplus w in auction a, the number in parentheses gives the efficiency e.

Session	1	1	1	2	2	2	3	3	3	4	4	4	Mean
Group	1	2	3	1	2	3	1	2	3	1	2	3	all gr.
PCA													
Score	1	0	0	1	1	0	1	1	0	1	1	0	
$a = 1$	1584.00	1523.00	1584.00	1497.00	1523.00	1580.00	1522.00	1523.00	1557.00	1628.00	1558.00	1584.00	1555.25
	(0.973)	(0.936)	(0.973)	(0.920)	(0.936)	(0.971)	(0.935)	(0.936)	(0.956)	(1.000)	(0.957)	(0.973)	(0.955)
$a = 2$	1759.00	1672.00	1720.00	1831.00	1816.00	1846.00	1780.00	1832.00	1801.00	1880.00	1663.00	1678.00	1773.17
	(0.936)	(0.889)	(0.915)	(0.974)	(0.966)	(0.982)	(0.947)	(0.974)	(0.958)	(1.000)	(0.885)	(0.893)	(0.943)
$a = 3$	1856.00	1718.00	1692.00	1970.00	1900.00	1898.00	1946.00	1952.00	1996.00	1988.00	1880.00	1942.00	1894.83
	(0.922)	(0.854)	(0.841)	(0.979)	(0.944)	(0.943)	(0.967)	(0.970)	(0.992)	(0.988)	(0.934)	(0.965)	(0.942)
$a = 4$	2362.00	2222.00	2374.00	2332.00	2327.00	2357.00	2374.00	2325.00	2351.00	2386.00	2351.00	2374.00	2344.58
	(0.985)	(0.927)	(0.990)	(0.972)	(0.970)	(0.983)	(0.990)	(0.970)	(0.980)	(0.995)	(0.980)	(0.990)	(0.978)
Mean	*1890.25*	*1783.75*	*1842.50*	*1907.50*	*1891.50*	*1920.25*	*1905.50*	*1908.00*	*1926.25*	*1970.50*	*1863.00*	*1894.50*	*1891.96*
$a \leq 4$	*(0.954)*	*(0.901)*	*(0.930)*	*(0.961)*	*(0.954)*	*(0.970)*	*(0.960)*	*(0.962)*	*(0.972)*	*(0.996)*	*(0.939)*	*(0.955)*	*(0.954)*
$a = 5$	4289.50	4097.25	4396.50	4222.00	4022.25	4334.25	4136.50	4376.50	4289.50	4386.00	4327.00	4321.25	4266.54
	(0.961)	(0.918)	(0.985)	(0.945)	(0.901)	(0.971)	(0.926)	(0.980)	(0.961)	(0.982)	(0.969)	(0.968)	(0.955)
$a = 6$	5044.50	5088.50	4758.00	5088.50	4921.75	4912.75	4878.00	4957.50	5080.50	4984.50	4797.75	4864.75	4948.08
	(0.991)	(1.000)	(0.935)	(1.000)	(0.967)	(0.965)	(0.959)	(0.974)	(0.998)	(0.980)	(0.943)	(0.956)	(0.972)
$a = 7$	3759.00	3621.00	3757.00	3837.00	3759.00	3553.00	3759.00	3843.00	3699.00	3857.00	3909.00	3782.00	3761.25
	(0.958)	(0.923)	(0.957)	(0.978)	(0.958)	(0.905)	(0.958)	(0.979)	(0.942)	(0.983)	(0.996)	(0.964)	(0.958)
Mean	*4364.33*	*4268.92*	*4303.83*	*4382.50*	*4234.33*	*4266.67*	*4257.83*	*4392.33*	*4356.33*	*4409.17*	*4344.58*	*4322.67*	*4325.29*
$a \geq 5$	*(0.970)*	*(0.947)*	*(0.959)*	*(0.974)*	*(0.942)*	*(0.947)*	*(0.948)*	*(0.978)*	*(0.967)*	*(0.981)*	*(0.969)*	*(0.962)*	*(0.962)*
Mean	*2950.57*	*2848.82*	*2897.36*	*2968.21*	*2895.57*	*2925.86*	*2913.64*	*2972.71*	*2967.71*	*3015.64*	*2926.54*	*2935.14*	*2934.82*
all a	*(0.961)*	*(0.921)*	*(0.942)*	*(0.967)*	*(0.949)*	*(0.960)*	*(0.955)*	*(0.969)*	*(0.970)*	*(0.990)*	*(0.952)*	*(0.958)*	*(0.958)*
SAA													
Score	1	0	0	1	1	0	1	1	0	1	1	0	
$a = 1$	1628.00	1558.00	1568.00	1568.00	1604.00	1544.00	1520.00	1558.00	1548.00	1592.00	1584.00	1628.00	1575.00
	(1.000)	(0.957)	(0.963)	(0.963)	(0.985)	(0.948)	(0.934)	(0.957)	(0.951)	(0.978)	(0.973)	(1.000)	(0.967)
$a = 2$	1758.00	1766.00	1876.00	1856.00	1759.00	1676.00	1834.00	1696.00	1849.00	1808.00	1750.00	1836.00	1788.67
	(0.935)	(0.939)	(0.998)	(0.987)	(0.936)	(0.891)	(0.976)	(0.902)	(0.984)	(0.962)	(0.931)	(0.977)	(0.951)
$a = 3$	1968.00	1910.00	1980.00	1896.00	1718.00	1932.00	1872.00	1988.00	1996.00	1936.00	1996.00	1988.00	1931.67
	(0.978)	(0.949)	(0.984)	(0.942)	(0.854)	(0.960)	(0.930)	(0.988)	(0.992)	(0.962)	(0.992)	(0.988)	(0.960)
$a = 4$	2394.00	2081.00	2332.00	2244.00	2176.00	2222.00	2332.00	2327.00	2260.00	2332.00	2285.00	2386.00	2280.92
	(0.998)	(0.868)	(0.972)	(0.936)	(0.907)	(0.927)	(0.972)	(0.970)	(0.942)	(0.972)	(0.953)	(0.995)	(0.951)
Mean	*7748.00*	*7315.00*	*7756.00*	*7564.00*	*7257.00*	*7374.00*	*7558.00*	*7569.00*	*7653.00*	*7668.00*	*7615.00*	*7838.00*	*7576.25*
$a \leq 4$	*(0.978)*	*(0.928)*	*(0.979)*	*(0.957)*	*(0.921)*	*(0.932)*	*(0.953)*	*(0.954)*	*(0.967)*	*(0.969)*	*(0.962)*	*(0.990)*	*(0.958)*
$a = 5$	4396.50	4386.00	4202.00	4257.25	4465.50	4085.25	4291.75	4269.75	4306.00	4437.50	4269.75	4054.25	4285.13
	(0.985)	(0.982)	(0.941)	(0.953)	(1.000)	(0.915)	(0.961)	(0.956)	(0.964)	(0.994)	(0.956)	(0.908)	(0.960)
$a = 6$	5017.50	4940.00	4812.00	4706.25	4987.50	4843.25	4888.50	4987.50	5009.50	4973.50	4888.50	4780.25	4902.85
	(0.986)	(0.971)	(0.946)	(0.925)	(0.980)	(0.952)	(0.961)	(0.980)	(0.984)	(0.977)	(0.961)	(0.939)	(0.964)
$a = 7$	3746.50	3772.00	3686.50	3695.50	3847.00	3798.50	3913.00	3861.00	3837.00	3847.00	3795.00	3859.00	3804.83
	(0.955)	(0.961)	(0.939)	(0.942)	(0.980)	(0.968)	(0.997)	(0.984)	(0.978)	(0.980)	(0.967)	(0.983)	(0.969)
Mean	*4386.83*	*4366.00*	*4233.50*	*4219.67*	*4433.33*	*4242.33*	*4364.42*	*4372.75*	*4384.17*	*4419.33*	*4317.75*	*4231.17*	*4330.94*
$a \geq 5$	*(0.975)*	*(0.971)*	*(0.942)*	*(0.940)*	*(0.987)*	*(0.945)*	*(0.973)*	*(0.973)*	*(0.975)*	*(0.984)*	*(0.961)*	*(0.944)*	*(0.964)*
Mean	*2986.93*	*2916.14*	*2922.36*	*2889.00*	*2936.71*	*2871.57*	*2950.18*	*2955.32*	*2972.21*	*2989.43*	*2938.32*	*2933.07*	*2938.44*
all a	*(0.977)*	*(0.947)*	*(0.963)*	*(0.950)*	*(0.949)*	*(0.937)*	*(0.962)*	*(0.963)*	*(0.971)*	*(0.975)*	*(0.962)*	*(0.970)*	*(0.960)*

Table D.2: Study 2 results from OLS regressions of SAA and PCA prices *without interaction terms* in model (2). *, **, and *** denote significance at the 10%, 5%, and 1%-level, respectively. Robust standard errors are calculated at the independent group level and are given in parentheses.

		mean A (1)		mean A (2)		mean B (1)		mean B (2)	
Type		-379.0		15.7		-59.3		21.5	
is PCA	t	(207.5)	**	(34.4)		(38.5)		(12.1)	*
Auction		-41.3		-27.4		-3.2		-5.3	
Number	a	(24.0)	**	(13.6)	**	(1.5)	**	(2.6)	**
Comprehen.		-88.8		-23.1		-4.4		5.1	
is high	h	(31.0)	***	(37.1)		(7.2)		(12.0)	
Mean		17.6		24.9		0.1		2.4	
Signal	$\overline{s}$	(17.5)		(10.2)	**	(0.8)		(2.1)	
has CV		219.6		219.4		23.1		50.4	
Component	c	(69.9)	***	(40.4)	***	(7.2)	***	(13.8)	***
Interaction		27.8		-		-4.3		-	
t and a		(27.0)		-		(5.2)		-	
Interaction		131.6		-		18.9		-	
t and c		(68.9)	*	-		(23.9)		-	
Interaction		14.5		-		4.4		-	
t and $\overline{s}$		(20.4)		-		(4.2)		-	
Interaction		-0.5		-		54.5		-	
t and CV		(81.9)		-		(25.3)	**	-	
Observations		168		168		168		168	
R^2		0.33		0.26		0.29		0.21	
$\overline{R}^2$		0.29		0.24		0.24		0.18	
AIC		2,192		2,201		1,744		1,754	

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List of Abbreviations

AIC	Akaike Information Criterion
ANOVA	Analysis of Variance
AV	Affiliated Values
CO_2	Carbon Dioxide
CPRS	Carbon Pollution Reduction Scheme
CtV	Closest-to-Vickrey
CV	Common Value
DCCEE	Department of Climate Change and Energy Efficiency
E$	Experiment Dollars
ECA	English Clock Auction
ETS	Institute of Economic Theory and Statistics
FCC	Federal Communications Commission
GSM	Global System for Mobile Communications
HRB	Highest Rejected Bid
IISM	Institute of Information Systems and Management
IPCC	Intergovernmental Panel on Climate Change
KIT	Karlsruhe Institute of Technology
LAB	Lowest Accepted Bid
LTE	Long Term Evolution
MU	Money Units
NETT	National Emissions Trading Taskforce
NGERA	National Greenhouse and Energy Reporting Act
NO_x	Mono-nitrogen Oxides
OLS	Ordinary Least Squares
PCA	Package-clock Auction
IPV	Independent Private Values
Ofcom	Office of Communications
ORSEE	Online Recruitment System for Economic Experiments
RGGI	Regional Greenhouse Gas Initiative
SAA	Simultaneous Ascending Auction
SFTB	Straightforward Truthful Bidding
UI	User Interface
UMTS	Universal Mobile Telecommunications System
UNSW	University of New South Wales
USBA	Uniform-price Sealed-bid Auction
VCG	Vickrey-Clarke-Groves

In recent decades, multi-item auctions have been established as an essential instrument for large-scale government sales of natural resources and for various other applications. For example, since the 1990s, radio spectrum rights auctions have been shaping the wireless communications industry, which plays a vital role in society's development. Further, since the beginning of the new millennium, greenhouse emissions permit auctions have been helping to channel emissions permits to the "right" emitters, charging those emitters whose emissions would be too expensive to avoid, while forcing other emitters to carry out affordable abatement measures. In both auction applications, there has been a lively academic and political debate on various design aspects, such as the choice between open vs. closed, simultaneous vs. sequential, and combinatorial vs. non-combinatorial designs. This book presents two experimental studies that deal with the comparison of several multi-item auction designs for two specific applications – the sale of radio spectrum rights in the 2.6 GHz band in Europe, and the sale of emissions permits in Australia.

In order to tackle the complexity of experimental situations such as the ones just mentioned, this book presents a toolkit of instruments for warranting the scientific criteria of control, reproducibility and validity in the design of economic laboratory experiments. In particular, the proposed instruments seek to improve and to control subjects' comprehension by applying the empirical and theoretical results of cognitive research, and by reverting to state-of-the-art technological and psychological research. The proposed toolkit includes modularized video instructions, comprehension tests, a software integrated learning platform, a graphical one-screen user interface, and comprehension-based group matching.

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