Auctions for Renewable Energy Support

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Abstract

Climate change mitigation has become a political target with high significance and broad social acceptance. An integral part of this target is the reduction of greenhouse gas emissions. The term *energy transition* summarizes the activities in different parts of the energy sector to shift the generation of energy from conventional to renewable energy sources. It is a major challenge to control the costs and speed of this conversion and to appropriately synchronize it with other related activities including transmission grid expansion and the electrification of the transport sector.

To promote renewable energy sources, which are not yet competitive with conventional power plants, governments around the world increasingly decide to implement competitive auction mechanisms. Auctions promise to enable a controlled expansion at lowest costs. Those arguments and good experiences from recent projects led to the implementation of auctions in many countries around the world. Nevertheless, the promotion of renewable energy support is still a relatively new application of auctions and lacks a coherent analysis of practical experiences and the theoretic background. Therefore, the analyses in this thesis enhance and complement the existing research and contributes to the literature by applying auction-theoretic analyses on the field of auctions for renewable energy support.

This thesis presents four different analyses of auctions for renewable energy support. Two analyze specific design elements auction-theoretically,

one complements the theoretical research by an agent-based model and one by an experimental approach. The first analysis highlights the implications of prequalifications and penalties on realization rates and auction prices and provides policy implications regarding an appropriate auction design. Discriminatory design elements gained relevance in auctions for renewable energy support through the recent trend of technology-neutral and cross-border auctions. The more distinct groups of bidders participate in the same auction, the more possibilities arise to implement discriminatory design elements. This theoretical analysis presents the opportunities and threads of discriminatory design elements and highlights the relationship between auction targets and auction design.

The third analysis in this thesis combines auction-theoretical research with an agent-based model to enhance the understanding of the bidding behavior in a real-world auction. This new insight explains the effects of given design elements and bidder beliefs on the auction outcome and facilitates improvements to the future auction design. Finally, this thesis contributes to the research on common value auctions. The analysis adapts the common value framework to the conditions of auctions for renewable energy support and systematically compares the most common pricing rules and different competition levels in multi-unit common value procurement auctions. The risk of the winner's curse is severe in such a setting, however, in contrast to theoretical predictions, the pricing rules have no significant influence on the experimental outcome.

This thesis is based on four papers prepared at the Institute for Economics (ECON) in the Research Group for Strategic Decisions under the supervision of Professor Karl-Martin Ehrhart at the Karlsruhe Institute of Technology (KIT) and is written in English.

Kurzfassung

Die Bekämpfung des menschengemachten Klimawandels ist aktuell eines der wichtigsten politischen Ziele und besitzt große öffentliche Akzeptanz. Die Verringerung der Treibhausgasemissionen ist eine notwendige Bedingung, um dieses Ziel zu erreichen. Der Begriff *Energiewende* fasst dabei alle Aktivitäten zur Umstellung von konventioneller zu erneuerbarer Energieerzeugung zusammen. Die wesentliche Herausforderung der Energiewende ist deren Umsetzung im Spannungsfeld zwischen Kosten und Zeit.

Da Erneuerbare Energien im Vergleich zu konventionellen Kraftwerken noch nicht wettbewerbsfähig sind, wird ihr Ausbau staatlich gefördert. Für diese Förderung werden weltweit vermehrt Auktionen eingesetzt, da diese eine Kosten- und Mengenkontrolle versprechen. Obwohl mittlerweile in vielen Ländern Auktionen durchgeführt werden, sind die Erfahrungswerte und die theoretische Analyse noch unvollständig. Die Forschung dieser Doktorarbeit erweitert die vorhandenen Untersuchungen und trägt durch die Anwendung von auktionstheoretischen Methoden im Feld der Auktionen für Erneuerbare Energien zur Literatur bei.

Diese Doktorarbeit beinhaltet zwei auktionstheoretische Analysen von besonderen Designmerkmalen von Auktionen für Erneuerbare Energien. In den zwei weiteren Arbeiten werden die auktionstheoretischen Methoden durch eine agentenbasierte Modellierung und durch eine experimentelle Untersuchung ergänzt. Im ersten Abschnitt dieser Doktorarbeit wird der Zusammenhang zwischen Präqualifikationen und Realisierungsraten bezie-

hungsweise Auktionspreisen analysiert und erläutert. Auf Basis dieser Ergebnisse werden Empfehlungen hinsichtlich einer geeigneten Gestaltung der Auktion gegeben. Durch die Öffnung von Auktionen für verschiedene Technologien oder Bieter aus verschiedenen Ländern haben diskriminierende Gestaltungselemente in Auktionen für Erneuerbare Energien erheblich an Bedeutung gewonnen. Durch die Teilnahme verschiedener Bietergruppen eröffnen sich neue Möglichkeiten aber auch Herausforderungen im Auktionsdesign. Die in dieser Doktorarbeit verfasste Analyse zu diskriminierenden Designelementen zeigt insbesondere den engen Zusammenhang zwischen den Zielen der Auktion und deren Ausgestaltung auf.

Im dritten Abschnitt wird die auktionstheoretische Forschung um eine agentenbasierte Modellierung ergänzt. Die neu gewonnenen Einsichten erklären die Auswirkungen des Auktionsdesigns auf das Auktionsergebnis und tragen somit zu einem besseren Verständnis der Wechselbeziehungen bei. Die vierte Analyse in dieser Doktorarbeit befasst sich mit Common-Value Auktionen unter den Rahmenbedingungen von Auktionen für Erneuerbare Energien. Dabei wird ein systematischer Vergleich zwischen den beiden meistverwendeten Preisregeln mit verschiedenen Wettbewerbsniveaus vorgenommen. Unter allen Parametern ist das Risiko des Fluchs des Gewinners erheblich, aber das Ergebnis unterscheidet sich – im Gegensatz zur theoretischen Erwartung – nicht signifikant zwischen den beiden Preisregeln.

Die Grundlage dieser Doktorarbeit sind vier Papiere, welche am Institut für Volkswirtschaftslehre (ECON) in der Forschungsgruppe Strategische Entscheidungen unter der Betreuung von Professor Karl-Martin Ehrhart am Karlsruher Institut für Technologie (KIT) erarbeitet wurden. Die Arbeit ist in englischer Sprache verfasst.

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List of abbreviations

ABM	Agent-Based Model
ANOVA	Analysis of Variance
BMWi	German Federal Ministry of Economic Affairs and Energy
BNetzA	German Federal Network Agency
CDF	Cumulative Distribution Function
CV	Common Value
DP	Discriminatory Price
EU	European Union
EEG	German Renewable Energy Sources Act
FiT	Feed-in Tariff
GE	Monetary units in the experiment
IPV	Independent Private Values
IV	Interdependent Values
kW	Kilowatt
kWh	Kilowatt hour
LCOE	Levelized Costs of Electricity
LRB	Lowest Rejected Bid rule in UP auctions
MW	Megawatt
MWh	Megawatt hour

PaB	Pay-as-Bid
PV	Photovoltaics
RE	Renewable Energy
UK	United Kingdom
UP	Uniform Pricing

List of functions and variables

$\beta^{SA}(\theta)$	Bidding function in the second-price auction with signal θ
$\beta^{UP}_{(k,n)}(x)$	Equilibrium bidding function in the CV UP auction
$\beta^{DP}_{(k,n)}(x)$	Equilibrium bidding function in the CV DP auction
$\Delta(q^{\pm})$	Change in the support costs induced by $q^{\pm}$
$\Delta'(q^{\pm})$	Differentiation of $\Delta(q^{\pm})$ with respect to $q^{\pm}$
δ	Discount factor $\in$ (0,1)
ε	Uncertainty parameter, maximum difference between c and x
$\varepsilon_k(p)$	Elasticity of supply for Technology k at price p
λ	Relative bidder density of bidder class A and B
λ^e	Auctioneer's estimation of λ
λ^t	Degression factor in round t
$\Pi(x, z)$	Expected profit function of the bidder with signal x when bidding $\beta^{DP}_{(k,n)}(z)$
$\pi(\theta, s, p)$	Winning bidder's profit function
π_i	Bidder i's profit
$\pi_D(\theta, s, p, t)$	Winning bidder's profit function including security
$\pi_E(\theta, s_{PQ}, p, t, e)$	Winning bidder's profit function including prequalification
$\pi_Q(\theta, s, p, t, q)$	Winning bidder's profit function including penalty

$\pi_W(\theta, s, p, t, q, w)$	Winning bidder's profit function including asset value
ϱ	Cost ratio of the bidder class B and A
ϱ^e	Auctioneer's estimation of ϱ
θ_i	Bidder i's expected project costs
$\underline{\theta}$	Lowest possible expected costs
$\bar{\theta}$	Highest possible expected costs
$\tilde{\theta}$	Cut-off costs to participate in the auction
μ	Mean of distribution F
a_k	Lower interval boundary for k-bidders' marginal costs
$a_{converted,w}$	Agents of type $Randflaeche$, weak
$a_{converted,s}$	Agents of type $Randflaeche$, strong
a_{arable}	Agents of type $Ackerflaeche$
b_e	Cost optimizing bonus given ϱ^e and λ^e
b_i	Bid of Bidder i
b_i^t	Bid of Bidder i in round t
$\mathbf{b_i}$	Vector of all bids b_i^t from round t to round T
b^+	Monetary bonus for a given bidder group
b^-	Bid bonus for a given bidder group
$\hat{b}$	Unique cost minimizing bonus
$b = (p, \mathbf{q})$	Price-quality bids
$b_{(i)}$	i-lowest bid of a bidder
C	Random variable of the common production cost
c	Realization of C
$\underline{c}$	Lower boundary of the distribution of C
$\bar{c}$	Upper boundary of the distribution of C

c_i^t	Bidder i's costs in round t
$c(\theta_i, s)$	Bidder i's total realization cost function
$c_a(\mathbf{q})$	Auctioneer's integration cost function
$c_b(\mathbf{q})$	Bidders' cost function depending on quality $\mathbf{q}$
$comp$	Initial assumption on competition
D	Auction demand
d_k	Upper interval boundary for k-bidders' marginal costs
d^t	Total demand in round t
$E[\pi_i(\mathbf{b_i})]$	Bidder i's expected profit function
$E[P^{UP}_{(k,n)}]$	Auctioneer's expected price function in the CV UP auction
$E[P^{DP}_{(k,n)}]$	Auctioneer's expected price function in the CV DP auction
e	Participation costs
F	Agent's belief on the bid distribution of the other bidders
G	Distribution function of S
G_{PQ}	Distribution function of S_{PQ}
$K(p)$	Auctioneer's total cost function depending on price p
$K_k(p)$	Auctioneer's costs of supporting k-bidders
k	Number of sold goods in the CV auction
$MC_k(x)$	Technology-specific marginal cost function of Technology k
m_k	k-bidder density in a given interval
N	Set of bidders

n	Number of bidders
n^t	Number of bidders in round t
n_s^t	Number of successful bidders in round t
p	Award price in the auction
p^*	Award price without discrimination
p_{lim}^t	Price limit in round t
p_k	Technology-specific award price for Technology k
p_k^e	Cost optimizing maximum price given ϱ^e and λ^e
p_k^{max}	Technology-specific maximum price for Technology k
$\hat{p}_k^{max}$	Unique cost minimizing maximum price
Q	Minimum quota for a given technology
Q_e	Cost optimizing quota given ϱ^e and λ^e
$\hat{Q}$	Unique cost minimizing quota
q	Penalty payment in case of non-realization
$q^{\pm}$	Volume shift through discrimination
q_i	Quantity offered by bidder i
$q_{(i1)}$	Quantity offered by the bidder with bid $b_{(i)}$
$\mathbf{q}$	Vector of the characteristics of a RE project
r	Reservation price
S	Uncertain cost component
S_{PQ}	Uncertain cost component with prequalification
$S_k(p)$	Supply function of Technology k
s^t	Total supply in round t
$s(p, \mathbf{q})$	Auctioneer's scoring function
$\bar{s}$	Highest (absolute) realization of S
$\bar{s_{PQ}}$	Highest (absolute) realization of S_{PQ}
$succ$	Initial assumption on successful bidders
T	Last auction round
t	Auction round
t_v	Monetary value of the security

$range(T)$	Rounds per iteration
w	Asset value of the bidder
x	Bidders private cost estimation
x_i	Bidder i's private cost estimation
Y_k	k lowest cost estimate of the $n-1$ competitors

Chapter 1

Introduction

The recent *Fridays for Future* (Fridays For Future, 2019) campaign draws public attention to climate change awareness and mitigation measures. The principal claim of the campaign is the compliance with the targets of the Paris Agreement (United Nations Framework Convention on Climate Change, 2015), in particular to limit global warming below 2 degrees Celsius above pre-industrial levels. A cornerstone to achieve the associated greenhouse gas emission reduction is the expansion of renewable energy (RE). As a result, the 2030 targets of the European Commission (European Commission, 2014a) explicitly set greenhouse gas emission reduction and RE expansion targets. Although this expansion receives broad social support, it lies between the conflicting priorities of politics, economics and environment.

RE sources are defined as naturally replenishing energy sources such as wind, water, tides, waves, geothermics and sunlight. The potential of these sources in principal meets many times the human energy demand (Ellabban et al., 2014). RE sources are distinguished whether they provide energy for electricity, heating or transport purposes (Ragwitz et al., 2009). This thesis will focus on the electricity sector.[1]

Although RE sources are in principal available for free, RE plants still

[1]For the sake of simplicity, I refer to electricity from RE sources with the term RE.

require support to achieve expansion targets. However, the form of support as well as affected stakeholders and technologies underwent significant changes in the last two decades. The support payment developed from administratively set feed-in-tariffs (FiTs), that is each operator receives a fixed rate per produced unit of electricity of the RE source, to more market oriented approaches. The market orientation has several facets. First, RE suppliers do not receive a previously set support payment but payments are determined in a competitive process. Second, RE suppliers have to compete in direct marketing of their electricity (Wassermann et al., 2015). Although there are many more market oriented specifics, this thesis will focus on the competitive set support payments.

The development of the support mechanisms is also reflected in the development of RE technologies and of RE suppliers. Both became more market oriented. Construction and operation of RE plants is now an economic factor while there exists a high innovation pressure on the technology side (New Energy Update, 2019). This pressure led to a maturation of technologies so that they are now at a crossroad of economic development. The costs for electricity generation from RE sources, in particular of photovoltaics (PV) and wind, are similar to those of newly built conventional energy sources, yet they still require support. The two main reasons are the asymmetry between investment costs and operations costs and the accompanying dependence on interest rates (Steffen, 2018) and the variable nature of REs, especially wind and PV. Those RE sources produce energy when the sun is shining or the wind is blowing, which need not be the times when there is electricity demand. This discrepancy results in a technology specific market value and requires additional measures to achieve a sustainable electricity system (Joskow, 2011).

1.1 Political background

In recent years auctions have become the prevalent competitive mechanism to determine support payments for REs. Such auctions are now implemented in Europe, Latin America and most recently in Africa as well as some other countries. The number of countries implementing auctions is still growing (IRENA, 2019; Wigand et al., 2016). Table 1.1[2] lists some of the countries which implement auctions as well as the year of the first auction. In Europe REs are mostly supported to replace conventional power plants while in Latin America and Africa REs are required to meet the increasing electricity demand (IRENA, 2019).

The principle of auctions for RE support is similar across most implementations. The auctioned good is a predetermined amount of energy (MWh) or capacity (MW). Those bidders are awarded that supply this good at lowest support costs. The support payment is guaranteed for a given time period or amount of energy. Usually, there are other benefits for the supplier besides the support payments, e.g. feed-in priority or grid connection.

The convergence to auctions in Europe was caused by a decision of the European Commission on state aid in the context of REs. From 2017 onward member states of the European Union (EU) have to implement competitive mechanisms, i.e., auctions, to support REs (European Commission, 2014b). This decision had great impact not only on the energy legislation in EU countries but also beyond as further countries benefited from public awareness and experiences with auctions in the EU.

Germany adapted its RE legislation in 2016 (Deutscher Bundestag, 2016). The Renewable Energy Sources Act (EEG) supported REs with an administratively set FiT from 2000 on. The support amount was al-

[2]This table is based on the data from the AURES II (`http://aures2project.eu/`) project.

Table 1.1: Summary of selected countries conducting auctions for RE support.

Country	**Eligible technologies**	**Year of introduction**
Brazil	Wind	2009
	PV	2014
China	Wind	2003
	PV	2016
France	PV	2012
	Wind	2017
Germany	PV	2015
	Wind	2017
	Wind offshore	2017
Great Britain	Multi-technology	2014
India	PV	2010
	Wind	2017
Italy	Wind	2012
Mexico	Multi-technology	2015
The Netherlands	Multi-technology	2011
	Wind offshore	2016
Saudi-Arabia	PV	2017
Slovenia	Multi-technology	2016
South Africa	Wind	2011
	PV	2011
Spain	Multi-technology	2016

ways controversial (Plickert, 2013). With the change of legislation, from 2017 on all RE suppliers were obliged to participate in auctions to receive support.[3] Already before this, there were six pilot auctions for ground-mounted PV plants in 2015 and 2016.

Although the recent success and proliferation of auctions, early experiences were rather disappointing. In the United Kingdom (UK) and Ireland the realization rates, that is, the share of awarded RE projects that were actually built, was very low (Menanteau et al., 2003), while in Brazil the realization period, that is the time between award and actual grid connection, was very long (Bayer et al., 2018). Those experiences proved the challenges of auctions for REs and that there is no one-size-fits-all auction

[3]Small RE suppliers are exempt from this legislation and still receive an administratively set FiT. However, the amount of support is adapted according to the results of recent auctions.

design.

There is a large variety of design elements in auctions for RE support around the globe. One main distinction between the different auctions is the choice of participation conditions for different technologies. Some countries implement only technology-specific auctions where in each auction only one RE technology can participate. Other countries implement multi-technology auctions where two or more technologies participate. Those auctions are sometimes referred to as technology-neutral auctions although real technology-neutrality is rarely achieved (Kreiss, 2019). In multi-technology auctions, it is common to discriminate the different technologies either deliberately to achieve the respective targets or unintentionally if the circumstances do not allow otherwise. For example, if due to the environmental legislation the required permits for different technologies may differ significantly.

Further distinctions in the auction design affect geographical differences and the participants of the auctions. In some auctions there are restrictions for some geographical areas based on, e.g. grid restrictions. It is also not uncommon to favor some specific bidder groups, e.g. citizen energy projects (Lundberg, 2019). A more recent trend for auctions for RE support is the opening of the support schemes for participants from different countries (Kitzing and Wendring, 2016). The actual implementation can be diverse. Either one country opens the auction unilaterally or both countries open them mutually (von Blücher et al., 2019).

Although the actual design of the auctions is diverse, there are three overall auction targets that each country prioritizes differently. (1) Auctions shall reduce the costs of RE support as the FiT is not set administratively anymore but determined through competitive market mechanisms. (2) This market mechanisms guarantee an efficient support, that is those projects are awarded that require least support in order to produce a given amount of RE. And (3), auctions enable a quantity control of RE expansion. The auction volume determines the number of supported RE and, thus, the RE expansion can be controlled with respect to budget constraints, RE expansion targets or grid expansion requirements (del Rio and Cerdá, 2014; Mora Alvarez et al., 2017b; Haufe and Ehrhart, 2018).

Particular political challenges for the design of auctions for RE support accompany those targets. This thesis will highlight the conflicts between the three main targets which cannot be resolved. As bitterly experienced in the first auctions, non-realization of awarded projects is a major risk of the RE expansion and, thus, hampers target achievement. Then, the opening of the auctions for different technologies and/or participants from different countries is a particular challenge for a fair auction design. Finally the prospective energy market design and the integration of RE is a challenge of the future.

1.2 Auction-theoretic background

Auctions are a popular market mechanism when public resources are sold, e.g. oil and gas leases (Capen et al., 1971) or spectrum licenses (McMillan, 1995; Cramton, 1997). As another example, the EU CO_2 emission trading system has already applied market mechanisms to reduce and control CO_2 emissions for years (Ehrhart et al., 2005; Ellerman et al., 2015). There is also a wide range of procurement auctions, either in the public sector, e.g. for investments in infrastructure and in the private sector where industrial procurement auctions play a big role in awarding huge supplier contracts (Spulber, 1990; Herbsman et al., 1995).

All those implementations vary widely with respect to the auction design. In reference to Haufe and Ehrhart (2018) in this thesis I will concentrate on auction designs that satisfy the following basic principles:

1. All bids are binding.
2. The *best* bid wins.[4]
3. All awarded bidders receive a payment higher than or equal to their bid.

The following section will provide insights in the game-theoretic background of auctions for RE support. Technological, political or economical disruptive events are only some more (external) factors that have an influence on the auction outcome and the bidder behavior, but these are out of scope of this thesis and will not be analysed. Examples, therefore, are changing balancing power requirements or an accelerated coal phase-out.

1.2.1 Auction format

From an auction-theoretic perspective there are specific characteristics of auctions for RE support. First, those are procurement auctions where the state does not sell a good but buys one. In this case, the state buys renewable electricity that either replaces or obviates electricity from conventional electricity sources. The procured good is usually either capacity or energy and, thus, a divisible good. Depending on the size of the auction it is either common or inevitable that multiple bidders are awarded.[5] Thus, most auctions for RE support are multi-unit auctions. To determine the number of awarded bidders it is essential to know the size of the respective projects and, thus, the bidders have to submit price-quantity-bids. That is, the bidders do not only have to state the bid price but additionally the

[4] And the rules what is regarded as *best* bid are determined ex-ante.

[5] One exemption are auctions for offshore wind were usually one particular site and, thus, only one bidder is awarded.

size of the planed project in case of award. Unless otherwise specified the demand from the different potential suppliers is considered homogeneous.

For multi-unit auctions there exist variations of the common pricing rules for single-unit auctions. The two most common ones with respect to RE auctions are discriminatory price (DP) auctions[6] and uniform price (UP) auctions. In the standard independent private value (IPV) auction model with single project bidders, the equilibrium bidding strategies in both pricing rules yield the same outcome with respect to prices and allocation (Weber, 1983; Engelbrecht-Wiggans, 1988). However, in real world application other conditions apply. For instance, bidders potentially participate with more than one project and, thus, the results may be inefficient (Vickrey, 1961; Ausubel et al., 2014).

The RE auction format has further special characteristics. The auctions are conducted periodically. However, it is not a sequential auction in the proper sense. If a project is awarded it cannot participate in any further auction. If a project is not awarded in an auction it may participate in a future auction conditionally on the limited validity of all required permits. That is, some bidders may participate in subsequent auction with the same or different projects, some bidders may stop participating and some may start bidding in future auctions so that there is no common set of bidders for subsequent auctions

1.2.2 Characteristics of participants

Not only the auction format but also the bidders feature some special characteristics. Two of those characteristics require special attention. First, the project costs between bidders are not completely independent but – depending on technology and other factors – there are common cost and value components. The costs of RE projects are highly depending on tech-

[6] DP auctions are sometimes referred to as pay-as-bid (PaB) auctions.

nology and raw material costs, that is the costs for PV modules and wind turbines are similar for all projects (European Commission, 2016; Yu et al., 2017). On the other hand – depending on the remuneration type – the revenue of each project is depending on the electricity spot market price (see Section 1.2.3). Due to the time lag between auction, realization and operation of the RE plants, there exist not only common costs and values but those cost and values are partly uncertain. That is, in the context of RE auctions the IPV model does not apply but the interdependent values (IV) auction model (Wilson, 1969).

The participant composition is another important factor. If there are different technologies or bidders from different countris competing in one auctions, or if bidder groups of the same technology or country are heterogeneous, e.g. due to different sizes, geographical regions or ownership structures, then the bidders are considered asymmetric. A set of asymmetric bidders also has an influence on the bidding behavior and auction outcome (Maskin and Riley, 2000). This is not only true from an auction-theoretic perspective but also from a political perspective as there are more different groups of stakeholders involved. The higher the heterogeneity of bidders the more potential for discrimination in auctions. This work will elaborate this topic in more detail in Chapter 3.

1.2.3 Framework conditions

Besides the auction format and the participants characteristics this work analyzes further influencing factors on the auction. In the context of auctions for RE support there is a time period between conduction of the auction and realization of the project in which the RE plants have to be built. However, the bidders have to prepare their projects even before participating in the auction. For example, they have to obtain the required permits to realize the project, negotiate contracts with suppliers or carry out feasibility studies. However, if they are not awarded the costs to prepare the projects are sunk. A rational bidder factors those costs in when deciding to take part in an auction.

The auctioneer sets the prequalification requirements and, therefore, indirectly affects the auction outcome. The same holds for any kind of penalty in case of non-realization or project delay. By considering the respective probabilities and consequences bidders price a potential penalty in when deciding on their bid. However, prequalification requirements reduce project uncertainties and increase the probability of a timely project realization. Chapter 2 will elaborate on this topic.

Another important auction design choice is the remuneration type. In most cases the FiT is actually a feed-in-premium.[7] That is, the RE supplier receives a support payment on top of the wholesale market price of the produced electricity. A crucial difference is the question whether this premium is fixed or sliding and in case of a sliding premium whether it is symmetric or asymmetric. The auction result is usually referred to as support level but the meaning for the RE supplier is significantly influenced by the type of remuneration. The principles of the most common types of feed-in premiums are illustrated in Figure 1.1.

If the remuneration is a fixed feed-in-premium (c) then the support level is essentially a predetermined payment per unit of produced electricity that a RE supplier receives independent of the additional revenue from the electricity wholesale market price. If the feed-in-premium is sliding, then the RE supplier receives the difference between the electricity wholesale market price and the support level as additional payment. The differences between symmetric (a) and asymmetric (b) arise if the wholesale market

[7] Nevertheless, in this work the term FiT is used to generally describe the support payment independent of the actual implementation if not stated otherwise.

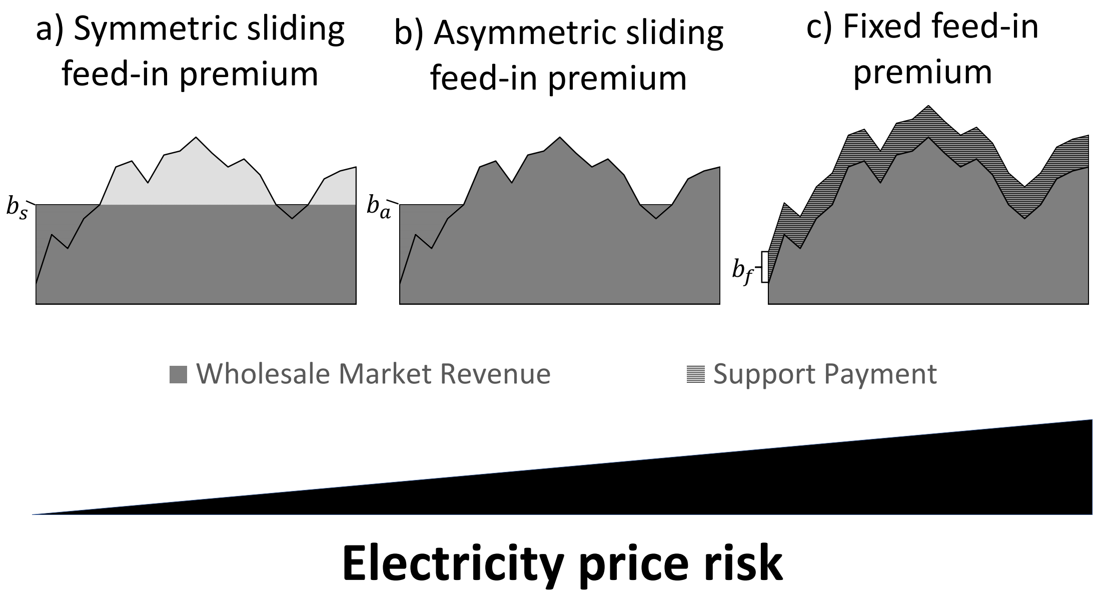


Figure 1.1: Illustration of the most common remuneration types.

price is higher than the support level. In the symmetric case the RE supplier has to pay back the overcompensation, in the asymmetric case not. There are further differences and details, e.g. grid connection costs and feed-in-priority to distinguish remuneration types. However, the major difference is to what extent bidder face the electricity market risk. This is highest under a fixed feed-in-premium and lower than under a sliding feed-in-premium (Kitzing and Ravn, 2013). This work does not further detail the implications of the remuneration type.

1.3 Objective

The recently increased interest in climate change awareness requires an objective foundation of the discussion. A cornerstone of climate change mitigation is the energy transition and the expansion of REs. This work aims to contribute to this discussion by connecting theory and practice.

The energy transition requires the interaction and cooperation of many stakeholders: research and development of new technologies in universities and companies, investors and banks to back the project developers, construction and operation of the RE plants as well as new grid connections to name only some of them. Even more, every taxpayer and electricity consumer is directly or indirectly affected. There is a high expectation that policy makers create suitable framework conditions. Additionally, all stakeholders have a self-interest to influence the energy transition in their favor.

Therefore, it is important to answer the raised questions scientifically and unbiased. In the literature, there is research on political and technical issues regarding RE support and the energy transition and the auction-theoretic literature concentrates on other application fields or is more general. Hence, the link between auction theory and the field of auctions for RE support is a gap in the existing literature. This work takes up questions from practice and analyzes them auction-theoretically. The results of the analyses are processed in order to translate them into policy implications. Thereby, it is not only a goal to deliver theoretical results but to provide important practical insights and to contribute to the ongoing political discussion.

1.4 Approach

The covered research questions in this thesis are real-world issues regarding the implementation of auctions for RE support and those are analyzed through a combination of different approaches. The respective situations are modeled abstractly and theoretical analyses are applied. Thereby, this thesis applies game-theoretic solution concepts and extends them with an agent-based model (ABM), a thorough policy analysis and a laboratory experiment.

A main concern regarding the implementation of auctions for RE support is the potential of non-realization and project delays (Mitchell and Connor, 2004; Held et al., 2014; Bayer et al., 2018). To prevent this risk, auctioneers require physical and financial prequalifications and implement penalties. This, however, comes at a price. While prequalifications reduce cost uncertainty it also means that bidders have to invest in their projects prior to the auction and, thus, before they know whether their projects are awarded or not. It is therefore crucial to find the right balance between prequalification requirements, sunk costs and realization rates. Chapter 2 auction-theoretically analyzes the implications of penalties, physical and financial prequalifications on the auction outcome from the perspective of both, the bidders and the auctioneer.

Chapter 3 applies an auction-theoretic analysis of discriminatory design elements in the field of auctions for RE support and combines it with a thorough policy analysis. Such instruments are a bonus for a particular group of bidders, different maximum prices depending on the bidders characteristics or minimum and maximum quotas. All instruments favor one or several particular groups of bidders. An analysis of discriminatory design elements is important due to the increased number of auctions open to different bidder groups, for example for different technologies. The analysis thereby contrasts the auction-theoretic results with the actual political targets and elucidates the trade-offs between different targets. Further, it compares the discriminatory design elements with respect to their robustness to misestimations in a simplified model.

Chapter 4 provides insights into an actual auction implementation. A combination of auction theory and ABM enhances the understanding of auction outcomes. The actual data of six auctions for ground-mounted PV plants in Germany in the years 2015 and 2016 is fed into an ABM. The behavior of the agents is modeled with respect to auction theory. Through this approach it is possible to conduct a backward analysis to understand the auction results and to further analyze some *What if* cases.

In Chapter 5 the auction-theoretic analysis of multi-unit common value (CV) auctions is complemented by an experimental study. This thesis extends the existing literature for CV auctions by a systematic comparison of different auction formats in combination with different competition levels. The different competition levels are modeled through a different number of demanded goods and, therefore, the CV theory is complemented for multi-unit auctions. The analysis finds a stark difference between theoretical and experimental results. This thesis provides three main explanations for those differences.

The thesis concludes in Chapter 6. Here, overarching conclusions and implications are drawn from the results of the analyses, and an outlook for further directions of research is presented.

Chapters 2 to 5 are based on four papers, which have been edited slightly for consistency and coherence in this thesis. Table 1.2 illustrates the authors, title and reference for each paper.

Table 1.2: Overview of the papers prepared for this thesis.

Chapter	Authors	Title	Reference
2	Jan Kreiss, Karl-Martin Ehrhart, Marie-Christin Haufe	Appropriate Design of Auctions for Renewable Energy Support – Prequalifications and Penalties	Kreiss et al. (2017)
3	Jan Kreiss, Karl-Martin Ehrhart, Marie-Christin Haufe, Emilie Rosenlund Soysal	Different cost perspectives for renewable energy support: Assessment of technology-neutral and discriminatory auctions	Kreiss et al. (2019)
4	Marijke Welisch, Jan Kreiss	Uncovering bidder behaviour in the German PV auction pilot – Insights from agent-based modelling	Welisch and Kreiss (2019)
5	Karl-Martin Ehrhart, Jan Kreiss	Multi-unit common value procurement auctions -– theoretical and experimental analysis	Ehrhart and Kreiss (2019)

Chapter 2

Appropriate design of auctions for renewable energy support – prequalifications and penalties

A key driver for auctions for RE support is the efficient and cost effective achievement of RE expansion targets. Therefore, this chapter focuses on the task of designing auctions for RE support as a means of contributing to the fulfillment of RE targets. Here, the problem of non-realization comes to the fore, which is considered to be one of the main risks in auctions for RE support, particularly concerning the expansion target and the acceptance of auctions for RE support (del Rio and Linares, 2014).

We auction-theoretically analyze, the influence of different measures on the non-realization risk. From a theoretical point of view, this risk only arises if bidders are uncertain about their project costs. In the case of solar power systems, for example, the future PV module price, which is a crucial cost component, is uncertain due to fluctuations and political decisions (European Commission, 2016). Another relevant cost component, the costs of capital, is also uncertain, especially in the current political and economic situation in Europe (Francis et al., 2014).

2.1 Definitions

We analyze the designated measures to ensure realization: financial and physical prequalifications and penalties. A financial prequalification is a payment a bidder has to deposit before the auction or after the award. This payment is regarded as security. The bidder regains it if he is either not awarded or realizes his project in time.

Physical prequalifications are project specific requirements the bidders have to fulfill in order to participate in the auction. These requirements reduce the bidders' uncertainties. Examples are a land-use plan or a feasibility study. An essential characteristic of physical prequalifications is that bidders have to conduct them in any case to realize their project. The auctioneer might force the bidders to comply with these requirements before the auction. But then the costs of the bidders to meet these requirements are sunk. Thus, a bidder has to decide whether he fulfills the prequalifications and participates in the auction or not. There exist other qualification criteria, which are not related to a specific project but to the bidder. Examples are past experiences with the bidder or technological know how. We consider those criteria as access requirements rather than prequalifications.

Penalties are a measure taken by the auctioneer to punish awarded bidders in case of non-realization or delay. Examples are a lower support level, a shortened support period, a termination of the contract, and an exclusion from future auctions (Held et al., 2014). In contrast to prequalifications, a penalty may become effective only after award. While a penalty involves the risk of a future expense for a bidder, a financial prequalification involves the risk of not regaining a past expense.

These measures are usually included in auctions for RE support, but there is no general understanding of how they affect bidding behavior and

Table 2.1: Selected examples of conducted RE support auctions in reference to Mitchell (1995), Pollitt (2010) and Wigand et al. (2016).

Country	**Germany**	**UK**	**California**	**Netherlands**	**France**	**Brazil**
Year of Introduction	2015	1990-2001	2011-2015	2011	2011	2007
Technology	PV	multi-technology	multi-technology	multi-technology	PV	biomass, PV, wind/multi-technology
Price Rule	DP / UP	DP / UP	DP	DP	DP	DP
Physical Prequalification	yes, early auction	yes, early auction	yes, late auction	yes, late auction	yes, late auction	yes, late auction
Financial Prequalification	bid bonds (50€/kW)	no security, project must meet 'normal standards'	development deposit ($20/kW), performance deposit (5% lifetime revenue)	no security, bank statement for huge projects	no security, evidence of capital	bid bonds (5% investment)
Penalty	Reduction of FIT			loses support right, exclusion for 3 years, fine for huge projects	support duration reduced	end of contract, penalty payment for underproduction
Realization Period	18-24 months	not specified	18-36 months	3-4 years	18 months	1-5 years
Realization Rate	> 90%	~ 30%	> 75%	depending on year from 11% to 100%	< 50%	low, ~ 30% on time

the auction outcome and how they interact. This chapter provides an auction-theoretical analysis of the effect of these particular measures, with the intention of assisting auctioneers regarding the appropriate design of an auction in order to achieve the predefined targets.

Auctions for RE support are often conducted as multi-unit auctions in the form of static sealed bid auctions either with DP or UP. We conduct our analysis to single-unit auctions, where we consider the first-price and second-price payment rule. This simplification facilitates the identification and illustration of effects and the derivation of results, which can be transferred to the multi-unit equivalent.

Table 2.1 summarizes the key design criteria and results of RE support auctions in different countries where realization rates are available. The characteristics of the auctions in the different countries do not lend themselves to direct comparison because auctions designs are highly context specific. The physical prequalifications are especially diverse. For example, a construction permit in one country does not have the same cost implication or legal meaning as in another. Therefore, we only distinguish between cases in which the auction is early in the project development process, and those in which it is late. This timing acts as a means of qualitatively describing the level of physical prequalification. The level of financial prequalification can be compared more directly. In Brazil, California and Germany the securities have a similar value, at about 5% of the expected investment or revenue. In the other countries there were no financial prequalifications. The type of penalties was also very different between the auctions. Either the support was decreased (e.g. in Germany by 0.003 €/kWh per year) or the particular bidder was excluded from future auction rounds (e.g. in the Netherlands).

Some general conclusions can be drawn. The project realization rate is often quite low. There is probably not only one reason or design criteria responsible for this apparently poor performance. For the auctions in the UK (Mitchell and Connor, 2004) and in France (Held et al., 2014) the low financial prequalifications are considered are thought to have been the main reason for the low realization rates. It is a different story in Brazil, where many awarded projects could not be realized in time due to the unavailability of grid connections (IRENA and CEM, 2015). The physical prequalifications could be said to have been insufficient. IRENA and CEM (2015) and Kopp et al. (2013) show also other examples for RE support auctions worldwide. In general, the implementation and enforcement of financial and physical prequalifications cannot be seen as standard in RE support auctions.

The remainder of this chapter is organized as follows. Section 2.2 introduces a general auction-theoretic model. Based on the model, Section 2.3

analyzes the effects of the three measures (financial prequalification, physical prequalification, penalties) and motivates the transfer of the results to multi-unit auctions. Section 2.4 concludes and assesses our results in order to provide assistance for policy makers in the auction design process.der characteristics.

2.2 Model

A RE support auction is a procurement mechanism for energy or capacity in which bidders with different production plants compete for an award. The awarded bidders will receive a financial support, the level of which is derived from the bids in the auction.

For our analysis, we make use of the IPV approach (Vickrey, 1961) with an additional common cost parameter. There are n ex ante symmetric bidders, who are risk-neutral, i.e., they maximize their expected profit. The bidders are characterized by individual cost parameters $\theta_1, ..., \theta_n$, which represent their expected project costs. These costs depend on different factors as the technology (e.g. PV or wind turbine) and the location (i.e., the expected solar radiation or wind strength). For comparability, θ_i can be expressed as bidder i's expected project costs allocated to the expected amount of energy the plant will produce during its lifetime or the support period respectively. The individual cost parameters $\theta_1, ..., \theta_n$ are private information and are modeled as independent realizations of the random variable Θ, which is distributed on the interval $\left[\underline{\theta}, \overline{\theta}\right]$.

Besides the individual costs, there are cost uncertainties that affect all bidders in the same way, such as the future development of material costs, e.g. PV module prices (European Commission, 2016), capital costs (Francis et al., 2014), and possibly the cost of obtaining social and environmental permits. The uncertainty of these costs is captured by the random variable S with distribution G on the interval $[-\bar{s}, \bar{s}]$ and an expected value of zero, i.e., $\mathrm{E}[S] = 0$. The random variable S is the same for all bidders, but its realization s is unknown prior to the auction. The common cost parameter s is drawn after the auction and only matters for the winning bidder.

The cost function $c(\theta_i, s)$, which is assumed to be the same for all bidders, captures bidder i's total costs to realize his project and increases in the two cost parameters θ_i and s. Throughout this chapter in all illustrations and the referring explanations we use the linear cost function $c(\theta, s) = \theta + s$ and a uniformly distributed random variable S on $[-\bar{s}, \bar{s}]$.

In the following, we analyze a RE support auction in which one plant is awarded. The auctioneer sets a reservation price (i.e., maximum price) r, which caps the possible bids. We consider the two main single-unit sealed bid auction formats, the first-price auction and the second-price auction. In both formats, the bidder with the lowest bid wins the auction. In the first format, he receives the price he bid, whereas in the latter format, he receives the price of the second lowest bid (McAfee and McMillan, 1987). In Section 2.3.4 we transfer the results to multi-unit auctions, in which several plants are awarded. Since in our auctions plants are awarded, the findings are valid independently of whether the auctioned good is capacity or energy.

Since all bidders are ex ante symmetric, we consider a representative bidder. Let p denote the award price of the auction. Then, the profit of the winning bidder is

$$\pi(\theta, s, p) = p - c(\theta, s). \tag{2.1}$$

Depending on s, the winning bidder's profit might become negative, i.e., the bidder suffers a loss if realizing the project.

2.3 Analysis

2.3.1 Financial prequalifications (securities)

Financial prequalifications are widely used in auctions for RE support, particularly in the form of a security, which has to be deposited before the auction or at the point of award. In the case of non-realization of the awarded project, the auctioneer retains the security (Bundesministerium für Wirtschaft und Energie, 2015). The purpose of these requirements is twofold. On the one hand, they aim to ensure the financial capacity of a bidder to realize the project in the event that support is awarded. On the other hand, it is an enforcement mechanism to ensure that the winning bidder realizes his project (Held et al., 2014; Klessmann et al., 2015).

To model financial prequalifications auction-theoretically, we refer to the work of Waehrer (1995), which was extended by Parlane (2003) and Board (2007). The model introduced in Section 2.2 is thereby augmented by the non-realization option.

Let t_v denote the monetary value of the security, $t_v \geq 0$. If the bidder does not realize the project, the auctioneer will retain the security and the bidder suffers a loss of $-t_v$. If s turns out to be high, the bidder might choose the option not to realize. Then, the auctioneer will retain the security t_v. With this extension the bidder's profit is[1]

$$\pi_D(\theta, s, p, t_v) = \max\left\{p - c(\theta, s), -t_v\right\}. \tag{2.2}$$

With the security the bidders insure themselves against high losses. They eliminate all cases where the project realization is more expensive than not regaining the security. If the security is equal to zero, the bidders do not face any risk of losing money. A high security induces bidders to

[1] Since a rational bidder accounts for timing of payments and costs in his bid, the timing does not affect our findings in principal. Therefore, for the sake of simplicity and illustration we neglect the timing of payments and costs, which is an usual approach in auction-theoretical analyses.

accept a higher loss through project realization than a lower security.

If the combination of the award price p and the common cost component s is such that the profit from realizing the project $p - c(\theta, s)$ is lower than the costs of non-realization $-t_v$, according to (2.2) the bidder will not build the project. The probability that this case occurs decreases in p. If the award price is sufficiently high (i.e., $p > c(\theta, \bar{s}) - t_v$) the awarded bidder will always realize, independent of s. In general, the realization probability depends on the distribution of the uncertain cost parameter S, its impact on the cost function c, the value of the security t_v, the competition level and the auction format.

Figure 2.1 illustrates the impact of the award price on the realization probability. It displays two different cases with high t_h and low t_l values of the financial prequalification. As S is uniformly distributed, the realization probability is linear in the award price p. Note that the general effects are independent of the specific value of t. First, for all award prices $p < c(\theta, -\bar{s}) - t_v$, the bidder never realizes. Even with the best realization of S as $-\bar{s}$, the costs of non-realization are lower than the costs of realization, $-t > p - c(\theta, \bar{s})$. Second, the other extreme is given by $p > c(\theta, \bar{s}) - t_v$, where the bidder always realizes. Third, in between these two boundaries, the bidder realizes whenever it is best for him, i.e., if $p - c(\theta, s) > -t_v$. Thus, the realization probability increases in the award price p.

The non-realization option also affects bidding behavior. Without this option, the bidders bear the full risk of the uncertainty in S. That is, a winning bidder has to complete the project, even if S realizes as $\bar{s}$ and this induces a big loss. Rational bidders account for this risk in their bidding strategy. In this scenario, the non-realization risk is zero. The corresponding profit function in case of winning is given by (2.1). For every type θ, the expected profit of the winning bidder is linear in the

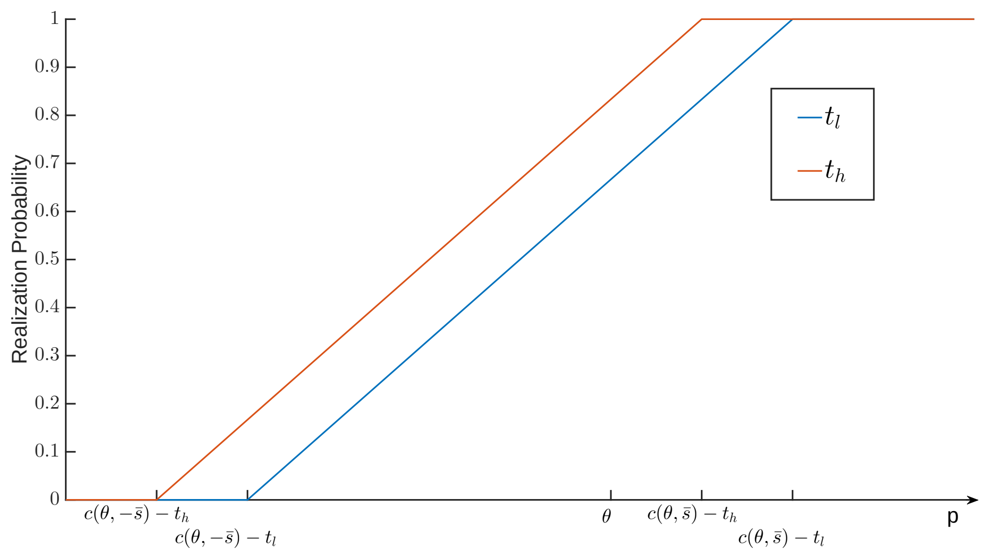


Figure 2.1: Impact of the award price p on the realization probability for two different financial prequalifications t_h and t_l.

award price p.

Figure 2.2 illustrates the two scenarios with and without the non-realization option in reference to Parlane (2003). The dashed line corresponds to expected profit of the winning bidder in the scenario without the option, where the bidder has to realize. Here, the expected profit increases linearly in the award price and is zero for $p = \theta$.

The graph looks different in the scenario with the non-realization option (solid line in Figure 2.2). For all award prices $p < c(\theta, -\bar{s}) - t_v$, the bidder never realizes. Thus, the left part of the graph is horizontal at $-t_v$. For $p > c(\theta, \bar{s}) - t_v$, the bidder always realizes. Thus, the graph corresponds to the dashed line. In between these two cases, the realization probability increases in p, which induces the convex shape of the expected profit curve.

In order to assess the effect of different values of financial prequalification, we compare two different security values, a low value t_l and a high value t_h, $t_l < t_h$. The effect that different securities have on a bidder's

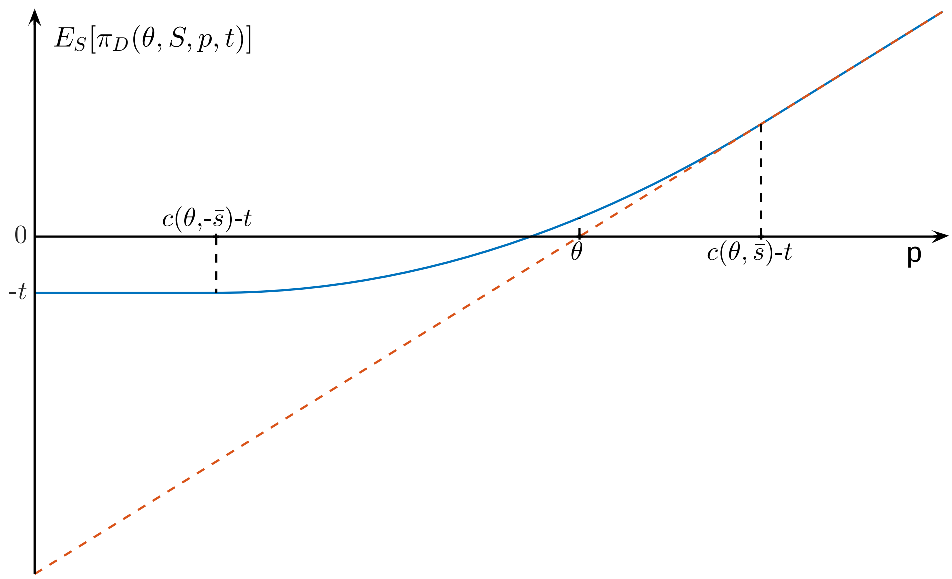


Figure 2.2: Expected profit of the awarded bidder for a given θ, in reference to Parlane (2003), Figure 1.

realization probability subject to the award price p is illustrated in Figure 2.1. The curves are parallel shifts of each other. A higher security leads to a left shift, a lower to a right shift bidders will realize their projects with a higher probability in case of the higher security t_h. The reason is, that the bidder accepts a bigger loss (equal to the value of the security) before he chooses not to realize.

What is the impact of the non-realization option on bidding behavior and the auction outcome? In the scenario without the option, bidders face a higher risk of loss induced by a high realization of S. With the non-realization option, this risk is smaller because bidders have the opportunity to avoid the negative consequences of high s (depending on the value of $-t$). Since bidders incorporate their loss risk, they submit higher bids if the risk is higher. Hence, independently of the auction format, the non-realization option induces bidders to submit lower bids (Parlane, 2003; Board, 2007).

Independently of the auction format, lower bids lead to a lower award price and a lower award price increases the probability of non-realization (Figure 2.1). That is, the non-realization option per se increases the non-realization risk.

We illustrate this by means of the second-price auction. In both scenarios, it is a weakly dominant strategy (with respect to the expected profit) to submit a bid $\beta^{SA}(\theta)$ so that the expected profit of winning the auction at $p = \beta^{SA}(\theta)$ is zero, i.e.,

$$E_S\left[\pi_D(\theta, S, \beta^{SA}(\theta), t_v)\right] = 0. \tag{2.3}$$

It is obvious that $\beta^{SA}(\theta)$ positively depends on θ. In both scenarios, $\beta^{SA}(\theta)$ is determined by the intersection point of the respective expected profit function and the x-axis (Figure 2.2). Hence, the non-realization option reduces the award price and, thus, increases the non-realization risk compared to the virtual situation, in which the bidders bid as they were in the scenario without the non-realization option. This also holds for the first-price auction.[2]

Figure 2.3 illustrates the effects of two different securities on bidder's expected profit (all other variables stay the same). The solid blue graph illustrates the scenario with the low security t_l, the solid red graph for the high security t_h, and the dashed line the scenario with enforced realization. Obviously, the difference between the red and the dashed graph is much smaller than between the blue and the dashed line. Also the gap starts to open at a lower level of p. The reason is that a higher security induces a higher risk. A winning bidder will lose more money if he does not realize

[2]Note that a higher competition level induces a lower award price and, hence, a higher non-realization risk. This holds independent of the auction format.

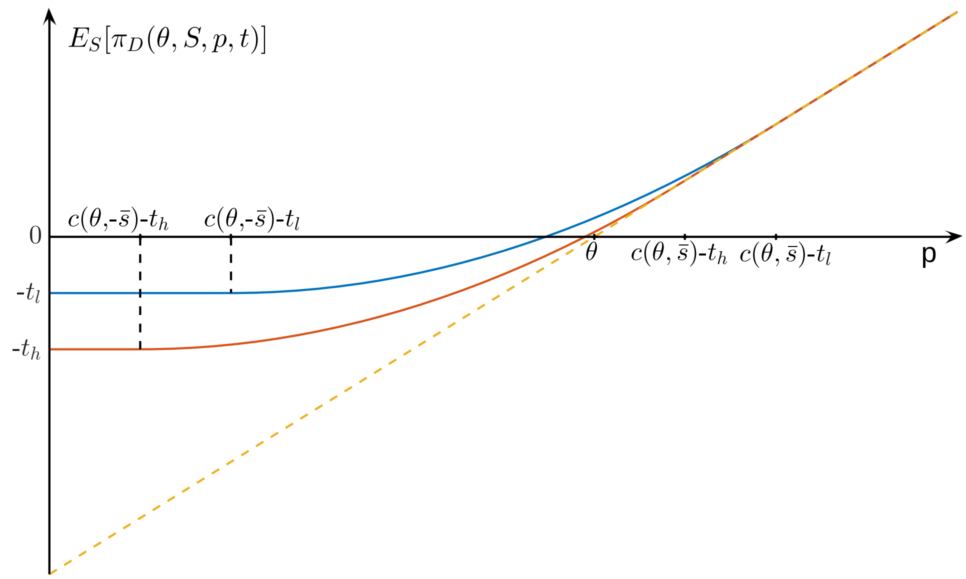


Figure 2.3: Expected profit of the awarded bidder for a given θ with different financial prequalifications t_l and t_h.

the project. As a consequence, the bidder is willing to accept a higher loss through realizing the project than in the case of lower security.

Bidders incorporate the higher risk in their bids, which leads to higher bids. This can be seen in the simple example of the indifference price, which is the award price at which the bidder is indifferent between winning and losing the auction because his expected profit, given this award price, is zero. In a second-price auction, a bidder exactly submits the indifference price as his bid, which is indicated by the intersection of the respective graph and the x-axis in Figure 2.3. The greater the risk is, the higher the indifference prices. In general, higher securities lead to higher realization rates but also to higher expected award prices.

Combining the results, illustrated in Figure 2.3, we conclude that with higher securities the award prices increase and the positive effect on the realization probability is reinforced, as higher prices lead to higher realization probabilities.

Next, we compare the two auction formats with respect to the expected award price and the non-realization risk. In the standard IPV model, the second-price auction and the first-price auction lead to the same expected award price (Revenue Equivalence Theorem (McAfee and McMillan, 1987)), which also applies to procurement auctions. This also holds if we introduce a uncertain common cost component S.

However, the equivalence of expected award prices no longer holds if the bidders have the non-realization option at cost $-t_v$. The expected award price and, thus, the bidders' expected profits are higher in the first-price auction than in the second-price auction (Parlane, 2003; Board, 2007). This is due to the effect that the non-realization option induces risk-neutral bidders to behave as they were risk-loving in an IPV framework without the option. This is expressed by the convex shape of the expected profit function (Figure 2.2). In an IPV framework without the non-realization option, risk loving bidders submit higher bids than risk-neutral bidders in the first-price auction but they submit the same bids (weakly dominant strategy) in the second-price auction. Hence, risk-loving leads to a higher expected award price in the first-price auction but not in the second-price auction. Therefore, in the framework with the non-realization option, the expected award price in the first-price auction is higher than in the second-price auction. This also implies that the winning bidder has a higher expected profit in the first-price auction compared to a second-price auction.

In Germany, where the auction format for ground mounted PV changed between UP and DP in the first four auctions, differences in the outcomes of the two auction formats cannot be identified. Although the realization rates are lower under UP than under DP, the differences are only minor.

The main reason is that the auction process has just started and it appears that the process is not yet settled as the prices are still decreasing significantly independent of the auction format.

Since the realization probability is positively related to the award price, the realization probability is lower in the second price auction than in the first-price auction. Furthermore, the differences between the two auction formats with respect to award price and non-realization probability can be significant (Board, 2007).

2.3.2 Physical prequalification

In the context of auctions for RE support, physical prequalification criteria are defined as requirements that all potential bidders must fulfill in order for a bid to be acceptable. Examples are a feasibility study, a land-use plan, a construction permit or further country specific permits (Minister van Economische Zaken, 2015; Bundesministerium für Wirtschaft und Energie, 2015). The reason for these requirements is to ensure serious bids (del Rio and Linares, 2014). Physical prequalifications do seek to ensure that bidders are capable of realizing their projects. Instead, it is a guarantee for the auctioneer that the bidders are 'serious' and genuinely intend to realize their projects and that they are confident that this is possible within the auction criteria (location, time frame, etc.).

Most of the costs that occur through the prequalification requirements accrue in the course of project realization, independent of whether an auction is conducted. For example, the bidders are required to have a construction permit if they aim to build a PV installation on the roof. As those costs accrue prior to the actual auction they are considered as sunk costs. If a bidder is not awarded in the auction, he might halt the development process. In this case, the bidder has no benefit from the previous investment.

Since physical prequalifications are usually activities bidders must perform regardless of the existence of an auction, they do not generate additional costs. But they may reduce bidder's uncertainty regarding future costs and project feasibility. A construction permit is a good example. The expected costs for the permit itself may be known, but it is unknown if all requirements for this permit are met. If not additional costs might be incurred to meet the requirements or it might transpire that the project is not feasible at all. However, physical prequalifications are only worthwhile if the bidder realizes the project, otherwise these costs are sunk, e.g. the bidder is not awarded or decides not to realize the project after the award.

In the following, we analyze the impact of physical prequalifications on bidding behavior, the auction outcome and the realization probability. We assume that all bidders conduct the same physical prequalifications, which results in sunk costs. Further, we assume that conducted physical prequalifications reduce the level of cost uncertainty.

As before, bidder's costs are modeled by the additional uncertain component S with distribution G on the interval $[-\bar{s}, \bar{s}]$ and $\mathrm{E}[S] = 0$. That is, positive and negative deviations from the expected costs are possible, as it could work better (no complications) or worse (additional measures necessary) than expected. A reduction of cost uncertainty due to physical prequalification activities is captured by the random variable S_{PQ} with distribution G_{PQ} and realization s_{PQ}.[3] Bidder's sunk costs induced by the physical prequalification activities are described by variable e. We analyze the effects of physical prequalifications in the framework set out Section 2.3.1 with the non-realization option and financial prequalifications in form of a security t. Hence, the bidder's resulting profit function in case

[3] G is a mean-preserving spread of G_{PQ} (Mas-Colell et al., 1995).

of winning is

$$\pi_E(\theta, s_{PQ}, p, t_v, e) = \max\{p - c(\theta, s_{PQ}), -t_v\} - e. \tag{2.4}$$

Figure 2.4 shows the expected profit curves of two cases that differ in the degree of uncertainty S (blue curve) and S_{PQ} (red curve). For this illustration, we use uniformly distributed random variables S and S_{PQ} on the intervals $[-\bar{s}, \bar{s}]$ and $[-\bar{s}_{PQ}, \bar{s}_{PQ}]$ with $\bar{s}_{PQ} < \bar{s}$. The red curve represents the case of reduced uncertainty due to physical prequalification activities. The dashed line represents the case with enforced realization. The difference in the degree of uncertainty leads to different shapes of the curves. The beginning and end point of both graphs are identical. However, the red curve is more bent within a shorter interval and lies below the blue curve. This results, according to the considerations in Section 2.3.1, in bidders submitting higher bids in the prequalification case with a lower degree of uncertainty, which thus yields higher expected award prices.

With a higher degree of uncertainty, a lower realization s is more probable than with less uncertainty. Hence, with higher uncertainty a positive profit is possible at a lower award price. This can be seen in Figure 2.4, where $c(\theta, -\bar{s}_{PQ}) - t_v > c(\theta, -\bar{s}) - t_v$. On the other hand, the worst case does not get worse. Even if S realizes very high and the bidder would suffer a high loss, he can choose not to realize. The costs of non-realization are the same in both cases. Thus, with less uncertainty, a bidder wins less in the best case, but faces the same risk in the worst case. As a result, he submits a higher bid. This is also revealed by the indifference price, i.e., the award price where the bidder is indifferent between winning and losing the auction. In Figure 2.4, these prices are the intersection points between the respective curve and the x-axis. The lower the uncertainty the higher

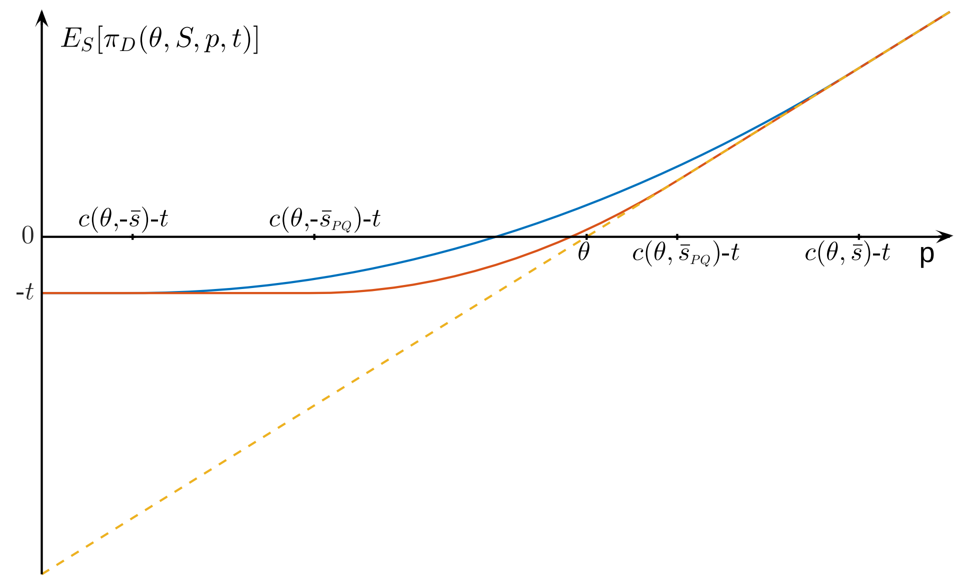


Figure 2.4: Expected profit of the awarded bidder for a given θ with different uncertainty intervals.

the indifference price, but it is still lower or equal to the indifference price without the non-realization option.

In order to analyze the effect on non-realization, one has to distinguish two cases: the realization probability is below or above 50%. Since the realization probability also depends on the financial prequalification t_v and the cost function c, the cases are analogous to award prices lower or higher than $c(\theta, 0) - t_v$.

If financial and physical prequalifications lead to a realization probability greater than (or equal to) 50%, an increase in the physical prequalification and hence a decrease in the uncertainty leads to a higher realization probability. This has two reasons. Firstly, a higher award price means that even a high realization of S_{PQ} results in a positive profit and, hence, the project will be realized. Secondly, the probability of a high realization of S_{PQ}, that induces the bidder to abandon the project, is lower than of S.

The effect of physical prequalifications on the non-realization risk is ambiguous if the realization probability is lower than 50%. On the one hand, the reduced uncertainty of S_{PQ} increases the award price, which in turn increases the realization probability. On the other hand, the reduced uncertainty of S_{PQ} induces that the probability of a low s is lower. As a result, for the same award price the realization probability decreases.

We obtain similar results if we model the uncertainty reduction of physical prequalifications by changing the shape of the distribution G and shift probability mass from the tails to the center of the distribution.

Sunk costs

Beside the effect of uncertainty reduction, physical prequalifications influence bidding behavior also in another way. As already mentioned, the costs of achieving physical prequalifications are sunk as they also accrue if a bidder is not awarded in the RE support auction.

In the auction-theoretic literature, two different types of sunk costs are considered: entry fees and participation costs. The entry fee has to be paid by all bidders in order to participate in the auction and will not be refunded after the auction (Levin and Smith, 1994; Menezes and Monteiro, 2005; Krishna, 2002). Participation costs accrue through the preparation of the bids and the participation in the auction (Menezes and Monteiro, 2000; Samuelson, 1985; Tan and Yilankaya, 2006). Both forms of costs are sunk costs. In contrast to the entry fee, the auctioneer does not directly benefit from the participation costs and they need not to be the same for all bidders. Obviously, participation costs reflect the concept of physical prequalifications in RE support auctions. We assume that the participation costs, denoted by e, are deterministic and the same for all bidders.

Before any costs incur, a bidder considers whether he wants to participate in the auction or not. A bidder will only participate, if his expected profit is non-negative. The expected profit depends on the bidder's costs (respectively his cost signal), the number of bidders (i.e., competition level), and the reservation price r (i.e., maximum price).

Costs and maximum price are essential for the bidder's expected profit in case of winning, whereas the number of competitors influences the probability of winning. Auction-theoretically, there exist specific costs $\tilde{\theta}$, which correspond to an expected profit of zero, and therefore, are called cutoff costs (Samuelson, 1985). A bidder with $\tilde{\theta}$ is indifferent between winning and losing the auction. Bidders with costs higher than $\tilde{\theta}$ will not participate in the auction. The cutoff costs $\tilde{\theta}$ are calculated indirectly by[4]

$$(r - \tilde{\theta}) \cdot \text{Prob}\{\tilde{\theta} \text{ are the lowest costs among all bidders}\} = e. \qquad (2.5)$$

The term $(r - \tilde{\theta})$ is the profit if the bidder has costs $\tilde{\theta}$ and is the only participant, which is the case if his costs are the lowest. The left hand side of (2.5) describes bidder's expected profit (without e), which has to be equal to the participation costs e, so that the total expected profit of the bidder with $\tilde{\theta}$ is zero. For costs lower than $\tilde{\theta}$, the expected profit is positive and those bidders have an incentive to participate in the auction. Thus, a bidder with $\tilde{\theta}$ knows that he will only win the auction if all other bidders have higher costs. Then, the award price p equals the maximum price r, as he is the only participant. Therefore, he bids $\tilde{\theta}$ in the second-price auction and r in a first-price auction, which leads to $p = r$ in both auction.

[4] Equation (2.5) is derived from Menezes and Monteiro (2000) who analyze sunk costs in sales auctions.

From (2.5) follows how the variables influence the cutoff costs. A high maximum price r leads to higher cutoff costs, while a high number of potential bidders and high participation costs e have the opposite effect (Menezes and Monteiro, 2005; Tan and Yilankaya, 2006). That is, high participating costs have the same effect as a low maximum price. Both exclude bidders with high costs from the auction (Krishna, 2002).

The impact of participating costs on bidding behavior is more diverse. In the second-price auction, nothing changes for participating bidders. If a bidder has costs below $\tilde{\theta}$, he truthfully bids his costs in the symmetric equilibrium. However, in contrast to the model without participation costs, this is not a (weakly) dominant strategy. Under certain conditions, asymmetric equilibria can exist (Tan and Yilankaya, 2006).

In the first-price auction, participating costs influence the bidding behavior directly. Also, a bidder only participates in the auction if his costs are not higher than $\tilde{\theta}$. A bidder with $\tilde{\theta}$ bids r and the symmetric bidding function is strictly decreasing, i.e., bidders with lower costs submit lower bids. As a consequence, fewer bidders participate, but those with lower costs (Menezes and Monteiro, 2000).

The result for the auctioneer is twofold: In the symmetric equilibrium of both auctions, the outcome is efficient, if at least one bidder participates. Participation costs exclude bidders efficiently in that sense that only the bidders with the lowest costs participate. The auction outcome is inefficient if the participation costs are so high that no bidder participates.

In both auctions, the expected award price is either equal to or higher than a case without participation costs. This result can be transferred to the auction model with the non-realization option (Section 2.2). Here, a higher award price yields a higher realization probability. This also holds if sunk costs are the reason for a higher award price.

Finally, the fact that sunk costs generate losses for non-awarded bidders may have a deterrent effect on potential participants. This will reduce competition and increase award prices. In the context of repeated auctions for RE support and time-limited project permits, bidders who have not been successful so far are more or less forced to underbid their costs in order to increase the probability of being awarded.[5] The potential for sunk cost losses may also harm the acceptance of auctions for RE support, which may hinder their future implementation.

2.3.3 Penalties

Another measure, which is often used to increase the realization probability of RE projects are penalties. In contrast to the physical or financial prequalifications, penalties do not require any effort by the bidders prior to the auction. Penalties become effective if an awarded bidder does not abide by the agreement that results from the auction award. In the context of RE support auctions, basic contents of such an agreement are the support level, the supported capacity, the support duration, and the beginning of the support. Bidders are responsible to realize the project in a given time frame.

There are different ways to penalize a breach of contract. Examples are a lower support level, a shorter support period, a termination of the agreement, or the exclusion of the bidder from future auctions (Held et al., 2014). Although not all of these measures have a directly monetary impact, all of them can be evaluated financially. Therefore, we treat penalties as monetary payments.

Penalties extend our approach such that an awarded bidder does not only lose his security in case of non-realization but also has to pay the penalty q. We do not analyze the combination of different levels of physical

[5] This is also referred as sunk cost fallacy (Wilson and Zhang, 1997).

prequalifications with penalties to reduce complexity. Hence, the resulting profit in (2.2) extends to

$$\pi_Q(\theta, s, p, t_v, q) = \max\{p - c(\theta, s), -t_v - q\}. \tag{2.6}$$

A necessary condition for a bidder to pay the penalty is that he is capable of doing so. If he is not, he will have to declare bankruptcy and lose all his assets. The assets held by individual companies can vary a great deal. Large companies will naturally have more capital than smaller project companies, which are only founded for the purpose of the specific project (Board, 2007).

Consider a representative bidder with an asset value w. There are three cases to be distinguished. First, an awarded bidder realizes the project at costs $c(\theta, s)$, receives the payment p and regains the security t. If the bidder does not realize the project, he has two options: either he pays the penalty and loses the security or he does not pay the penalty, declares bankruptcy and loses his assets and the security. As a rational bidder always chooses the option that is best for him, his profit is

$$\pi_W(\theta, s, p, t_v, q, w) = \max\{p - c(\theta, s), -t_v q, -t_v - w\}. \tag{2.7}$$

This model and the implications are related to the work of Burguet et al. (2012) and Chillemi et al. (2009).

What is the effect of penalties on bidding behavior, the auction outcome, and the realization probability? Without penalties, the value of the security is the limit for accepted losses through realization. The non-realization option at costs t prevents the bidders from high downside losses. The bidders consider this possibility in their bidding strategy and bid more aggressively, i.e., submit lower bids (see Section 2.3.1). With a penalty, the limit for losses changes to the maximum of security t_v and assets w or penalty q. Thus, individual bidding behavior also depends on the individual asset value w, and variation in companies' assets induces some bidders to underbid their cost signal more than others.

As stated in Section 2.3.1, a higher security t induces less aggressive bidding and hence higher award prices (see Figure 2.3). If all bidders face the same risk in case of non-realization, efficiency is preserved because the bidding behavior of all bidders is affected in the same way and the order of bids does not change. A bidder with lower costs (i.e., lower θ) still submits a lower bid than a bidder with higher costs (in both first- and second-price auction).

This does not hold in the case of different non-realization costs caused, for example, by different assets. Due to lower assets w and hence a lower risk, a bidder with higher costs may submit a lower bid than a bidder with lower costs. Figure 2.5 illustrates this case with the example of a second-price auction, in which Bidder 1 (blue graph) and Bidder 2 (red graph) participate. Bidder 1 has a lower asset value but a higher cost signal and thus higher realization costs than Bidder 2, i.e., $w_1 < w_2$ and $\theta_1 > \theta_2$ and thus $c(\theta_1, s) > c(\theta_2, s)$ for all s. We assume a very high penalty q that is larger than the assets of the two bidders w_1 and w_2. The bidding strategy of each bidder in the second-price auction is to bid the indifference price $\beta^{SA}(\theta)$, where $E_S\left[\pi_W(\theta, S, \beta^{SA}(\theta), t_v, q, w)\right] = 0$.

The decision of an awarded bidder concerning the realization of the project depends on the realization of S. If

$$p - c(\theta, s) > -t_v - w, \tag{2.8}$$

the bidder realizes the project, otherwise, he does not. Bidder 1 has higher project realization costs than Bidder 2, $c(\theta_1, s) > c(\theta_2, s)$ but lower non-realization costs, $-t_v - w_1 > -t_v - w_2$. In the example, illustrated in

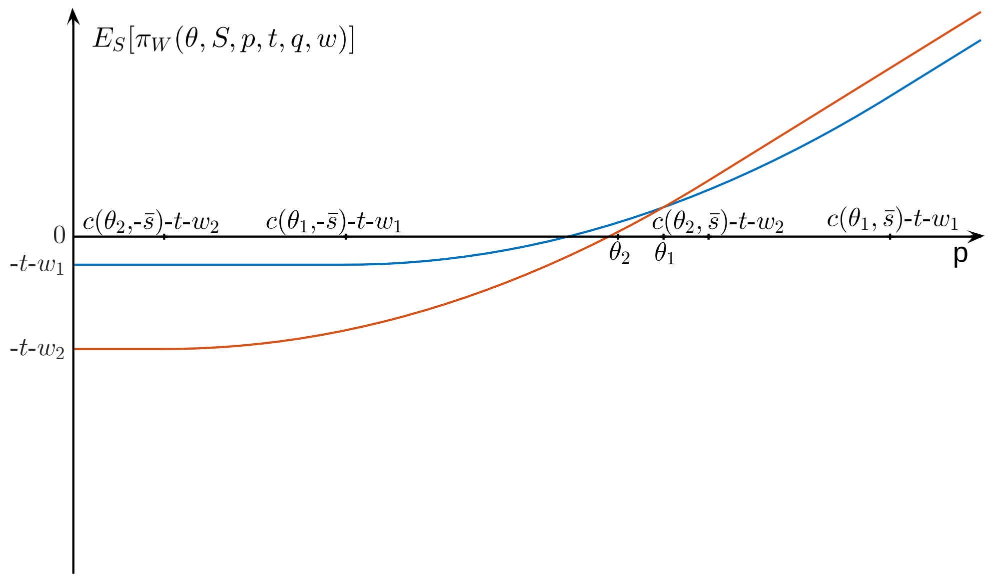


Figure 2.5: Expected profit for two bidders with different type and risk.

Figure 2.5, Bidder 1, although he has higher realization costs, wins the auction, as his indifference price, which corresponds to his bid, is lower than Bidder 2's bid. This outcome is inefficient. Furthermore, the non-realization probability of Bidder 1 is higher than the one of Bidder 2.

In general, if the case of a penalty q and a financial prequalification t_v is compared to the case of a monetary equivalent financial prequalification $t_v^{eq} = t_v + q$, the first case leads to a lower expected support level but the downsides are a lower expected realization probability and a potentially inefficient auction outcome. This holds in particular if there is only a penalty and the financial prequalification is zero ($t_v = 0$, $t_v^{eq} = q$).

2.3.4 Transferability of the results to multi-unit auctions

Many of the RE support auctions are conducted as multi-unit auctions in the form of static sealed bid auctions either with DP or UP.[6] Here, we briefly explain how the results of the two single-item auctions, as derived in the sections before, can be transferred to the two multi-item auctions with single-project bidders. With respect to bidders' strategic incentives, the DP auction corresponds to the first-price single-item auction and the UP auction with LRB rule corresponds to the second-price single-item auction. In the UP auction, as in the second-price auction, it is optimal for the bidders to submit their indifference price (expected profit equals zero) as their bid. In the DP auction, as in the first-price auction, bidders have an incentive to exaggerate their indifference price in their bid subject to their costs and the competition level. Moreover, in the reference case of the standard IPV model, the Revenue Equivalence Theorem in the form of the same expected (average) award price also holds for the two multi-item auctions (Ausubel et al., 2014). Therefore, one can expect the same effects and differences as in the two single-item auctions.

2.4 Conclusion and policy implications

The expansion of REs faces various challenges and there remain technical and political obstacles to overcome. The overriding challenge is to reach specific expansion targets in time and at the lowest possible costs. Therefore, effectiveness and efficiency are fundamental aims. But they are not always compatible. One of the main reason for introducing auctions is to obtain efficient outcomes. Additionally, auctions enable the auctioneer to control expansion through selection of the auctioned volume or budgetary envelope. The issue we addressed in this chapter is that not all awarded

[6] For the rules and the theoretical analysis of these auctions see, for example, Ausubel et al. (2014).

Table 2.2: Overview of different auction design options and their respective effects on the auction outcome.

Auction design option	Desired effects	Undesired effects
Financial prequalifications	• higher expected realization probability	• higher expected support level
Physical prequalifications additive to financial prequalifications	• reduced cost uncertainty • higher expected realization probability	• sunk costs • reduced competition level • higher expected support level
Penalties additive to financial prequalifications	• higher expected realization probability	• higher expected support level • potentially inefficient
Penalties substitutive to monetary equivalent financial prequalifications	• lower expected support level	• lower expected realization probability • potentially inefficient
Second-price auction in comparison to first-price auction	• lower expected support level	• lower expected realization probability

bidders may realize their projects and hence the expansion target may be missed. Therefore, we recommend generally auctioning a higher volume than needed to reach the expansion targets.

The bidders face various uncertainties regarding their costs on the one side and the option not to realize the project after the auction on the other side. Hence they will stop development of the project if the costs of realization are higher than the costs of non-realization. We analyzed different measures that affect this realization probability. Table 2.2 provides an overview of the auctioneer's design options and the respective effects.

The first and most distinct measure is a financial prequalification. The bidders deposit a security and only regain it in case they realize the project. This measure makes non-realization less attractive and hence higher financial prequalifications lead to a higher probability of realization. Depositing a security also has an influence on the expected support level of first-price and second-price auctions. In general, the non-realization option of the project reduces the bids since the worst possible outcome for the bidders is not to regain the security. However, counterintuitively, the expected support level is not equal in the two auction formats. The expected award price the auctioneer has to pay is higher in a first-price auction than in a second-price auction and as a consequence the non-realization probability is higher in the second-price auction. While retaining the same basic conditions, a higher award price yields a higher realization probability. This holds for whatever caused the lower award price. One possibility is the choice of the auction format as mentioned above; another could be increased competition.

Furthermore, financial prequalifications have a direct impact on the effect of physical prequalifications. If the uncertainty regarding realization costs is reduced due to physical prequalifications, then, the resulting support level increases because the bidders will still not realize their project in the bad cases, and the best cases yield a lower profit. The implications for the realization probability depend on the interaction of physical and financial prequalifications. If the deposited security is relatively high in comparison to the uncertainty, higher physical prequalifications lead to higher realization rates. If this is not the case, the effects are working in opposite directions and no clear statement is possible. However, physical prequalifications lead to sunk costs for bidders that are not awarded. This implicates that only bidders with a positive expected profit choose to participate in the auction and the expected support level remains constant or increases.

Finally, there is the possibility of penalties that are not covered by the securities. If all companies are able to pay this penalty in case of non-realization, it has the same effect as a monetary equivalent financial prequalification. But this might not be the case. Often small project companies without small assets take part in auctions for RE support. Such companies could declare bankruptcy in case of non-realization and therefore not pay the penalty. As the assets of all companies might differ, the incentives to take risks in the auction might also be different. As a consequence, the expected support level and the expected realization probability decrease and there might be inefficient auction outcomes because bidders with higher costs might also take higher risks and vice versa.

Nevertheless, the most difficult challenge is the right parametrization of the different measures. It is hard to evaluate the actual level of uncertainty the bidders face as well as their assets and willingness to accept bankruptcy and losses. The right parametrization also depends on the emphasis for the different goals by the auctioneer. Is a high realization rate necessary to satisfy expansion and policy targets or is the main goal to minimize the costs that are necessary to reach the expansion target also including retained securities and paid penalties? A third possibility is that the auctioneer is not interested in an expansion at all but is forced to conduct auctions. Such an auctioneer might be delighted by a low realization probability that may also be accompanied by low award prices. So there is a lot of potential to use or abuse the measures discussed here.

What an auction designer needs to keep in mind is that the exact achievement of expansion targets cannot be controlled very well. An expansion of auctioned volume to compensate for expected non-realization also results in a higher support level. This means that the realization probability increases, hence, not only is more volume awarded but a higher percentage of this volume is realized.

Our recommendation to design an efficient auction with a sufficiently high realization rate is to have a high financial prequalification and an adjusted physical prequalification. It should not be too high in relation to the securities and also to limit the sunk costs effect. We do not recommend the introduction of penalties that are not covered by financial prequalifications. Furthermore, according to the result of analysis there is a preference for the first-price auction over the second-price auction.

Chapter 3

Different cost perspectives for renewable energy support: Assessment of technology-neutral and discriminatory auctions

Although there is a convergence of opinions regarding the selection of RE promotion mechanisms to auctions, there is disagreement about the definition of efficiency, the type of costs to be considered, and the appropriate auction design. Particularly within the EU, there have been heated debates regarding the advantages and disadvantages of technology-neutral auctions compared to those of discriminatory auctions.[1] Technology-neutral auctions are open to all RE technologies and do not discriminate positively or negatively among participants, whereas discriminatory auctions treat different classes of participants differently.[2]

Non-discriminatory, technology-neutral auctions theoretically result in an outcome that minimizes the pure generation costs of RE sources (e.g. Myerson, 1981; McAfee and McMillan, 1989). With reference to this defi-

[1]Note that, in this context, discriminatory does not relate to the payment rule.

[2]The extreme case is a technology-specific auction, restricted to a specific technology, and, within such auctions, there might be further discrimination regarding e.g. the location or the ownership structure of the RE source.

nition of efficiency, the European Commission proposes technology-neutral auctions (European Commission, 2014b). This, however, may conflict with other targets, particularly with (1) the internalization of integration costs and (2) the minimization of the support costs through a reduction of the producer rent and, thus, prevention of windfall profits[3]. Although target (1) is based on an energy system perspective of efficiency, target (2) restricts the definition of efficiency to the support costs. In fact, these two targets are set by EU member states: for example, the consideration of integration costs in Germany (Deutscher Bundestag, 2016) or the minimization of support costs in the UK (Department of Energy and Climate Change, 2014).

This chapter contributes to the discussion on technological neutrality and different targets by applying auction-theoretic knowledge, particularly about discriminatory instruments, to the task of designing an appropriate auction for RE support. We formalize this discussion by analyzing different design options and their implications on the auction outcome, thereby highlighting the trade-offs between different cost perspectives. The implementation of discriminatory elements in auctions allows pursuing targets (1) and (2). We consider two forms of discrimination. We refer to the first as quality-based and to the second as cost-based. Both forms of discrimination can reduce the total costs for the consumers; however, they may lead to inefficiencies with respect to the minimization of generation costs. Further, we analyze cost-based discriminatory instruments with respect their robustness to misestimations. Therefore, we implement a model with linear marginal costs and apply the three discriminatory instruments. We then compare the results with correct and incorrect estimations of the bidders' strength and number. The theoretically equivalent instruments

[3]Due to the higher variance of production costs, windfall profits are considered to be more relevant in technology-neutral auctions than in technology-specific auctions (Held et al., 2006).

have practical differences.

We combine auction-theoretic methods with practical examples and experiences from past auctions. We theoretically analyze different forms of discrimination and several discriminatory instruments to evaluate auction design options against the underlying economic principles for the future promotion of REs. Thus, the game-theoretic principles of auction theory and their application to RE support are combined in an in-depth analysis.

The remainder of this chapter is structured as follows. Section 3.1 provides a comprehensive literature review on both technology-neutrality and auctions for RE support. Section 3.2 addresses the conflicting views on relevant costs of REs and provides a consistent definition. A clear separation of the cost components is imperative for our undertaken analysis. In Section 3.3 we present the variety of policy objectives for successful RE support allocation and relate these to the cost definitions. In Section 3.4 we analyze how the two approaches for discriminating among bidders in auctions, namely, quality-based and cost-based discrimination, perform with respect to the policy objectives. We show that both approaches are suitable for the auctioneer to reduce consumers' overall costs and, thus, policy makers ought to consider discriminatory design options. We conclude this chapter with Section 3.5.

3.1 Literature review

The topic of neutral or discriminating governmental support has been widely discussed in the literature. Aghion et al. (2009) contrast neutral and specific support mechanisms for R&D subsidies. Azar and Sandén (2011) discuss the advantages and disadvantages of technology-neutral and technology-specific support mechanisms in the context of climate change mitigation measures. Calculations based on optimization models support

EU's opinion that technology-specific support is costlier than technology-neutral allocation (Jägemann et al., 2013; Jägemann, 2014). In contrast, there are arguments in favor of technology-specific support, for example, in terms of integration costs, dynamic efficiency, and market failures (de Mello Santana, 2016; Gawel et al., 2017; Lehmann and Söderholm, 2018). The literature also discusses the general differences between neutral and discriminatory support instruments, especially regarding cost-effectiveness (Lehmann and Söderholm, 2018), and also addresses their potential application through auctions (Frontier Economics, 2014). However, the literature lacks a detailed theoretic analysis of discriminatory design elements in the context of auctions for RE support, which this chapter provides.

Further discussion in the literature focuses on the benefits of auctions as a support mechanism in general. Weitzman (1974) laid the foundation for the theoretical comparison between quantity-based mechanisms, that is, auctions, and price-based mechanisms, that is, administratively set *FITs*. In recent years, studies comparing different mechanisms have reached different conclusions. Menanteau et al. (2003) argues based on case studies that FITs have been suitable for ensuring a capacity expansion but that auctions are more effective in reducing support costs. Butler and Neuhoff (2008), however, notes that auctions might reduce costs, but are less effective due to low realization rates. Further concerns against auctions are the uncertain investment conditions, especially for immature technologies (Lauber, 2004; Mitchell et al., 2006; Batlle et al., 2012; del Rio and Linares, 2014), small actors (Grashof, 2019), and high transaction costs (Agnolucci, 2007; del Rio and Linares, 2014). Grashof et al. (2018) questions whether auctions actually reduce support costs. On the other hand, there are further arguments in favor of auctions. Borenstein (2012) states that auctions are more appropriate to deal with market failures and externalities than administratively set FITs. Furthermore, extensive case studies show an increased application of auctions and that these are accompanied by major price reductions (IRENA, 2015, 2017; Wigand et al., 2016). However, the aim of this chapter is not to discuss the suitability of auctions in general, but to analyze discriminatory instruments used in auctions. We show that these instruments can help to mitigate or minimize some of the risks mentioned above.

The different views on technology-neutrality versus discrimination stem from different interpretations of efficiency, cost-effectiveness, and costs in general, resulting in different definitions of political targets. del Rio and Cerdá (2014) identify two views on cost-effectiveness for RE support schemes: minimization of generation costs and minimization of consumer costs. When support schemes minimize generation costs, defined as all costs related to installation and generation of REs, the allocation of support secures an efficient deployment of RE sources. From a system perspective, an efficient allocation maximizes the total welfare (Smith, 1962). Policy makers may also seek to maintain the approval of the general population for their RE support policies by aiming to minimize consumer costs. Consumers' costs are not only affected by the cost of electricity, but also by the support and integration costs of REs. Either with levies or taxes, consumers pay for investments in new RE plants, the electricity network, and reserve capacity. Policy makers might seek to secure a certain RE penetration level at the lowest cost for those bearing the costs of the support scheme. All three views appear among the political targets of support schemes in different countries.

3.2 Definition of relevant costs – a basis for discussion

To analyze the different targets and to evaluate different auction formats with respect to these targets, we first provide an overview of the costs of RE in line with Joskow (2011) and Hirth (2013). In general, there are two perspectives: that of the bidders (project developers) and that of the auctioneer (government). Both perspectives are necessary to understand the reasoning behind the identified target conflicts between windfall profits and integration costs in non-discriminatory auctions.

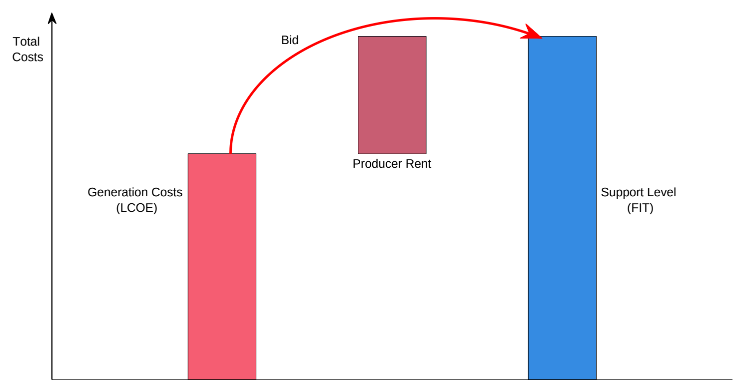


Figure 3.1: Relevant costs of RE sources from a bidder perspective.

From a bidder's perspective, costs can be divided in two parts: investment costs and operational costs. In the case of RE sources[4], most costs occur as investment costs, whereas operational costs are rather low. The *levelized costs of electricity* (LCOE), the costs equivalent to a unit of generated electricity (Short et al., 1995), combine both components and are often simplified to the term *generation costs*. LCOE represent the net present value of the total life cycle costs (including both investment and operational costs) of a RE source per unit of electricity generated. For the RE installation to provide a return on the investment, project developers

[4]In this chapter, we focus on variable RE sources like PV and wind. However, other RE sources exist, such as biomass, which are dispatchable and rely on fuel inputs.

require a surplus in addition to LCOE. We term the surplus per unit of generated electricity *producer rent*. If we assume the installation is granted with support through a FIT, then the FIT should cover both LCOE and producer rent. Thus, we define *support level* to be LCOE plus the producer rent, which is effectively the revenue obtained by the awarded bidder. The costs from a bidder's perspective are illustrated in Figure 3.1.[5]

Windfall profits arise if the producer rent of a specific class of bidders is disproportionately high (Haas et al., 2011). These bidders have a competitive advantage not resulting from good management or innovations but from factors outside bidders' influence, for example, the cost advantage of a technology.

The auctioneer, the representative of the energy consumers in the auction, has a different perspective (Figure 3.2). Consumers have to bear not only the support costs paid to the awarded producers but also the *integration costs*, for which the producers are not responsible, for example, grid integration, balancing power, and contingency costs.[6] Integration costs are determined by grid costs, technology, the resulting generation profile, and other design characteristics indirectly affecting the costs of the RE source, such as alignment and height. The sum of the support level and integration costs is referred to as the *overall costs* from a consumer perspective or *System LCOE*.[7]

Integration costs are influenced by the technology type and the location of the RE source (Hirth et al., 2015) and include potential differences

[5]For simplicity, we assume a FIT to be the remuneration type applied; however, the analysis can easily be generalized to other types of remuneration types, for example, a feed-in premium, either sliding or fixed. When participating in an auction, bidders determine their bid based on their individual generation costs and, where applicable (e.g., discriminatory pricing), on an assumption regarding the competition level. In general, the lower the competition level, the higher the producer rent.

[6]This chapter focuses on the costs of REs. From a consumers' perspective, one may consider all components of the electricity bill including the electricity costs of all energy sources and record the additional RE support payments separately. However, for a given share of REs the implications of both views are equivalent.

[7]Note that System LCOE include the producer rent because it measures the cost of the RE if the auctioneer were to buy it from the producer and integrate it into the system.

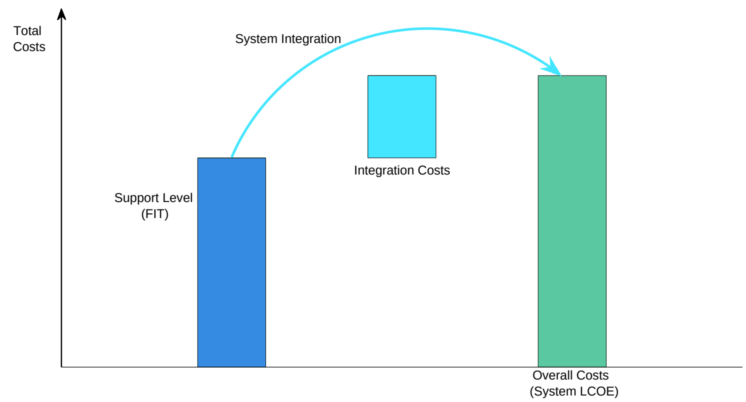


Figure 3.2: Relevant costs of RE sources from the consumers' perspective.

between the market price of RE sources and the average spot market price. Based on these characteristics, which we henceforth refer to as the quality of the RE source, the auctioneer can calculate the integration costs. The resulting net costs for the consumers equal the difference between System LCOE and the average spot market price. The payment of these costs is the net transfer from the auctioneer as a result of offering support to and ensuring the integration of a RE project under the given market conditions.

Figure 3.3 illustrates an example of a non-discriminatory, technology-neutral auction, in which nine bidders with equal-sized projects from two technologies, A and B, participate. The technologies differ with respect to the cost structure: the average generation costs of Technology A are lower than those of Technology B. The overall auction volume (demand) constitutes five projects. The five bidders with the lowest bids are awarded. All examples in this chapter are illustrated in the case of a UP auction where the lowest rejected bid (LRB) determines the price.[8] Thus, the sixth lowest bid determines the price p^*.

Non-discriminatory auctions allocate support to projects with the low-

[8] The results also hold for the DP auction (Vickrey, 1961; Myerson, 1981). In particular, DP does not prevent windfall profits, as the bidders with a disproportionate advantage bid disproportionately less aggressively.

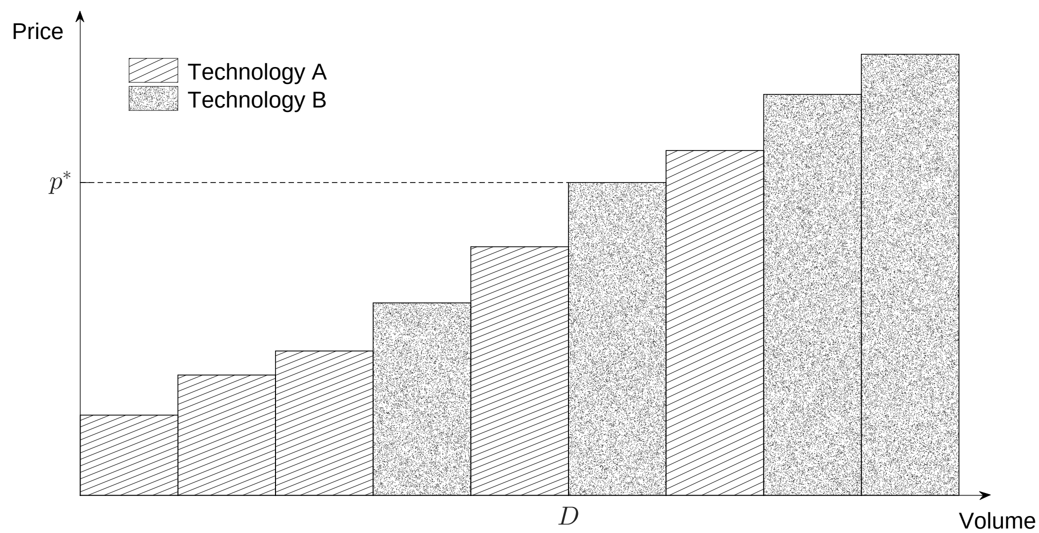


Figure 3.3: Example of a two-technology, non-discriminatory UP auction with LRB.

est generation costs (LCOE). However, these auctions neither necessarily prevent windfall profits nor consider integration costs. Policy makers have to consider these trade-offs when designing auctions for RE support. We show that by introducing discrimination in auctions, it is possible to minimize the overall costs and the support costs.

3.3 Political targets for RE support auctions

The definition of relevant costs is crucial for political target setting in the context of RE support and determines the framework for the auction design. In this section, we analyze the approach presented in the European Commission's State Aid Guidelines, as this is the fundamental document regulating auction design in all EU member states. Furthermore, we provide examples of national policy targets and contrast them with the respective auction design.

3.3.1 EU State Aid Guidelines

The European Commission considers competitive bidding mechanisms such as auctions as an appropriate support allocation mechanism. This is apparent from the “Guidelines on State aid for environmental protection and energy 2014—2020" (henceforth referred to as the State Aid Guidelines), which proclaim that competitive bidding will be obligatory for all new support schemes for which member states wish to obtain state aid approval beyond 2017 (European Commission, 2014b). The State Aid Guidelines are the superior directive regarding RE support in the EU (European Commission, 2014b) and refer to the cases of state aid for promoting RE expansion. Although there are certain exemptions, for example, for small installations and demonstration projects, the competitive bidding requirement has led to significant changes in the support policies across the member states.

Throughout the State Aid Guidelines, there are two reoccurring concepts related to the reasoning behind auctions. The first concept is minimization of any support payments, that is, ensuring that the aid is proportionate. Section 3.2.5.1 of the State Aid Guidelines specifies the general conditions and targets of the support mechanisms for REs, e.g. with respect to the support level:

> “Environmental and energy aid is considered to be proportionate if the aid amount per beneficiary is limited to the minimum needed to achieve the environmental protection or energy objective aimed for" (European Commission, 2014b, 3.2.5.1, §69).

Depending on the interpretation of aid, the proportionality requirement can have two meanings. If aid focuses on the actual price of the RE, the proportionality principle aims to minimize the support level. However, if the aid also includes integration costs, the proportionality principle implies minimizing the overall cost of the auctioneer.

Furthermore, according to the State Aid Guidelines, technology neutrality will (normally) also lead to aid minimization:

> “Market instruments, such as auctioning or competitive bidding process open to all generators producing electricity from RE sources competing on equal footing at EEA level, should normally ensure that subsidies are reduced to a minimum in view of their complete phasing out" (European Commission, 2014b, 3.3.1, §109).

The State Aid Guidelines do not foresee any contradiction between technology-neutral auctions and minimizing the aid, although technology-neutrality is, in principle, a tool for minimizing generation costs.

The second reoccurring concept in the State Aid Guidelines is market distortions: the state aid must not lead to reduced economic efficiency by distorting markets. In this respect, the guidelines also refer to the design of RE support auctions:

> “[...] If such competitive bidding processes are open to all generators producing electricity from RE sources on a non-discriminatory basis, the Commission will presume that the aid is proportionate and does not distort competition to an extent contrary to the internal market.[...]” (European Commission, 2014b, 3.3.2.1, §126).

Hence, the European Commission prescribes a technology-neutral, non-discriminatory auction, and, since the European Commission requires its member states to strictly adhere to this guideline, it forces them to implement technology-neutral auctions for RE support. Although technology neutrality is an instrument for minimizing generation costs, the State Aid Guidelines prescribe technology neutrality for ensuring the minimization of aid and a reduction in market distortions. Thus, there is a conflict between target setting and the proposed auction design. Moreover, as the following examples show, most auctions where multiple technologies compete include discriminatory design elements and are not "neutral" in the actual sense.

3.3.2 National targets

At country level, we find differences in the interpretation of costs, in the target settings, and in the auction designs. In this section, we provide examples of implemented multi-technology auctions and contrast them with their respective target setting. The examples cover auctions in North and Latin America as well as in EU member states. Table 3.1 contrasts the discussed auctions for RE support with respect to auction design and targets.

Most countries' target is to reduce the costs for RE through the auctions. Although it is ambiguous and not always clear what costs each country actually addresses, support costs play an important role. For example, the UK's target is reducing support costs through a discriminatory auction format (Department for Business, Energy & Industrial Strategy, 2017): RE technologies are split into different "pots" depending on the maturity of the technology and compete against each other within each pot. Additionally, there are different maximum prices for the different technologies (Department of Energy and Climate Change, 2014). The Netherlands also pursues the reduction of support costs by a multi-technology auction with technology-specific maximum prices (European Commission, 2012; Minister van Economische Zaken, 2015).

California focuses on a different cost category. There, bidders are divided into "buckets" of technologies with similar electricity generation profiles. Although in principle the buckets are neutral, they ensure that only RE technologies with similar profiles compete against each other. This discriminatory approach not only considers generation costs but also integration costs through a better utilization of existing infrastructure and load profiles (Public Utilities Commission of the State of California, 2010). The Mexican auction design pursues the same target. Depending on the location and the regional load profile, the participating projects are evaluated and the bidders receive a corresponding bid bonus (Centro Nacional de Control de Energia, 2017; IRENA, 2017). In other words, the bidders accounting for the least total system costs are awarded. In all four approaches, the discriminatory auction design can be explicitly justified by the minimization of costs for the consumer.

Germany, however, states additional specific auction targets in its RE law: cost efficiency, actor diversity, expansion goal achievement, and optimal grid and system integration (Deutscher Bundestag, 2016, EEG (2017), §39i). From 2018 onward, technology-neutral auctions have been conducted for PV and wind onshore, in addition to technology-specific auctions for both technologies. Although the free competition between PV and wind adheres to the non-distortion principle of the State Aid Guidelines, the auction design includes discriminatory instruments to achieve the additional targets (Bundesministerium für Wirtschaft und Energie, 2017).

3.4 Discriminatory auctions

Technology-neutral, non-discriminatory auctions ensure that the projects with the lowest generation costs (LCOE) are deployed first, although not necessarily those with the lowest overall costs (System LCOE). Furthermore, although the bidders with the lowest bids are awarded, technology-neutral auctions do not necessarily minimize the support costs, as we show

Table 3.1: Examples of multi-technology auctions in different countries (Public Utilities Commission of the State of California, 2010; Wigand et al., 2016; Bundesministerium für Wirtschaft und Energie, 2017; IRENA, 2017; Department of Energy and Climate Change, 2014).

Country	California	Germany	Mexico	The Netherlands	UK
Technologies	RE technologies	Wind and PV	RE technologies	RE technologies	RE technologies
Objective of discrimination	Minimize overall costs	Reduce integration costs and support level	Minimize overall costs	Minimize support level	Minimize support level
Discriminatory design elements	Quotas depending on load profile	Regional quota, location bonus and different maximum prices	Location and load profile bonus	Different maximum prices	Technology pots and different maximum prices

in this section. Based on the target conflicts identified in Section 3.2 and the examples of Section 3.3, we analyze different discriminatory design elements auction-theoretically and contrast them with the given political targets. We discuss two possible approaches that reduce the overall costs: (1) including integration costs (Figure 3.2) into the bidding process and (2) reducing the support costs (Figure 3.1). We call the first approach quality-based based discrimination and the second one cost-based discrimination.

Discrimination can only be successfully implemented if bidders have qualitative differences that can be objectively distinguished, for example, technology, design, or location. If such differences do not exist or cannot be identified, discrimination is arbitrary and inapplicable to the goal of minimizing aid payments or of successfully pursuing other targets (Myerson, 1981). Generation costs (LCOE) differ structurally among groups of bidders (IRENA, 2015). The overall costs and revenues of a specific RE source depend on different factors, of which some are observable. Likewise, integration costs can be assigned according to specific observable characteristics of the bidders.

3.4.1 Quality-based discrimination

Mexican auctions for RE support discriminate among bidders based on the location and the conformance of load and generation profile of their project. The discrimination is implemented as a bid bonus. Bidders are not awarded based only on their price bid but, additionally, on a factor depending on their location and load profile. This approach is in line with the analysis of Newbery (2017) and Pérez-Arriaga et al. (2017), who indicate that the market value of a RE source has to be considered in any efficient support mechanism. This explicitly includes the location of the RE plant. The underlying auction-theoretic principle is the concept of scoring auctions (Che, 1993; Asker and Cantillon, 2008); however, it has hitherto not been analyzed for RE auctions. In the case of RE support, scoring auctions enable the internalization of integration costs and, thus, the reduction of overall costs and aid payment. The following section describes the functionality of scoring auctions and how to implement them for RE support. Moreover, it illustrates the opportunities and risks based on the examples of Section 3.3. Auctions with quality-based discrimination are commonly implemented in other industries, for example, in the private sector (Perrone et al., 2010), for public tenders for highway construction (Herbsman et al., 1995) and military goods (Che, 1993), and also in the energy sector (Bushnell and Oren, 1994; Chao and Wilson, 2002).

In contrast to a non-discriminatory auction, where the requested support level is the only award criterion, additional criteria are relevant in scoring auctions. The bids are tuples $b = (p, \mathbf{q})$. The first component, p, is the support level or price, as in any non-discriminatory (price-only) auction. The additional "quality" component $\mathbf{q}$ contains the characteristics of the project relevant to the integration costs, for example, the location of the RE project, its technology, and its design (e.g., the alignment of the PV-modules or height of a wind turbine). In the auction, each bidder decides on the deployed quality level $\mathbf{q}$. Depending on the chosen option, a bidder incurs costs $c_b(\mathbf{q})$, subject to the quality $\mathbf{q}$ of the project.

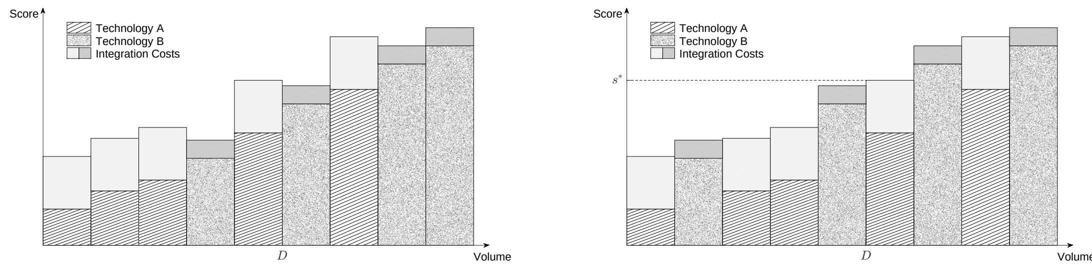
The auctioneer evaluates each submitted quality component $\mathbf{q}$ through a cost function $c_a(\mathbf{q})$, which assigns a monetary value to $\mathbf{q}$, corresponding to the integration costs induced by $\mathbf{q}$. This generates a hierarchy for all possible quality vectors, that is, an order based on what would be better in terms of lower integration costs. We say that vector $\tilde{\mathbf{q}}$ has a higher quality level than vector $\mathbf{q}$ if $c_a(\tilde{\mathbf{q}}) < c_a(\mathbf{q})$, that is, if $\tilde{\mathbf{q}}$ yields lower integration costs than $\mathbf{q}$.

In the Mexican example, project quality is evaluated with respect to the resulting integration costs. The regional component factors address the potential grid costs; the load profile component measures the match between the load and the generation profile . The components reflect the costs the Mexican government would have to bear given the project characteristics. Usually, the cost function $c_a(\mathbf{q})$ is common knowledge among all bidders.

The auctioneer calculates a score for each bid $b = (p, \mathbf{q})$ based on the scoring function

$$s(p, \mathbf{q}) = p + c_a(\mathbf{q}) \,, \tag{3.1}$$

that is, based on the sum of the support level and integration costs. The bids with the lowest scores, accounting for the lowest overall costs, are awarded. This concept maintains the desirable characteristics of a price-only auction whereas the focus shifts from efficiency with respect to generation costs to overall system efficiency.



(a) In ascending order of generation costs. (b) In ascending order of scores (System LCOE).

Figure 3.4: Example of a two-technology scoring auction where the integration costs are priced in.

Figure 3.4 extends the example in Figure 3.3 by including integration costs. The integration costs of Technology A are higher than those of Technology B and are equal for each project with the same technology. If the score (3.1) requires to add the integration costs to the generation costs, the different integration costs change the ordering of the projects. In part (a) of Figure 3.4, the projects are sorted in ascending order of generation costs (this is the same order as in Figure 3.3). Sorting the projects in ascending order of their scores (part (b) of Figure 3.4) two projects of Technology B and only three of Technology A (compared to four before) are awarded. This example illustrates that the projects with the lowest generation costs do not necessarily occasion the lowest overall costs.

A great challenge for the practical implementation of a scoring rule in the complex energy market with many uncertainties and interdependent variables is the correct evaluation of different quality levels and the resulting integration costs $c_a(\mathbf{q})$. This evaluation was also a major challenge in Mexico, where the regional bonus greatly affected the outcome of the first auction round and was abandoned afterwards. For the bidders, it is equally hard to determine the exact costs $c_b(\mathbf{q})$ for the different qualities $\mathbf{q}$, for example, the different locations or technologies.

Although it is hardly possible to calculate the costs $c_a(\mathbf{q})$ and $c_b(\mathbf{q})$

exactly beforehand – for the bidders or for the auctioneer – a scoring auction can still be an appropriate choice. A scoring rule can be restricted to specific characteristics that are easily measurable for the auctioneer on the one side, and possible for the bidders to influence on the other side, for example, the location and the corresponding direct grid cost of a RE source. The more information is available the more this helps a scoring auction to select those RE projects that occasion the least overall costs. However, even with little information, a scoring auction still improves the outcome compared to a price-only auction with respect to overall system efficiency.

Although a scoring auction represents the actual integration costs the most precisely, other discriminatory measures can also have a positive effect. Especially for costs which increase stepwise, a maximum quota is a sensible measure. Such a quota was, for example, implemented in auctions for onshore wind in Germany, with grid restrictions in the northern part of the country.

In conclusion, appropriate discrimination implemented based on the different characteristics of different RE sources reduces the overall costs and, thus, the aid payment. Although a full implementation is hard to accomplish, even a partial implementation improves the result from an overall system perspective. Furthermore, the example of California illustrates that discriminatory design elements can help to control the expansion of RE so that it is even more in line with the actual needs and the demand. The match of the generation and load profile through respective quotas supports the expansion of RE where it is most sensible.

3.4.2 Costs-based discrimination

In multi-technology auctions, projects may not only differ in the integration costs but also in the generation costs. The auctioneer can take advantage of these differences through discriminatory auctions to reduce the support level. In the following, we analyze the principles of cost-based discrimination, which requires different types of RE sources (e.g., wind and solar) with systematically different cost structures. Our results are related to the monopolistic third degree price discrimination. Schmalensee (1981) and Varian (1989) lay the foundation for the analysis of discriminatory market mechanisms, while McAfee and McMillan (1989) and Bulow and Roberts (1989) apply this approach to auctions.

We set up a model auctions for for RE support. The detailed model and the derivation of the results are presented in Appendix A.1. Consider a RE auction with a given demand D (e.g., capacity [MW] or energy [MWh]) and two classes of bidders with different technologies A and B with different cost structures. The bidders' LCOE are represented by increasing marginal cost functions, where the marginal cost curve of Technology A lies below that of Technology B, that is, Technology A has a cost advantage over Technology B. However, we assume that some B-bidders have to be awarded in the auction to efficiently meet the demand D, that is, based on the lowest generation costs.

We analyze three discriminatory instruments: *quota*, *maximum price*, and *bonus*. A minimum quota $Q < D$ for Technology B guarantees a supply of at least Q.[9] A maximum price p_A^{max} for Technology A implies that A-bidders with higher costs than p_A^{max} do not participate. A monetary bonus $b^+ > 0$ is an additional payment to the awarded B-bidders.[10]

[9] A maximum quota for Technology A is to be considered equivalent.

[10] A monetary malus for Technology A in the form of a deduction on the award price is to be considered equivalent.

Another type is the *bid bonus*, which reduces the bids of the B-bidders by b^-, but not their award prices. Each instrument implies a supply shift from Technology A to Technology B and different prices for the awarded A-bidders and B-bidders.

For example, the following have been implemented: maximum price in multi-technology auctions in the Netherlands (Minister van Economische Zaken, 2015), a bonus depending on the location in German auctions for onshore wind (Deutscher Bundestag, 2016), and quotas depending on the availability in Californian auctions (Public Utilities Commission of the State of California, 2010) (see Table 3.2).

In Appendix A.1, we prove that the three discriminatory instruments are theoretically equivalent with respect to their effects. First, they reduce the support cost below the level of a non-discriminatory auction. Second, every auction outcome, including the cost-minimizing outcome, achievable by one instrument can also be achieved with another instrument. If any of the three discriminatory instruments is employed so that it leads to the support cost minimum, the price difference between the awarded B- and A-bidders is the same.[11]

Figure 3.5 illustrates the effect of a technology-specific maximum price in the example of Figure 3.3. In the auction with a demand of five projects, the auctioneer sets a maximum price p_A^{max} for Technology A, which is lower than the clearing price p^* without discrimination. This leads to a change in the awarded projects and prices. The three A-projects with the lowest costs and, additionally, the two B-projects with the lowest costs of this technology are awarded (the awarded projects are outlined in bold), whereas the fourth A-project that would have been awarded in a non-discriminatory auction is not awarded. Although it is not the projects with

[11] The price difference then equals the difference of the reverse relative elasticity of supply of the two classes of bidders for the respective market clearing prices.

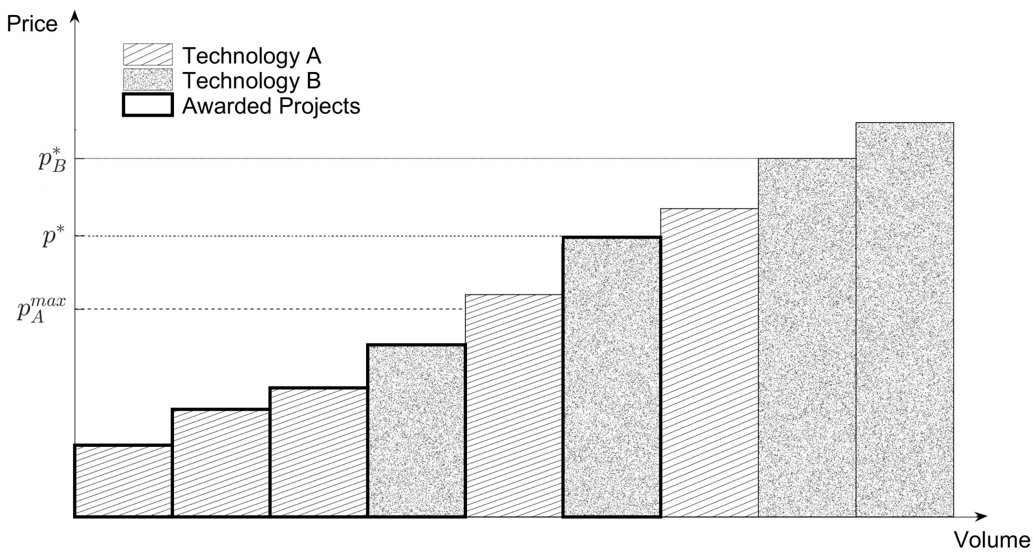


Figure 3.5: Example of a two-technology, discriminatory auction with a maximum price and a award price for each technology.

the lowest costs that are awarded, the total support costs decrease. The two awarded B-projects receive $p_B > p^*$, which, however, is compensated by the lower award price $p_A = p_A^{max} < p^*$ of the three awarded A-projects.[12]

The intuition behind the cost-reducing effect of discrimination is that the auctioneer utilizes the different cost structures and reduces the support level at the expense of a lower producer rent. Since some B-bidders receive a higher payment but many A-bidders receive a lower payment, the overall costs are reduced. However, cost reduction through discrimination always involves an inefficient outcome because the cost-reducing effect involves awarding some B-bidders, although there are A-bidders with lower costs.

It might be difficult for the auctioneer to obtain detailed information about the cost structure of the different bidder classes. However, even without this knowledge, the auctioneer can reduce the support level through

[12]The expected results are the same for an auction under DP. In such an auction, the bidders do not bid their costs but a higher price to gain a profit in case of an award.

a discriminatory instrument that reduces the price difference between the two bidder classes. The evaluation of the auctions in Germany, the Netherlands, and the UK supports these considerations. In Germany, wind onshore projects receive a bonus depending on the expected generation of the wind turbines, which in turn depends on the location. Without discriminatory measures, due to the geographic differences regarding wind penetration, good locations near the coast would have a disproportional advantage and would receive windfall profits. Although the actual bonus might be too low, it still reduces the support level. The same can be observed in the Netherlands and the UK. The mere fact that the maximum prices for the different technologies have become effective (Wigand et al., 2016) indicates a reduction in the support level although it is not clear if the optimal maximum prices would be higher or lower.

Although the three discriminatory instruments are theoretically equivalent, from a practical and political perspective, they differ and have specific advantages and disadvantages, particularly with respect to their robustness against false estimation. In Appendix A.2.1 we apply the three discriminatory instruments to a model with linear marginal costs. Then, in Appendix A.2.2 we compare the three instruments with respect to their robustness.

From those additional analysis, it follows that if discriminatory instruments are applied cautiously at a low level, they are expected to reduce costs compared to non-discrimination, whereas a parameterization that is too ambitious (i.e., more than the optimal value) may increase the support level. If a quota is set too low or the maximum price set too high, they are not effective, whereas a bonus always has an effect. In other words, if the cost difference between Technology A and B is underestimated, the bonus might be favorable but if it is overestimated, the bonus is the least preferable option.

The combination of a bonus and a maximum quota for the B-bidders offers an advantageous solution. The maximum quota for the B-bidders aims to limit the number of B-bidders privileged by the bonus. Thus, the bonus only applies to the B-bidders with the lowest costs. Although discrimination is always effective through a bonus, the risk of overcompensation and high support costs in case of a wrong parameterization is constrained by a maximum quota. Hence, the positive effects of discrimination are maintained, whereas the negative effects are restricted.

A political advantage of a quota is that it can be implemented as "non-discriminatory" in the way that every group of bidders (technology, region, etc.) has a (the same) minimum quota. It could be argued that this represents a level playing field, on which all bidders have the same "advantage." This quota only determines the minimum supply by the high-cost bidders, whose effective quota is expected to reduce the support level.

Table 3.2: Characteristics of the different forms of discrimination.

	Quality-based discrimination	**Cost-based discrimination**
Basis of discrimination	Induced integration costs	Cost structures
Target of discrimination	Minimization of overall costs	Minimization of support level
Examples	Quota in California, Quota in Germany (wind onshore), Bonus in Mexico	Bonus in Germany (wind onshore), Different maximum prices in the Netherlands, Different maximum prices in the UK

Table 3.2 summarizes the characteristics of the different forms of discrimination in auctions for RE support with respect to the basis, target, and examples of the respective form of discrimination.

3.5 Conclusion

The recent trend regarding auction design indicates more open auction formats where bidders from different technologies or from different countries participate. The European Commission suggests that a technology-neutral auction becomes the design standard. Yet, at the moment, technology-specific auctions are more commonly implemented. Although pure, technology-neutral auctions minimize the generation costs theoretically, this chapter illustrates the trade-offs associated with discriminatory auctions. We discuss two types of discrimination in multi-technology auctions from an auction-theoretic viewpoint but also empirically. We link general economic concepts with a real-world application and consider the resulting challenges. Depending on the targets and available information, discriminatory auctions may be reasonable. In other words, we show that discriminatory auctions can reduce the auctioneer's overall expenses for supporting RE sources.

The first type of discrimination involves including externalities by discriminating among the bidders based on the different characteristics of their projects. This approach considers the resulting implications on the overall system costs. The applicability of quality-based discrimination also depends on the available information. For a full implementation, the integration costs of each bidding RE project are required. Nevertheless, even with less information, quality-based discrimination can be implemented successfully and even be combined with cost-based discrimination. It has been proven in practice that it is hard to retrieve the desired information but that the resulting outcomes are mainly favorable.

The second type of discrimination involves reducing the producer rent by discriminating among the bidders based on their different cost structures. Discriminating against low-cost bidders in favor of high-cost bidders reduces the support level through absorbing the different profits of the different bidders and, thus, reduces the producer rent, resulting in a lower support level. It requires less information and allows for three theoretically equivalent implementations, which, however, are different from a practical and political perspective. Depending on the available information, on uncertainties, and on the political targets, the three instruments have respective advantages and disadvantages and exhibit different robustness to inaccurate estimation. Here, a combination of two approaches (e.g., quota and bonus) is superior due to its higher robustness, whereas the benefits are preserved.

Finally, a reason why auctions are implemented to promote RE is the controllability of the support scheme. Discriminatory instruments, especially quality-based discrimination, preserve this controllability in multi-technology auctions. The advantage is a higher predictability and, thus, lower transaction costs for both the auctioneer and the bidders. The auctioneer incurs, for example, lower costs for adapting and expanding the grid, while the bidders incur lower capital costs.

In conclusion, the theoretical concepts of discrimination can be transferred to the area of RE support auctions and can have a positive impact on the essential expansion of RE sources with the lowest necessary overall system costs. There are differences between the theoretically optimal concepts and the practice, but examples show that the concepts can be implemented successfully. However, it should be noted that these concepts could also be misused for corrupt practices or for harming competitors. It is of utmost importance that policy makers clarify the auction targets so that they can choose the appropriate auction design.

Chapter 4

Uncovering bidder behavior in the German PV auction pilot – Insights from agent-based modeling

This chapter enables a deeper understanding of the ground-mounted solar PV auctions in Germany. The German PV pilot took place over six rounds in 2015 and 2016 in which both DP and UP schemes were implemented. We contribute to the understanding of the extreme price reduction in the six rounds of the pilot. Furthermore we investigate, how the different legislatory and auction design changes, namely the exemption for arable land bidders and the change between UP and DP influenced bidding behavior. Granted the opportunity to make use of detailed data on the pilot provided by the German Federal Ministry of Economic Affairs and Energy (BMWi), we statistically analyzed empirical outcomes of these auctions to define input parameters for our ABM. The model is further endorsed by game theory. We thus benefit from empirical experience to improve our model and at the same time learn from the modeling results how varying design parameters changes auction results. This two-sided learning offers new insights regarding the bidder behavior in auctions for RE support and the combination of methods provides decision support for policy makers from a novel scientific perspective.

The structure of this chapter is as follows: First, we provide a short literature review and introduction to our approach in Section 4.1. Then, in Section 4.2 we give some background information on the German solar PV pilot to introduce the topic. We provide an auction-theoretic background of bidding behavior in auctions - and the limitations for theoretical analysis of repeated multi-unit auctions are explained in Section 4.3. In Section 4.4 we describe our ABM, which incorporates implications of the theoretical analysis wherever feasible, but also insights from the empirical auction outcomes. This model then simulates the auction pilot with the given parameters on design and our knowledge on agent distribution in the German electricity market as well as on the price development of PV modules and generation of electricity from large-scale solar PV. Empirical auction outcomes are used to improve our modeling, however without pre-empting our model results. They instead allow for an optimal depiction of the distribution of participants in terms of e.g. costs and project sizes in the German large-scale PV sector. In the Section 4.5, we explain the bid prices and bidder distribution and evaluate how bidding evolved over the respective rounds. Specifically, we show the price development as compared to the actual prices, the distribution of bids over the six rounds and insights into the behavior of those bidders who submit bids for the restricted arable land areas. We conclude in Section 4.6.

4.1 Literature review and approach

The underlying research adds on to a strand of literature on auctions for RE that is relatively recent. In particular, this chapter applies an ABM, a well established methodology to simulate auctions and electricity markets but which has only recently been applied to assess RES auctions in particular (see Anatolitis and Welisch (2017), Welisch (2018) and Welisch (2019)). Earlier studies using an ABM to model auctions in a non-renewables context are e.g. Mizuta et al. (2000) or Hailu et al. (2011). Other recent papers dealing with auction-based renewables support are e.g. Haufe and Ehrhart (2018) which gives an overview of relevant auction design elements Winkler et al. (2018) which evaluates the performance of auctions for RE support or del Río (2017) and Mora Alvarez et al. (2017a) which give a qualitative overview on European experiences with renewables auctions. Other work looks into the theoretical background and implications of certain design elements, see e.g. (Kreiss et al., 2017, 2019). Specific country cases also exist, as for example Kylili and Fokaides (2015) who evaluate the functioning of an auction-based support scheme in Cyprus and Wigand et al. (2016) who summarize case studies across Europe.

By remodeling the auctions and looking into the detailed ABM outcomes, i.e., costs, distribution of bidder types and dropout rates, we enable a better understanding of the decision processes underlying the auctions and motivating the participants. An ABM allows to simulate different forms of behavior and makes the underlying procedures visible. We furthermore have some of the advantages of econometric analysis in our model, as we make use of empirical data and analyze the short time series of auctions that already took place before modeling the auction participants. By comparing model results to empirical outcomes, this chapter aims to provide an explanation for the steep drop in bid prices. The findings are also relevant in the eye of a current legislatory change: the Bundesländerklausel/Freiflächen-Öffnungsverordnung. This new law allows the German federal states (Bundesländer) to come up with their own restrictions or open their disadvantaged arable land for tendering of ground-mounted solar PV. This change in legislation led to an opening of these formerly restricted areas for upcoming auctions.[1] We show through our modelling how this could influence future auction outcomes and discuss the resulting policy implications.

4.2 Background on the German PV auction pilot

In the German ground-mounted solar PV auctions, the auctioneer is the German federal network agency (BNetzA). A sliding feed-in-premium to support large-scale solar PV installations for a support period of 20 years is tendered (Deutscher Bundestag, 2017). The auctioneer publishes the successful capacity amounts in detail. The lowest and highest accepted bids together with the weighted average winning bid are also made public. The actual bid prices and project costs remain private information.

In the auctions, participants submit their (sealed) bid in each round. Specifically, the bid contains a price in ct/kWh and a corresponding capacity in kW of their individual projects. The location of the project is also submitted (Deutscher Bundestag (2017), § 30), such that the auctioneer is immediately able to differentiate between disadvantaged arable land which is per definition not suitable for farming in its current state (in the following just referred to as arable land for simplification purposes) and other areas, namely the area adjacent to a highway or railway or a converted area which was previously used for military, business purposes, infrastructure or housing (named converted areas in the following). The difference between these two areas is a crucial feature of the German PV auction scheme, as the former is restricted due to reservations by the German farmer's association (Bauernverband), see e.g. Deutscher Landwirtschaftsverlag GmbH

[1] Bavaria and Baden-Württemberg have already made use of this law and opened up tendering on arable land for up to 30 projects (Bavaria) and up to 100 MW annually (Baden-Württemberg). For more details see the legal publications by the federal states of Bavaria (Bayerische Staatsregierung, 2017) and Baden-Württemberg (Die Regierung des Landes Baden-Württemberg, 2017)).

(2015). The described procedure holds for DP and UP auctions. Bids are chosen while the cumulative amount of capacity is lower than the demand. Immediately after the procured quantity is reached or surpassed for the first time, the auction round is closed. This procedure is implemented into our model in all its specifications (see also: Anatolitis and Welisch (2017)).

The German PV pilot consisted of six rounds, three in 2015 and 2016 respectively. In each round quantities between 125 and 200 MW were tendered. The ceiling price started at 11.29 c€t/ kWh [2] then decreased to 11.19 ct/kWh and then 11.09 ct/kWh for the remaining four rounds (Deutscher Bundestag, 2017). Two of the pilot rounds (rounds 2 and 3) were held as UP auctions and the rest were DP auctions. Their results, which will also be discussed in the following were a sharp decrease in support costs[3], which were previously administratively set with a FiT system.

4.3 Auction-theoretic foundations

Since 2015, the support payments for ground-mounted solar PV plants in Germany, are determined by repeated, static multi-unit auctions. This section will elucidate this auction design as well as the characteristics of the participating bidders auction-theoretically. It will explain how we transferred this framework into an ABM and where the limitations of transferability between theory and practice are. We will start with the auction-theoretic basics of the revenue equivalence principle and then add complexity by including repeated games, asymmetric bidders and CVs.

The multi-unit characteristic is common to most auctions for RE support, meaning that more than one project is awarded to supply the auction

[2] c€t are in the future only referred to as ct for simplification purposes.

[3] The auction mechanism determines the sliding feed-in-premium that the generator receives. The payment is composed of the electricity spot price and an additional support payment. The sum of both equals the sliding feed-in-premium and, thus, the auction result.

demand. In the analyzed case of large-scale ground-mounted solar PV auctions in Germany, the auction volume in the first round was 150 MW of installed capacity, the maximum bid volume was 10 MW and thus at least 15 projects had to be awarded. As there were also smaller bid volumes, in total 25 projects were awarded in the first auction. The demand of installed capacity is considered to be homogeneous.[4]

The two most common formats are the so called DP and the UP auction. The latter can be further divided into the highest accepted or the lowest rejected bidder setting the price. In a simplified setting, DP and UP auctions have the same expected revenue, given only bidders with single unit supply participate (Engelbrecht-Wiggans, 1988). Nevertheless, bidding behavior is quite different between the two pricing rules (Weber, 1983). Especially, it can be shown that a UP auction with the LRB rule (which is not the case in the German ground-mounted solar PV auctions) is incentive compatible: it is the optimal strategy for a participating bidder to submit her true costs independent of the bidding strategy of every other bidder. The bidder cannot improve her expected profit by deviating from this strategy. A participant's bid does not determine the price she receives in a UP auction, which is different in case of winning in a DP auction. Thus, in a DP auction a bidder has an incentive to exaggerate the costs in the bid in order to gain a positive profit in case of winning the auction.

As we do not encounter a one-shot auction, but a repeated auction with several rounds each year over a multi-annual time frame, the conditions deviate from this simplified theoretical basis. Even a bidder with only a single project has the possibility to participate in several auction rounds. Therefore, the strategic considerations from the one-shot auction have to be adapted (Milgrom and Weber, 2000). For the sequential DP auction,

[4] An exception for this is to be found in the locational differentiation between arable land and converted areas, which will be explained and discussed in the following.

the adaptation is rather straightforward. In a one-shot auction the bidder has to consider the possibility of being awarded and the profit in case of award. In a sequential auction, the bidder considers the additional positive expected profit from being awarded in a future round. Thus, the more auction rounds remain, the more the bidder increases her profit margin by adding on to her true costs. If the bidder has not been awarded before the last round, she then applies the same bidding strategy as in the one-shot auction.

It is less intuitive to understand why there is also a deviation in the bidding strategy for UP if there is a sequential (repeated) auction. If all bidders would bid their true costs, the lowest cost bidder would be awarded in the first round at the costs of the second lowest bidder and so on. Thus, the award price would rise in every auction round as the lowest cost bidders are always awarded and do not participate in the forthcoming rounds. As a result, a bidder would prefer an award in a later round as this would yield a higher price and, as a consequence, a higher profit. To compensate for this effect, bidders increase their expected profit by submitting higher bids the more auction rounds are left. In the last round they follow the strategy of a one-shot auction and bid their true costs. As a result, the award price of a repeated UP auction is the same in each round and also the same as in a repeated DP auction. That is, the bidders in round t of a repeated UP auction use the same bidding strategy as a bidder in round $t + 1$ in a DP auction (Weber, 1983). As explained beforehand and also shown by e.g. Bower and Bunn (2001), it is impossible to derive a theoretical comparison between DP and UP outcomes in terms of multi-unit, repeated auctions. The underlying auctions exhibited a high level of competition and little danger of collusion (described e.g. in Bower and Bunn (2001) as the main reason for deviating from theoretically derived bidding strategies). Therefore, we assume that bidders in the benchmark case all submit their true costs and in the UP case the bidders utilize the DP strategy of round $t + 1$ in all but the last round where they bid their true costs.

An additional difficulty for theoretical analysis of auctions for RE support is that the set of participating bidders changes over time and the number of rounds each bidder can participate in, may be different. Furthermore, the bidders could differ in other ways. For example, their cost structure could be substantially different and bidders could also differ with respect to the available information. In auction theory, such bidders are considered asymmetric (Maskin and Riley, 2000). If certain bidder types are discriminated against in the auction, as is the case for arable land bidders in this auction pilot, due to the restriction to 10 awarded areas per year, they adapt their respective bidding strategy and bid more aggressively.

Furthermore, many cost components for RE sources are the same for most or all participants. PV modules are a major cost component and, except for large customer framework contracts, those costs are similar for all participants. They are thus referred to as CVs (Wilson, 1969). Although we didn't implement uncertainty through common cost components in our ABM (the bidders know their respective costs exactly), the cost reduction in PV module prices was common for all bidders.

The implications of the mentioned characteristics on the auction outcome and the bidding behaviur are manifold. Depending on the framework, it is hard or even impossible to theoretically derive the bidding strategies and in some cases there are several theoretical bidding equilibria. For this reason, we incorporate insights from theoretical analysis into an ABM to better understand the results of the first auction rounds for PV installations in Germany. The next section illustrates how we transferred the theoretical implications into the ABM.[5]

4.4 Agent-based model

This chapter documents the ABM we used to assess the German ground-mounted solar PV auctions - its set-up and input parameters. The model builds on work by Anatolitis and Welisch (2017), makes use of the ABM infrastructure mesa and is programmed in Python. In principle, the model simulates multi-unit, multiple round auction schemes with a variety of participants that are subject to different constraints (see Section 4.4.2). Depending on whether it's a DP or UP auction the bidders make use of different strategies, which are depicted in sections 4.4.4 and 4.4.3. In this study, six rounds of DP and six rounds of UP were modeled to replicate the German large-scale PV auction pilot. Furthermore, in Section 4.4.5 we show a benchmark case, where all participants truthfully submit their costs. Contrasting these modeled rounds with the empirical auction outcomes enables a more detailed understanding of the underlying bidder behavior.

Learning is a crucial factor in auctions over several rounds. In our simulation, the participants learn the weighted average overall bid in DP and the highest awarded bid in UP (Anatolitis and Welisch, 2017). The ceiling prices for each auction round have been administratively set at 11.29, 11.18 (two rounds) and 11.09 ct/kWh (last three rounds) and were incorporated in the model, as have the auctioned quantities of 150 (two

[5]In addition to the mentioned characteristics, auctions for RE support face an additional complexity through the participation of multi-unit bidders. However, quantifying the influence of such bidders is beyond the scope of this analysis, thus, we did not include them in our model. The main problem behind this is, that theoretically both pricing rules (UP and DP) are inefficient in the case where bidders can supply multiple units (Ausubel et al., 2014). A bidder with the potential to supply more than one unit of the good has an incentive to increase the bid for the second best and the following goods or even to reduce supply. This strategy enables bidders to increase the profit for the first or better bids and thus maximize profit.

rounds), 200, 125 (two rounds) and 150 MW respectively. [6] To average over stochastic elements of the simulation (Hailu et al., 2011), the mean of a minimum of 100 simulation rounds is used for each final result in the following modeling cases. The next section gives insights into the model's parameters before we get into the bidding process according to the different pricing rules.

4.4.1 Model parametrisation

The model is run with the following parameters. For each agent type $a_{converted,w}$, $a_{converted,s}$ and a_{arable} the number of bidders (per type) for the first round is predefined as follows: $|a_{converted,w}| = 75$, $|a_{converted,s}| = 75$ and $|a_{arable}| = 0$. Arable land bidders are initialized at 0, because their participation was not allowed in the first year of the pilot (i.e. the year 2015, rounds 1-3). Then the demand d^t for each round $t \in range(T)$ in MW and the auction's price limit p^t_{lim} in ct/kWh are implemented. Furthermore, the auction rounds in which each agent can participate are limited to the duration of the auction pilot $range(T)$. Each agent takes these input factors into consideration in order to optimize her bidding strategy over the given time period.

The bidder initialization process is as follows. For each type of agent, the bidders are drawn from the same distribution function and each bidder i is randomly assigned her initial costs c^0_i from her corresponding cost distribution in ct/kWh and a project size q_i in MW (see Table 4.1). Each agent i is therefore characterized as

[6] In the last round, actually 160 MW have been auctioned, which is due to the fact that in earlier rounds around 10 MW had been returned (Bundesnetzagentur, 2016). As in our model, we do not offer agents the possibility to return bids, we leave the auctioned quantity at the originally planned 150 MW to achieve the planned total amount of 400 MW for the year of 2016.

$$a_i = (c_i^0, q_i).$$

Consequently, each agent only submits one bid in each round and the model does not allow for multiple bids. This is a simplification which does not strongly impact the outcomes of the present analysis - as the focus rather lies on shedding light on bid price optimization as well as the different bidder types and the impacts of changing the restriction on arable land areas. After the bid submission, the bids are sorted in ascending order where $b_{(1)}$ corresponds to the lowest bid and the bidders are awarded until supply equals demand: $d^t = s^t$ where $s^t = (q_{(1)} + q_{(2)} + ... + q_{(n_s^t)})$. For the arable land bidders (a_{arable}), who only start participating in 2016 there is a limit of 10 awarded projects per year (so for rounds 4-6). The strike price is determined depending on the applied pricing rule. Before a new round takes place, a certain amount of new bidders in each category is drawn.

Degression takes place in every round. First of all, bidders whose bid was more than 15% above the highest awarded bid (strike price) do not participate in the next round. Similar behavior was observed in the statistical analysis of the empirical auction outcomes, such that we assumed this threshold to be a realistic approximation of bidding behavior in the German PV auction pilot. The other bidders who were not awarded but whose project is below the cost-threshold, remain "live", i.e. continue participating with their respective project. All awarded bidders have a 50 % chance to either participate in the following round or the round after that. They participate with a new bid b_i^{t+1} considering their new costs c_i^{t+1} which were multiplied by the degression factor λ^t: $c_i^{t+1} = \lambda^t \cdot c_i^t$.

4.4.2 Agents

The agents in this model are the bidders or auction participants. They are assumed to behave rationally. This means their bid is based on their costs and they try to maximize their expected profit over time. An agent is further characterized by her attributes, namely the size of her PV project, and her bidding behavior – the bid function and the implemented learning algorithm (see also Anatolitis and Welisch (2017)). As explained in Section 4.4.3, learning of bidders takes place by updating the bidding function with results from previous auction rounds. We assume three different types of bidders that participate in the auctions: a strong and a weak type for the converted areas - which are the most commonly auctioned areas in Germany, where the strong type draws from a lower cost distribution than the weak type. The different cost distributions we assign to the bidder types have been derived from statistical analysis of the actual bids submitted in the German ground-mounted PV pilot auction and are thus evidence-based. We further assume a third category: bidders bidding for arable land. These are the strongest types in terms of costs, as arable land is very cheap and constructing there most likely has lower opportunity costs, due to a lack of alternative use - making these bidders more competitive than the other types. However, due to legal restrictions (Deutscher Bundestag, 2017) only 10 of these areas were allowed to be awarded in 2016. Therefore, their participation is restricted in the model to starting in round 4 (first auction in 2016).

In the first round, a certain amount of participants is predetermined. For this, we try to mirror empirically observed participation which amounts to about 180 bidders. Having access to the detailed German PV auction pilot data, we are able to implement very concise and realistic assumptions into our model concerning the agent's behavior and cost distribution. First of all, as the number of bidders decreases over time, we assume a drop-out of participants. This drop-out is determined endogenously by restricting further participation to only those bidders who bid a maximum of 15% above the awarded bid. Similar behavior was observed empirically in the data we received on the auction pilot. We assume this to be rational behavior concerning the decreasing award probability over rounds. If a bidder was awarded, we assign her a 50% probability of participating in the next round. This is also a realistic assumption examining the data on repeated participation.

Concerning new entry of bidders, we also assessed the auction results and found that the number of entering participants decreases over time. We therefore model new entry to be endogenously dependent on the previous auction outcome. Specifically, we assume that more strong than weak bidders enter in each round, as they have a higher estimate of their chances of winning, weak bidders being more easily deterred by decreasing prices over time. Thus, the number of new entrants depends on the amount of bidders in the previous round. Namely, also drawing on insights from empirical data, 10% of the number of previous weak and 20% of the previous strong bidders enter in each round. New bidders for arable land only enter to that extent as there are still projects available, i.e. if not all 10 were awarded in the first round of 2016.

Agents' costs are also based on the empirical auction data.[7] We assume that all agents draw their bids from a uniform distribution, which differs for the respective agent types. This cost distribution adapts dynamically to the previous strike price for newly entering participants. Furthermore, there is external cost degression which affects both new and remaining par-

[7] Specifically, we statistically evaluated the distribution of bids from the first auction rounds and assigned bidders a distribution. The development of these costs however draws on module price developments in the two years, in order to not merely replicate the empirical auction outcomes but to rather show the extent of price development possible due to technical developments.

ticipants equally. Specifically, this cost degression is piecewise and builds upon module price data and observed bidding behavior for the two years. We assume an overall decrease of 2% per round in 2015 and 3% per round in 2016.[8] For project sizes, we also refer to the empirical data and implement a random draw between 1 and 10 MW capacity for the converted area bidders as well as for the arable land bidders, as there is no empirical evidence to model a difference between those types when it comes to size.

Table 4.1: Agent distribution.

Agent type	**Converted areas - strong type**	**Converted areas - weak type**	**Arable land**
Number of bidders in first round	75	75	0
New draw of bidders per round	20% (around 15)	10% (around 8)	varied[9]
Range of capacity bid [MW]	1-10 MW		
Cost distribution [ct/kWh]	7.5-8	8-10	6-8.5
Type of distribution	Uniform distribution		
Cost degression	2% per round in 2015, 3% per round in 2016		
Time span	t = 0,1...5 (equals 6 rounds)		

4.4.3 Discriminatory pricing (DP)

In a DP auction every awarded bidder receives her bid. Therefore, when a bidder wants to maximize her expected profit $E[\pi(\cdot)]$ she has to weigh the possibility of winning in this round with the profit in case of winning and also the possibility to be awarded in an upcoming auction round. The possibility to be awarded increases with a lower bid but then the profit in

[8] The module price translates into an approximate cost decrease of 50%, and as we observed a steeper decline in 2016 (pvXchange Trading GmbH, 2017), we implement this change between the years.

case of winning decreases. The expected profit for rounds t=0,1,2,...,T for a representative bidder i is thus given as follows:

$$\max_b E[\pi_i(\mathbf{b_i})] = \sum_{j=t}^{T} \delta^{j-t}(b_i^j - c_i^j) \cdot Pr(\text{`awarded in round j'}) \\ \cdot \prod_{x=1}^{j-t} Pr(\text{`not awarded in round j-x'}) \qquad (4.1)$$

The bid vector $\mathbf{b_i}$ contains all bids b_i^t of bidder i from the current round t to the last round T. Furthermore, the discount factor $\delta \in (0, 1)$ represents the bidders' preference that the same profit is less favorable in a future round than in the current round. In combination with the bidders costs c_i^t in the specific round, the profit in case of winning can be calculated. As a bidder can (by assumption) only participate with one project in any given round, the bidder can only take part in a future round with the same project if she has not previously been awarded. Hence, for all rounds $t < T$, not being awarded in this round still leads to a positive expected profit as there is a positive probability of being awarded in a future round.

In (4.1), the probabilities to be awarded in a specific round and to not be awarded in all previous rounds are not elaborated. (4.2) accounts for this issue and shows where learning comes into play. We assume the bidders to have a rough estimation regarding their competitors in the first auction round and based on the results of the auctions, they adapt their beliefs. Therefore, we introduce a cumulative distribution function (CDF). This function $F(\cdot)$ captures an agent's belief on the bid distribution of the other participants. This belief contains both the expected number of competitors and their strength.

The bidders model the CDF as a normal distribution where they adapt the distribution through adjustment of the mean μ to the results of the previous rounds. In the first round, the agents base μ on their own signal and in the forthcoming rounds, they use the newly generated information to adapt μ to the overall mean bid of the previous auction round. Furthermore, the number of participants in the last round n^{t-1} and the number of awarded bidders n_s^{t-1} is considered for the forthcoming rounds (also accounting for the varying auction volume). Given these assumptions, from an agent's perspective, the probability $F(b_i^t)$ equals the probability that b_i^t is higher than the bid of one other bidder from the CDF $F(\cdot)$ and respectively $1 - F(b_i)$ depicts the bidder's probability of her own bid being lower than her opponent's.

Applying the concept of order statistics, the agents can calculate the expected probability of having a lower bid than a predefined fraction of other bidders. More precisely, based on the agents assumption on the strength of their competitors, the number of competitors and the number of successful bidders, the agent can calculate the probability of being awarded given a specific bid.[10] In the first round, they make an initial assumption on competition: *comp* and on the number of successful bidders: *succ*.

Based on the approach in Ahsanullah et al. (2013) and Anatolitis and Welisch (2017), we can calculate the expected profit of the agent i given a specific bid vector $\mathbf{b_i}$ as

[10] Moreover, as it is a multi-unit auction, the agents have to consider that not only the lowest bid is awarded but that there are different possibilities depending on the agent's position in the order of the bids.

$$\mathbf{E}(\pi_i(\mathbf{b_i})) = \sum_{j=t}^{T} \delta^{j-t} \left(b_i^j - c^j\right) \cdot \sum_{k=0}^{n_s^{t-1}-1} \binom{n^{t-1}-1}{k} F(b_i^j)^k \left(1 - F(b_i^j)\right)^{n^{t-1}-1-k} \cdot \prod_{x=1}^{j-t} \sum_{l=n_S^{t-1}}^{n^{t-1}-1} \binom{n^{t-1}-1}{l} F(b_i^j)^l \left(1 - F(b_i^j)\right)^{n^{t-1}-1-l}. \quad (4.2)$$

The bidders maximize the expected profit given in (4.2) by optimizing their bid vector $\mathbf{b_i}$. After every auction round, the bidders adjust this bid vector given the additional information from this last round. By incorporating this information, bidders improve their bidding function by learning between auction rounds. They can adapt their bids up or downwards, depending on the average bid and level of competition in the previous round. In addition, all bidders experience technological learning which lowers the costs for all bidders alike. It should be noted that this approach is based on auction theory, but does not consider the other bidders' behavior, i.e. their best response. Therefore, this approach has to be considered as a decision-theoretic optimization.

4.4.4 Uniform pricing (UP)

The main difference between DP and UP is the price determination. In the case of a UP auction, the agents also simultaneously submit their bids (b_i^t, q_i). Bids are rejected if they are above the ceiling price $(b_i^t > p_{lim}^t)$ or lower than zero $(b_i^t < 0)$, as foreseen by law. The uniform remuneration in our model is determined by the highest awarded bid $b_{n_s^t+1}^t$, which corresponds to the German PV auction scheme.

As already mentioned in Section 4.3, in an idealized setting in a UP auction it is a (weakly) dominant strategy for each bidder to bid her own costs. However, if the UP auction is repeated, the strategic considerations change and bidders increase their expected profit by deviating from this strategy. Given all further design parameters in this setting, it is difficult to determine an equilibrium bidding strategy for a UP auction where the bidder has no direct influence on her award price (Lykouris et al., 2016). We thus assume the equilibrium bidding strategy of the repeated UP auction which is to use in round t the same strategy as in a DP auction in round $t+1$ and submitting one's true costs in the last round (see Section 4.3).

4.4.5 Benchmark case

Finally, in a benchmark case we assume the bidders to apply the symmetric bidding strategy

$$\beta(c_i^t) = c_i^t \tag{4.3}$$

which assumes that bidders follow the same bidding strategy as in the one-shot UP auction, meaning they submit their true costs in every round.[11] As the corresponding pricing rule we use a UP with LRB. This provides us a comparison to both the empirical results and the results from the simulation of the DP and UP rule. The bidding process, selection of winning bids and drawing of new bidders in the respective rounds is the same in all three variations.

[11]The assumption of truth telling in a repeated auction is quite strong. However, with this benchmark case we do not claim full accuracy but rather want to provide the results of a what-if scenario as an additional comparison.

4.5 Results and discussion

In this section, we present findings from modelling the German ground-mounted PV pilot as six rounds of UP, DP and the benchmark case respectively. To provide adequate insights into the different bidding strategies of arable land bidders, we further simulate a distinct auction for 2016, taking into account their limits concerning the time horizon and the average capacity available for the allowance of 10 projects (55 MW). As competition in this separate simulation, we assume all arable land competitors as well as the lower cost converted area bidders, i.e. all direct competition in the lower bid range (see Table 4.3 for model results).

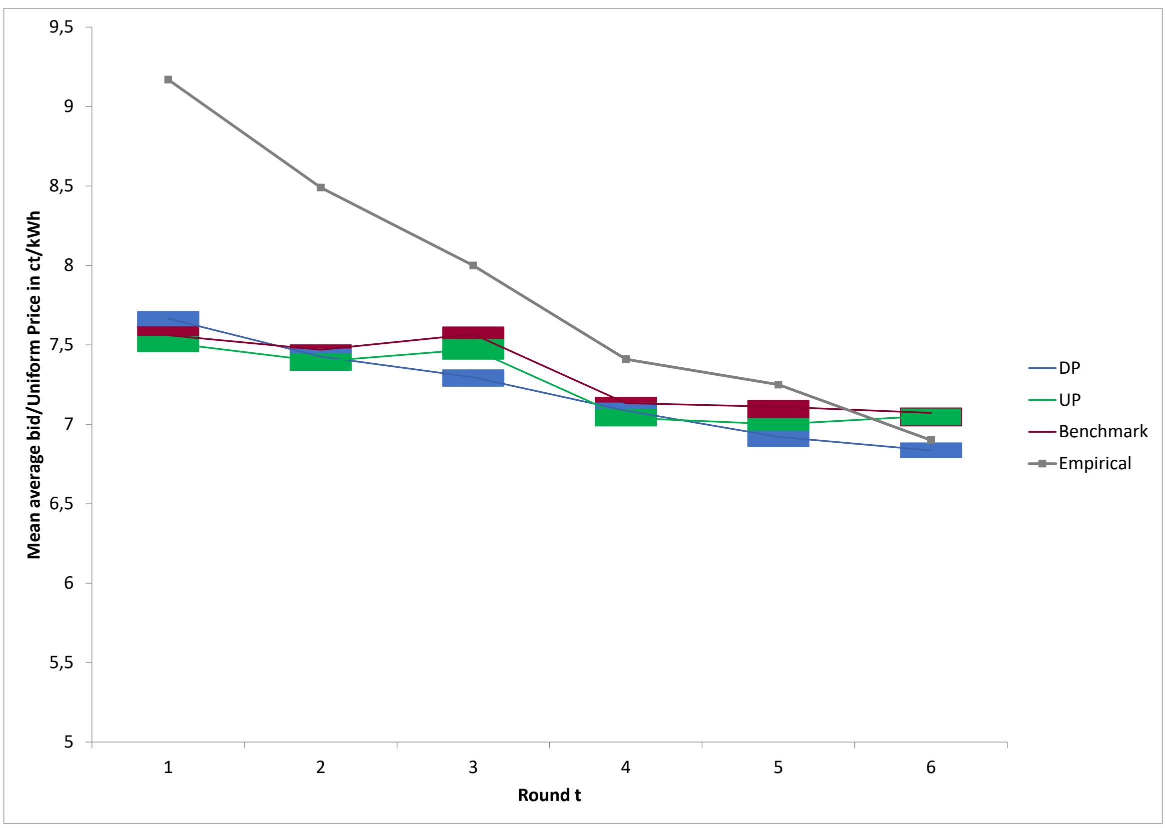


Figure 4.1: Comparison of the mean award price between the actual auction outcome and the model results.

Figure 4.1 shows a comparison of the auction outcome of the PV pilot auctions in Germany with our modeled DP results as well as a UP and a benchmark case.[12] The dispersion shown for the modeled results is the distribution over 100 simulation rounds.

We can see that the actual auction results of the PV pilot are substantially higher in the first three rounds compared to our modeled results. In the modeled DP case, all bids lie (at least slightly) below the empirical auction outcomes, showing that with the competition present in the German solar PV auctions and accounting for technology cost developments, lower auction results would have been possible from the start of the auction. Another explanation could have been learning effects and recovery of sunk costs from bidders in the actual auction in the transition phase between the administratively set support scheme and the auction-based system. This is a parameter which cannot be captured as easily in the ABM, as this kind of calculation has to take place before the auction itself. Further the average award price is decreasing with each round.

In the benchmark case, all outcomes but the last one are below the empirical auction outcomes. The results of the UP case lie between the DP and the truth telling outcomes. Both UP and the benchmark case are more volatile than the DP auction with respect to the auction volume and external effects (arable land bidders in Round 4). That is, in Round 3 the award prices increase compared to the previous round. So the price determining bid is more dependent on the auctioned quantity than the average bid in the DP case although those agents accounted for the additional demand. The same applies the other way around in Round 4 where the additional arable land bidders participate. To summarize this comparison, the UP case lies between DP and benchmark and has a greater reactions

[12] The empirical auction took place as one round of DP, two rounds of UP and three rounds of DP. The model results show six rounds of either pricing mechanism.

to a changing competition level than the DP case.

The model results show that bidding in the German pilot became more and more aggressive over time, potentially even inducing bidders to put up with small losses to secure their project realization.[13] This is in line with theory and empirical findings, showing that towards the end of a series of auctions, bidders become more aggressive as their probability to realize a successful bid decreases. To summarize, the sharp decline in award prices in the German PV pilot auctions cannot be explained by falling prices for PV modules alone, but may also have occured due to pressure on realization towards the end of the pilot or uncertainty about the continuation of the support scheme and future award possibilities. Comparing the empirical outcomes to our model results, it is highly possible that the bidders either reduced their profit margin or benefited from economies of scale or one or several of the previously described learning effects.

This finding is particularly substantiated by the DP modeling results, which are very much in line with the final three rounds. The reason for the monotonically decreasing prices in the DP model lies in the simulated expectation of a lower level of competition in the first round. Modeling this, we tried to approximate bidder behavior in the pilot where the first rounds exhibited high(er) prices. As bidders learn about the strong competition and low bid prices from previous rounds, they incorporate this knowledge into their strategies and reduce their bids and therefore their profit margin. Furthermore, bids decrease as the subset of non-competitive high-cost bidders becomes smaller over time and the successful bidders are increasingly cost-competitive. Without the assumption of a low competition level in the first round, the difference between model and empirical findings would be even higher and award prices would not decline throughout the auction

[13]Aggressive bidding in this case means that bidders decrease their profit margin and submit bids very close to their true costs in order to ensure that their project is secured.

rounds due to the higher auction volume in Round 3. Nevertheless, even modeling the earlier described two-way learning does not provide us with the empirically observed outcomes of the auction pilot.

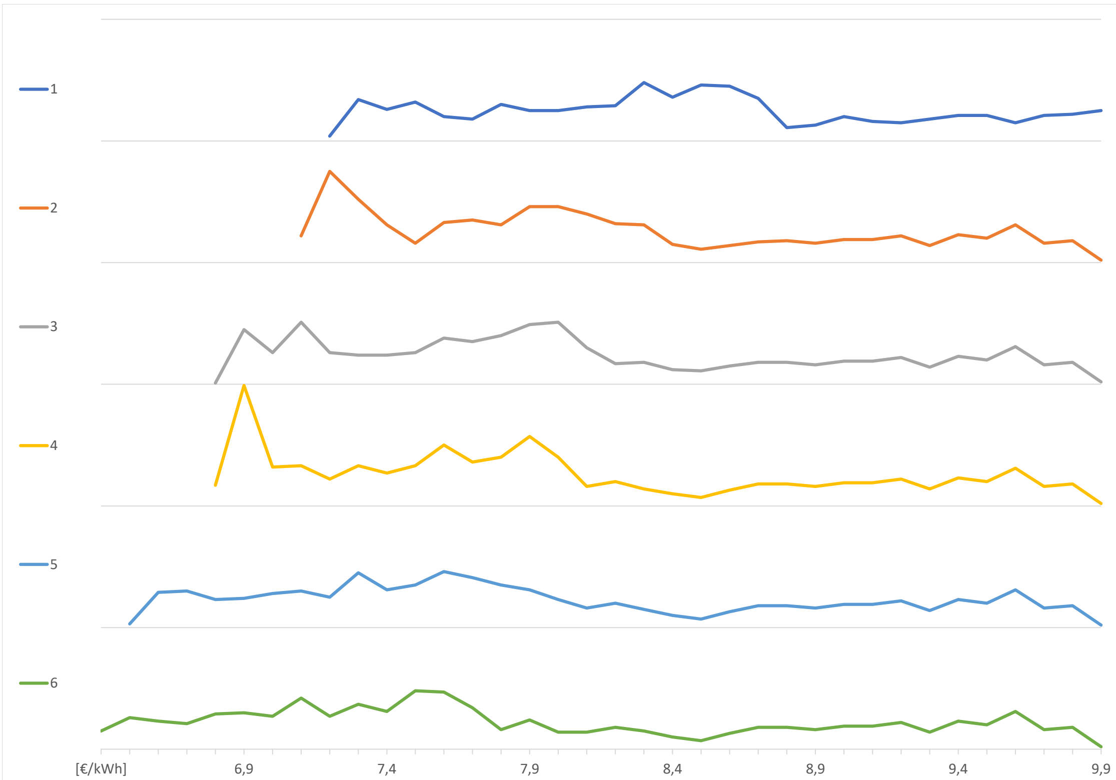


Figure 4.2: Comparison of the overall bid distribution for all six rounds in the DP model.

Figure 4.2 shows the distribution of bid prices averaged over five exemplary simulations of the auction pilot. Basically, we zoom into the development of the bids over time in more detail and the vertical variation shows the amount of bidders at each point of the bid price distribution. The figure distinguishes the distribution for the different rounds, starting with the distribution of all bids from the first down to the sixth round. Two general patterns regarding the bidding behavior are identifiable. First, the competitive bidders, i.e. those bidders with the lower costs and thus with bids on the left hand side of the figure, reduce their bid in the duration of the auctions. This can be seen by the shift to the left of the curve from round to round in general and the shift to the left of the first peak in particular. The distribution of the bids of the weaker bidders, i.e. the bidders on the right hand side of the graph is different. From the second auction round onward, the bid distribution remains constant. A possible explanation for this could be, that those bidders learn their low probability of being awarded and thus have already bid really aggressively (close to their true costs) at an early stage so that the timing only plays a minor role.

Table 4.2: Detailed results of the DP model.

Round	**Average supply**	**Mean overall bid**	**Mean awarded bid**	**Mean highest awarded bid**	**Average profit**
1	153.04	8.75	7.67	7.93	0.37
2	153.22	8.37	7.43	7.52	0.21
3	202.86	8.27	7.30	7.56	0.10
4	127.98	8.18	7.09	7.15	0.24
5	128.06	8.15	6.92	7.12	0.04
6	152.80	8.07	6.84	7.08	0.03

Table 4.2 further specifies the results of the DP model. It shows that the mean overall bid follows the same trend as the mean awarded bid illustrated in Figure 4.1. So not only the awarded bidders reduce their bids throughout the auction rounds but also the bidders in general. However, this trend is not as strong as for the awarded bidders. The explanation for this is already provided by Figure 4.2. Furthermore, not only the average bid is decreasing but as a result also the average profit of the bidders falls. The sole exception is Round 4 where the bidders on arable land participate for the first (and final) time, due to the legislative restriction described earlier.

We then open up the auction to a range of scenarios where we lift this limit on arable land bidding. We model scenarios which are already taking place or are planned for the near future, due to the so-called Bundesländerklausel/Freiflächen-Öffnungsverordnung. As explained earlier, this law enables German federal states (Bundesländer) to individually regulate the auctioning of arable land for large-scale ground-mounted solar PV. While the modeled costs thus show that the ABM is suitable to reproduce the findings from the PV pilot auctions, we are further interested in insights on agent behavior and composition. Specifically, we want to look into the impacts of allowing arable land bidders in 2016 and furthermore to show how auction results could change if the restrictions on these bidders' participation were lifted. Detailed results for the arable land bidders are shown in Table 4.3.

Table 4.3: Detailled results of the DP model for arable land bidders in Round 4.

Round	**Average supply**	**Mean overall bid**	**Mean awarded bid**	**Mean highest awarded bid**	**Average profit**
4	58.17	7.54	6.90	6.94	0.21

The depicted results are from a scenario where only the arable land bidders compete, as well as a small partition of very low-priced converted area bidders. Specifically, a separate auction is shown, where all relevant model parameters are reduced: available size (an average of 55 MW), time horizon (one year, i.e. three rounds) and the number and characteristics of participants. This scenario represents the optimization horizon of the arable land bidders, who basically compete amongst themselves and in the PV pilot only have a realistic award probability in the first round of 2016, due to the small amount of available land.

Model results from this scenario clearly illustrate that arable land bidders are amongst the most aggressive bidders. In all displayed criteria, the results are well below the values of the original scenario in Table 4.2.

Two main conclusions can be drawn from those model results. Firstly, the participation of arable land bidders reduces the award price and thus the support costs for RE. Secondly, by discrimination against arable land bidders[14] who have a cost advantage the support costs may be reduced even further (see Chapter 3). This is particularly visible when comparing the average profit of the bidders in the arable land auction to those of the overall auction scheme: in the discriminatory auction, the average profit is lower, reflecting more aggressive bidding behavior. This finding shows that by lifting the restriction as already planned or implemented in some parts of Germany, bid prices are bound to decrease even further. Having all bidders participate in the same auction without restrictions on arable land bidders, could however also lead this bidder type to increase their profit margin by correcting their bid towards the cost level of the competitors (converted areas). Which effect would be stronger would finally depend on the total amount of land freed up for this bidder type.

4.6 Conclusions

This chapter analyses bidder behavior in the German PV auction pilot which took place over six rounds in the years 2015 and 2016. For this, it uses a novel approach which combines insights from decision theory and data analysis which were both used to optimize an agent-based auction simulation model. Decision theory was used to model the agent's bidding behavior precisely, and an ABM was used to calibrate the characteristics of the agents based on empirical auction outcomes. We model six UP rounds and a DP scheme over the same time period, where agents account for several auction and auction round-specific parameters when optimizing their bidding strategy over time.

[14]Discrimination in that case is the restriction on a fixed number of awarded bidders.

The findings from modeling are then contrasted with the empirical auction outcomes. As the bidders are modeled according to empirical insights on bidder behavior, this comparison shows how the empirical results compare to a modeled decision theoretic optimization approach, assuming bidders behave rationally. This way we use the essence of theory, modeling and empirical data analysis to add a new contribution towards understanding auction-based support schemes. In particular, we find that the high bid prices in the first rounds and the monotonously decreasing price development can not merely be attributed to cost decreases in PV module prices. Potentially, the relatively high auction outcome in the first round can be explained by high uncertainty regarding the level of competition in the auction.[15] A further explanation are learning effects of auction participants that took place in the transition phase between the previous administratively set FiT and the auction-based support system. Furthermore, the sharp reduction in award prices towards the end of the auction pilot shows how bidding behavior became increasingly aggressive, potentially due to the high competition and the pressure to realize a project before the support scheme ends.

Moreover, we look at the bidders who submit projects for the limited arable land areas and their specific behavior. These bidders are the most cost-competitive types in the German large-scale solar PV auctions. In addition to the overall auction simulation, we model their optimization by taking them out of the auction and having them participate in a simulated separate environment - as the limitations on arable land actually caused a sort of discriminatory auction to take place. This simulation leads to two main conclusions. Firstly, the participation of arable land bidders reduces the support costs significantly, as those bidders are the most competitive

[15] Modeling sensitivities in terms of different expectations towards competition showed that this hypothesis is plausible under the given assumptions.

types. Secondly, discrimination induces arable land bidders to bid more aggressively, due to the higher competition level amongst the strongest types of bidders, as they compete for a very low amount of areas. Continuing this limitation and thus implicitly discriminating among bidder types, could actually even lead to lower bid prices and thus overall reduced support costs. How costs develop with the increased participation of the arable land bidder type, which will occur due to legislative changes and expanded opening of auction schemes towards this type of land use, thus depends on how participation of this bidder type will be implemented in the future.

In terms of further research it would be interesting to relax the assumptions on single-unit bidders and include more strategies for bidder types that enter the auction with several projects. Furthermore, an ex-post analysis of outcomes after the legislative change will be of interest, to see how this change has actually affected the overall bidding behavior.

Chapter 5

Multi-unit common value procurement auctions – theoretical and experimental analysis

Auctions for RE support are usually conducted as procurement auctions, in which the bidders (i.e., energy companies) compete with their projects for financial support. The prevailing design is a multi-item sealed bid auction, either as DP auction or UP auction (Wigand et al., 2016; del Río, 2017)[1].

The two most important RE sources, wind and solar, are characterized by a large proportion of common components, whose cost are the same for all bidders. This is caused by a high cost share for raw material (e.g., steel and copper in wind turbines), PV modules, and standardized electronic and mechanical equipment (Yu et al., 2017; IRENA, 2017).[2]. Due to long periods for the realization of the awarded projects, often several years, the projects are usually accompanied by a high degree of cost uncertainty, particularly their common cost components (Wigand et al., 2016). Thus, the problem of the winner's curse (e.g., Thaler, 1988) plays an important role

[1]For the theoretical analysis of multi-item auctions see, e.g., Ausubel et al. (2014).

[2]Generally, the stricter the bidding requirements are, the larger is the common cost component. This, for example, applies to offshore wind auctions, where the sites are pre-determined and even pre-developed and the total capacity is restricted (e.g. Bureau of Ocean Energy Management, 2018).

in the support of RE sources through auctions (IRENA, 2017). Beside the bidders, also the auctioneer has a strong interest in avoiding the winner's curse in order not to endanger the acceptability of the RE auctions and future participation.

Section 5.1 reviews the existing literature on CV auctions and illustrates the relation to auctions for RE support. In Section 5.2, we present the theoretical model of multi-unit CV procurement auctions, derive the unique symmetric equilibrium for DP and UP, and formulate our experimental hypotheses. Section 5.3 outlines our experimental setting and the results of the experiment are presented in Section 5.4. Section 5.5 concludes.

5.1 Common values in auctions

Common value auctions and the phenomenon of the winner's curse have been attracted attention for a long time and have been investigated intensively, theoretically, empirically, and experimentally. Most of theses studies consider single-unit sales auctions, in which the bidders receive private signals that are correlated with the ex ante unknown CV of the good being sold.

The theoretical analysis of CV auction started with Wilson (1969), followed by many other works,[3] including the general auction model by Milgrom and Weber (1982).

The empirical analysis of CV auctions and the winner's curse was initiated by a study of auctions for oil and gas leases (Capen et al., 1971). The winner's curse has since been identified in a number of fields, e.g., takeovers (Roll, 1986; Varaiya and Ferris, 1987), bank loans (Shaffer, 1998), (IT-)outsourcing (Kern et al., 2002), or even baseball (Cassing and Douglas, 1980).[4] In an investigation of CV procurement auctions, Hong and Shum

[3]See, for example, the survey by McAfee and McMillan (1987).

[4]For further examples see Hendricks et al. (1987), Hendricks and Porter (1988), McAfee and McMillan

(2002) find more conservative bidding (i.e., higher bids) if the competition level increases (i.e., the number of competitors increases), which is in line with theory.

The experimental analysis of CV auctions was initiated by Bazerman and Samuelson (1983) and their great coin jar experiment. In most of the following experiments, the CV and the bidders' signal are randomly generated, where two design are prevalent. The first is based on the approach of Wilson (1969) with a randomly generated CV and randomly drawn signals around the CV. This design was first implemented by Kagel and Levin (1986). The other is based on the wallet auction (Bulow and Klemperer, 2002), in which the CV is endogenously generated by the randomly drawn signals. This design is used, e.g., by Avery and Kagel (1997) and Goeree and Offerman (2002).[5]

We design our experimental in accordance with the prevailing conditions of actual RE auctions. The auctions are conducted as multi-unit procurement auctions with simultaneous sealed bidding. The demanded objects are homogenous CV goods, i.e., producing a good has the same common cost for all bidders, where we apply the design of Kagel and Levin (1986), which fits well with the conditions in RE auctions. The bidders have single-unit supply, i.e., each bidder can produce and deliver one good.

Within this framework, we investigate the effects of the competition level (i.e., relationship between number of goods and number of bidders) and the pricing rule (i.e, DP and UP) and their combination on the auction outcome. Here, we particularly focus on bidders' profit and, thus, the prices (i.e., auctioneer's rent) and on the occurrence of the winner's curse, or more precisely, on the frequency of awarded bids with a loss.[6]

(1987) and Thaler (1988).

[5]For an overview on auction experiments, see, e.g., Kagel and Levin (2016).

[6]Strictly speaking, the winner's curse refers to an expected loss, while in the experiment and in the real world, actual losses matter, which, therefore, can be termed as "ex post winner's curse".

Novelties of our study are the investigation of multi-unit auctions, the systematic comparison of DP and UP, and varying the competition level by altering the number of goods while keeping the number of bidders constant. These elements are relevant for real world applications, including RE auctions. The comparison of advantages and disadvantages of DP and UP has a long history in the economic literature (e.g., Ausubel and Cramton, 2011; Griffin, 2013), and is also intensively discussed in the context of RE auctions (e.g., del Río, 2017; Haufe and Ehrhart, 2018). Beside the aspect of maximizing auctioneer's expected rent, the controversial debates also include the question which format is better in preventing the winner's curse. This was one of the reasons why both formats were implemented in the PV pilot auctions in Germany in 2015 (Wigand et al., 2016). Finally, the number of auctioned goods is an important design element because this can be controlled by the auctioneer.

In experiments of Kagel et al. (1995) and Kagel and Levin (1986), in which single-unit sales auctions are implemented, the competition level is varied by the number of bidders, and they find that a lower competition level results higher bidder profit and a lower loss frequency. Experimental investigations of pricing rules are mainly concentrated on either a comparison of static and dynamic formats (Kagel et al., 1987; Kirchkamp and Moldovanu, 2004; Turocy and Cason, 2015) or a single price rule (e.g., Kagel et al., 1995; Goeree and Offerman, 2003). A finding of our study is that experimental results do not support the theoretical predicted differences between the DP and UP auction concerning bidders' profit and loss frequency.

There are several studies that focus on potential explanations for the winner's curse in CV auctions, e.g., limited liability (Hansen and Lott, 1991; Cox et al., 1999), level-k thinking (Eyster and Rabin, 2005; Crawford and Iriberri, 2007), bounded rationality (Charness and Levin, 2009), number of rounds (Ball et al., 1991; Lind and Plott, 1991), feedback to bidders and information conditions (Armantier, 2004; Brocas et al., 2017), comparison between experienced and inexperienced bidders (Dyer et al., 1989; Garvin and Kagel, 1994), and the joy of winning (Holt and Sherman, 1994). In this context, we refer to another finding of our study. We observe in both auctions, DP and UP, that the frequency of losses (i.e., the winner's curse) significantly decreases as the number of goods increases, which, however, cannot be attributed to an improvement in the bidding behavior, but simply to its heterogeneity.

5.2 Theory

We consider procurement auctions for k homogeneous goods. In the UP auction the goods are purchased at the same price, where the LRB rule is applied. In the DP auction the goods are purchased at different prices, which are determined by the awarded bids. There is a set N of n symmetric, risk-neutral single-unit-supply bidders, who have common cost, i.e., the same production cost for a unit of the good, and affiliated signals. Our approach is based on the well-known model of a sales auction for a CV good with a uniformly distributed value and bidders' signals independently drawn from a uniform distribution around the good's value (e.g. Kagel and Levin, 1986). The extension to multi-unit auctions is provided by Ehrhart and Ott (2019). In our approach, the common production cost are modeled by the random variable C, which is drawn from a uniform distribution on $[\underline{c}, \bar{c}]$. Given $C = c$, bidders' signals $X_1, X_2, \ldots, X_n$ are independent draws from a uniform distribution on $[c - \varepsilon, c + \varepsilon]$. Throughout this chapter, we restrict our analysis to signals in the interval $[\underline{c} + \varepsilon, \bar{c} - \varepsilon]$, so that from the individual perspective of a bidder with signal x, C is uniformly distributed on $[x-\varepsilon, x+\varepsilon]$. The model parameters of our experiment are shown in Table 5.1.

The symmetric equilibrium bid of the UP auction is given by

$$\beta^{UP}_{(k,n)}(x) = x + \frac{n-2k}{n}\varepsilon \tag{5.1}$$

and of the DP auction by

$$\beta^{DP}_{(k,n)}(x) = x + \varepsilon - \frac{k+1}{n+1}\varepsilon \cdot \exp\left(-\frac{n(\bar{c}-\varepsilon-x)}{2k\varepsilon}\right). \tag{5.2}$$

The derivation of the equilibrium bids is presented in Appendix B.1.[7]

The auctioneer's payment per good is the price she has to pay per good. The expected price in the UP auction and in the DP auction are

$$E[P^{UP}_{(k,n)}] = E\left[\beta^{UP}_{(k,n)}(X_{(k+1,n)})\right], \tag{5.3}$$

$$E[P^{DP}_{(k,n)}] = \frac{1}{k}\sum_{j=1}^{k} E\left[\beta^{DP}_{(k,n)}(X_{(j,n)})\right]. \tag{5.4}$$

Although (5.4) is calculated as an average expected price, for simplicity, we call (5.4) the expected price in the DP auction.

Given $C = c$, the expected value of the j-lowest signal $X_{(j,n)}$ is

$$\begin{aligned} E[X_{(j,n)} \,|\, C = c] &= c - \varepsilon + \frac{2j\varepsilon}{n+1} \\ &= c - \frac{n+1-2j}{n+1}\varepsilon\,. \end{aligned} \tag{5.5}$$

[7] The UP and DP equilibrium bids correspond to the equilibrium bids provided by Ehrhart and Ott (2019) for sales auctions with k goods with the same common value v, which is randomly drawn from a uniform distribution on $[\underline{v}, \bar{v}]$:

$$\begin{aligned} \beta^{UP}_{(k,n)}(x) &= x - \frac{n-2k}{n}\varepsilon\,, \\ \beta^{DP}_{(k,n)}(x) &= x - \varepsilon + \frac{k+1}{n+1}\varepsilon \cdot \exp\left(-\frac{n(x-\underline{v}-\varepsilon)}{2k\varepsilon}\right). \end{aligned}$$

These are the multi-unit extensions of the single-unit cases with $k = 1$ (e.g. Kagel and Levin, 2002).

In the UP auction, the bidder with the signal $X_{(k+1,n)}$ determines the price. By (5.5),

$$E[X_{(k+1,n)}] = E[C] + \frac{2k+1-n}{n+1}\varepsilon\,. \tag{5.6}$$

With (5.1) and (5.6), the expected price per good (5.3) yields

$$\begin{aligned} E[P^{UP}_{(k,n)}] &= E\left[\beta^{UP}_{(k,n)}(X_{(k+1,n)})\right] \\ &= E[C] + \frac{n-k}{n(n+1)}2\varepsilon\,. \end{aligned} \tag{5.7}$$

By (5.7), $E[P^{UP}_{(k,n)}]$ increases in ε. That is, the higher the bidders' uncertainty about the cost of the good, the higher is the expected price.

In the DP auction, the expected price (5.4) is given by[8]

$$\begin{aligned} E\left[P^{DP}_{(k,n)}\right] &= \frac{E\left[\sum_{j=1}^{k}\beta^{DP}_{(k,n)}(X_{(j,n)})\,|\,C\right]}{k} \\ &= \int_{\underline{c}+2\varepsilon}^{\bar{c}-2\varepsilon}\sum_{j=1}^{k}\int_{c-\varepsilon}^{c+\varepsilon}\left(x+\varepsilon-\frac{(k+1)\varepsilon}{n+1}\exp\left(-\frac{n(\bar{c}-\varepsilon-x)}{2k\varepsilon}\right)\right) \\ &\quad\cdot f_{(j,n)}(x|c)\,dx\,\frac{1}{k(\bar{c}-\underline{c}-4\varepsilon)}\,dc\,. \end{aligned}$$

What are the effects of varying the number of goods k for a given number of bidders n? Since the equilibrium bid strictly increases in the signal x for both auctions in the CV model, the awarded bidders' profit and the prices are completely correlated: a higher price is equivalent to a higher bidders' profit.

Corollary 1. *In the procurement auction with k common cost goods and*

[8] The conditional density $f_{(j,n)}(x|c)$ of the j-lowest signal of n bidders given c is

$$\begin{aligned} f_{(j,n)}(x|c) &= n\binom{n-1}{j-1}f(x|c)F(x|c)^{j-1}(1-F(x|c))^{n-j} \\ &= \frac{n!}{(n-j)!(j-1)!}\frac{(x-c+\varepsilon)^{j-1}(c+\varepsilon-x)^{n-j}}{(2\varepsilon)^n} \quad \text{for } x\in[c-\varepsilon,c+\varepsilon] \end{aligned}$$

n bidders, the following apply:

(i) In the DP auction the equilibrium bid $\beta^{DP}_{(k,n)}(x)$ decreases in k, while the expected average price $E[P^{DP}_{(k,n)}]$ and the awarded bidders' average expected profit increase in k if $\frac{\bar{c}-\underline{c}}{\varepsilon}$ is sufficiently large.

(ii) In the UP auction, the equilibrium bid $\beta^{UP}_{(k,n)}(x)$ decreases in k and also the expected price $E[P^{UP}_{(k,n)}]$ and the awarded bidders' expected profit.

(iii) The expected price in the UP auction is smaller than in the DP auction, i.e., $E[P^{UP}_{(k,n)}] < E[P^{DP}_{(k,n)}]$, and the difference $E[P^{DP}_{(k,n)}] - E[P^{UP}_{(k,n)}]$ increases in k. The same applies to the awarded bidders' (average) expected profit.

The first part of (i) follows from $\partial\beta^{DP}_{(k,n)}(x)/\partial k < 0$,[9] while (ii) directly follows from (5.1) and (5.7). That is, equilibrium bids for UP and DP decrease in k. Results (iii) reflects a general results for interdependent costs and affiliated signals (Ehrhart and Ott, 2019).

In the DP auction, the price effect of k is the same as in the IPV model, whereas in the UP auction, the price effect is different. Although an increasing k has a negative effect on both equilibrium bids of UP and DP, the price effects of k for UP and for DP are opposite. An increasing k effects an decreasing expected price in the UP auction.

Next, we consider winning bidders' loss probability. Although ex ante bidders expect positive profits in the auction equilibrium, ex post they can suffer a loss if the award price is lower than the actual cost.

In the UP auction, the bidder with the $k+1$-lowest signal determines the price. Thus, the probability that all k awarded bidders (i.e., the k bidders

[9] By (5.2),

$$\frac{\partial\beta^{DP}_{(k,n)}(x)}{\partial k} = -\frac{\varepsilon}{n+1}\left(1+\frac{n(k+1)(\bar{c}-\varepsilon-x)}{2(n+1)k^2\varepsilon}\right)\exp\left(-\frac{n(\bar{c}-\varepsilon-x)}{2k\varepsilon}\right) < 0\,. \tag{5.8}$$

with the lowest signals) suffer a loss is equal to $Prob\left\{\beta^{UP}_{(k,n)}(X_{(k+1,n)}) < C\right\}$. Since the UP equilibrium bid (5.1) does not depend on the position of the signal x in the interval $[\underline{c}+\varepsilon, \bar{c}-\varepsilon]$, the loss probability is the same for every c and with (5.1) becomes[10]

$$Prob\left\{\beta^{UP}_{(k,n)}(X_{(k+1,n)}) < C\right\} = \sum_{j=0}^{n-k-1} \binom{n}{j} \left(\frac{k}{n}\right)^{n-j} \left(\frac{n-k}{n}\right)^{j} . \quad (5.9)$$

In the DP auction, the k awarded bidders (i.e., the k bidders with the lowest signals) receive their bid and an awarded bidder suffers a loss if $\beta^{DP}_{(k,n)}(x) < c$. Other than in the UP auction, the DP equilibrium bid (5.2) depends on the position of the signal x in the interval $[\underline{c}+\varepsilon, \bar{c}-\varepsilon]$. Thus, the distribution of C has to be taken into account when computing the awarded bidders' loss probabilities, which is given by

$$Prob\left\{\beta^{DP}_{(k,n)}(X_{(j,n)}) < C\right\} = \frac{1}{\bar{c}-\underline{c}-4\epsilon} \int_{\underline{c}+2\epsilon}^{\bar{c}-2\epsilon} F_{(j,n)}\left({\beta^{DP}_{(k,n)}}^{-1}(c) \,|\, c\right) dc,$$
$$j = 1, \ldots, k . \quad (5.10)$$

Since (5.2) increases in x, the loss probability (5.10) continuously decreases from the bidder with the lowest signal to the bidder with the k-lowest

[10]
$$\begin{aligned} Prob\left\{\beta^{UP}_{(k,n)}(X_{(k+1,n)}) < C\right\} &= Prob\left\{X_{(k+1,n)} < c - \frac{n-2k}{n}\varepsilon\right\} \\ &= F_{(k+1,n)}\left(c - \frac{n-2k}{n}\varepsilon \,|\, c\right) \\ &= \sum_{j=0}^{n-k-1} \binom{n}{j} \left(\frac{k}{n}\right)^{n-j} \left(\frac{n-k}{n}\right)^{j} \end{aligned}$$

signal:

$$Prob\left\{\beta^{DP}_{(k,n)}(X_{(1,n)}) < C\right\} > Prob\left\{\beta^{DP}_{(k,n)}(X_{(2,n)}) < C\right\} > \dots$$
$$\dots > Prob\left\{\beta^{DP}_{(k,n)}(X_{(k,n)}) < C\right\} .$$

If the bidder with the j-lowest signal $x_{(j,n)}$, $j \leq k$, suffers a loss, all bidders with smaller signals also suffer a loss and their losses are higher. The loss probabilities for the values of our experimental setting are presented in Table 5.2. The loss probabilities under UP (5.9) are exactly calculated, while those under DP (5.10) are simulated. According to Table 5.2, the loss probability is much higher under UP than under DP for all k.[11] Table 5.2 also contains the expected prices and the awarded bidders' expected profits, in line with the properties described in Corollary 1.[12]

Table 5.1: Experimental setting.

Common-cost	C	$\sim U[\underline{c} = 125, \bar{c} = 325]$
Number of bidders per auction	n	6
Number of homogeneous goods	k	1, 2, 3
Uncertainty parameter	ε	18
Pricing rule		Discriminatory (DP), Uniform (UP)

5.3 Experiment setting

5.3.1 Hypotheses

Applying the results of the theoretical analysis (Section 5.2) to our experimental setting (Table 5.1) leads to the equilibrium outcomes for DP and UP and $k \in \{1, 2, 3\}$ (Table 5.2). These values are the basis for our ex-

[11] This does not generally apply. For example, Peeters and Tenev (2018) show for a special case of the wallet auction (Bulow and Klemperer, 2002) that the loss probability depends on the affiliation level. The loss probability is higher in the second-price auction than in the first-price auction for low affiliation levels, as in our case, whereas it is the other way round for high affiliation levels.

[12] The awarded bidders expected profit is equal to the expected value of the common cost of each good ($E[C] = 225$) minus the expected award price.

Table 5.2: Equilibrium bids, expected prices, profits, and losses in the experimental setting.

	DP auction			**UP auction**		
	$k = 1$	$k = 2$	$k = 3$	$k = 1$	$k = 2$	$k = 3$
Average difference between equilibrium bid and signal	17.8	17.4	16.9	12.0	6.0	0.0
Expected Price	230.1	232.6	234.9	229.3	228.4	227.6
Bidder's expected profit in case of an award	5.1	7.6	9.9	4.3	3.4	2.6
Loss probability in case of an award	0.02%	0.31%	1.14%	26.32%	31.96%	34.08%

perimental hypotheses, which are aligned with the theoretical benchmark outcomes of the actual auctions in the experiment (Table 5.3). Although the values in Table 5.2 and Table 5.3 slightly differ, they have the same pattern. The differences are also caused by the fact that in the experiment all variables (costs, signals, bids, prices, profits) are integers, while the theoretical values in Table 5.2 are computed with real numbers.

The following hypotheses summarize the theoretical findings. For the bidders, the DP auction is superior to the UP auction because they can expect higher profits and a lower loss probability, independent of the number of goods (i.e., competition level). For the auctioneer, the bidders' higher expected profits imply higher expected prices (i.e., payments) in the DP auction compared to the UP auction.

Hypothesis 1. *The awarded bidders' (average) profit and, thus, the expected (average) price in the DP auction is higher than in the UP auction for $k \in \{1, 2, 3\}$.*

Hypothesis 2. *The loss frequency is higher in the UP auction than in the DP auction for $k \in \{1, 2, 3\}$.*

While in the DP auction we expect a very small share of awarded bids leading to a loss, in the UP auctions the share is around 30% (Table 5.2 and 5.3).

5.3.2 Design of the experiment

In the experiment, we implement a multi-unit procurement auction with the parameters in Table 5.1. All parameters were common knowledge.

The treatment variables are the pricing rule and the number of demanded goods. There are six different treatments: the six combinations of the two pricing rules DP and UP with the three auction demands $k \in \{1, 2, 3\}$.[13]

We conduct twelve sessions: six with UP and six with DP. Each subject participates in one session. During a session, a subject participates in 40 auctions (rounds), each with six bidders and the same pricing rule but with different demands k. A session is divided in four sections of ten auctions (rounds) each. A section is characterized by the demand $k \in \{1, 2, 3\}$. To control the effect of the sequence of the different k, we vary the sequence between the six sessions; and to control learning effects, the demand k of the last section is the same as in the first section.[14] Each session is conducted with a matching group of 18 subjects. Thus, 216 subjects participate in the experiment.

We implement a stranger setting. In each round, three auction groups, each with six bidders, are randomly drawn from the matching group with 18 subjects. Each group plays an auction with the demand k of the section and the pricing rule of the session. Thus, each subject participates in 40 auctions under the same pricing rule, either DP or UP, but under three different demand levels $k \in \{1, 2, 3\}$.

[13] See B.6 for a detailed overview of payments and dates.

[14] In the six sessions of each pricing rule, we implement the following sequences of $k \in \{1, 2, 3\}$ in the four sections: 1-2-3-1, 1-3-2-1, 2-1-3-2, 2-3-1-2, 3-1-2-3, 3-2-1-3.

At the beginning of each section, the subjects are informed about the demand k, which applies to the following ten section rounds. At the beginning of each round, the subjects receive their private signals x_i, which are determined in the following way. First, C is randomly drawn from the uniform distribution of integers in the interval $[125, 325]$, which is not observed by the subjects. Given $C = c$, the individual signals X_i are randomly drawn from the uniform distribution of integers in the interval $[c - \varepsilon, c + \varepsilon]$. Then, the subjects submit their bids b_i. After all bids are submitted, the results of this round are revealed, which includes the true cost c, the award price p, and the individual profit π_i. The latter is zero if the bidder has not won and $p - c$ otherwise. This is common information, that is, all members of an auction group are informed about their competitors' private signals, bids, award, and profits.

The subjects' final payment consists of a show-up fee and their profits of twelve randomly drawn auction rounds, three from each section, which was made known to the subjects. For the total and average payments see B.6.

5.3.3 Conduction of the experiment

The experiment was conducted at the KD2Lab at Karlsruhe Institute of Technology (KIT). The experiment was programmed in oTree (Chen et al., 2016) and the participants were recruited using Hroot. At the beginning of the experiment written instructions were distributed (see a translation of the instructions in B.4) and read out loudly. Before starting the experiment, participants had to answer a series of control questions checking their understanding of the instructions (see B.5). Each session lasted around 90 minutes.

The average payment to the participants was 12.00 EUR. The lowest payment to a participant was 5.00 EUR and the highest payment was 21.00 EUR. For an overview of the total and average payments see B.6.

5.4 Experimental results

For comparability, in the analyses of the experimental data we only consider auctions with $c \in [\underline{c} + 2\varepsilon, \bar{c} - 2\varepsilon]$, so that for all cost signals x_i the equilibrium bidding strategies (5.1) and (5.2) apply. Unless otherwise specified, we analyze the first three different sections of each session and neglect the forth section, which is equal to the first. Since in the CV model of the DP- and UP-auction, the (average) price and the awarded bidders' (average) profit are completely correlated, it is sufficient to restrict the analysis only to one variable; the results also apply to the other. We use the awarded bidders' profit because the strong variation of the common cost c in the experimental auctions leads to strong variation of the price, which does not apply to the bidders' profit.

First, we examine if the sequence of the sections (given by k), as described in Section 5.3.2, has an effect. We conduct an analysis of variance (ANOVA) with the profit in case of an award and the share of loss, which does not reveal a significant differences between the different sequences.[15] Therefore, for our further analyses, we take the freedom to ignore the different sequences and merge the data.

5.4.1 Effects of the treatment variables pricing rule and number of goods

The block "Experimental outcome" in Table 5.3 shows the aggregated experimental data for the pricing rules DP and UP and the different demand (competition) levels $k \in \{1, 2, 3\}$. Under DP and UP, the awarded bidders'

[15] ANOVA: For the profit in case of award there are 525 observations (subjects' average profit in case on an award in each section), p-value: 0.690; for the share of loss there are 525 observations (subjects' average number of cases with a loss in each section), p-value: 0.308.

Table 5.3: Actual experimental outcomes and benchmark outcomes.

		DP auction			UP auction		
		$k=1$	$k=2$	$k=3$	$k=1$	$k=2$	$k=3$
Experimental outcome	Number of bids	942	942	1008	912	906	906
	Average profit per award	-6.24	-0.43	5.32	-3.97	0.01	2.64
	Share of awarded bids with a loss	69%	42%	23%	69%	43%	32%
Benchmark outcome	Avg. awarded bidders' profit	4.62	7.51	9.88	3.43	2.81	2.93
	Share of awarded bids with a loss	0%	0%	1%	30%	34%	29%
Difference between experimental and benchmark outcome	Avg. awarded bidders' profit	-10.86	-7.94	-4.56	-7.40	-2.80	-0.29
	Share of awarded bids with a loss	69%	42%	22%	39%	9%	3%

Table 5.4: Comparison of experimental and benchmark outcomes on matching group level.

Difference between experimental and benchmark ...		DP auction				UP auction			
		Total	$k=1$	$k=2$	$k=3$	**Total**	$k=1$	$k=2$	$k=3$
... profit	<0	**18**	6	6	6	**14**	6	5	3
	>0	**0**	0	0	0	**4**	0	1	3
	p-value	**<0.001*****	0.031*	0.031*	0.031*	**0.031***	0.031*	0.219	1
... share of loss	<0	**18**	6	6	6	**13**	6	4	3
	>0	**0**	0	0	0	**5**	0	2	3
	p-value	**<0.001*****	0.031*	0.031*	0.031*	**0.097**	0.031*	0.688	1

profit increases if the number of goods k increases, i.e., the competition level decreases. While the average profit of the awarded bids is positive under DP and UP (1.48 and 0.67), it is negative for $k = 1$ and it is positive for $k = 3$. The analogous trend is observed for the share of the awarded bids with a loss for the bidder because the award price is lower than the actual cost c. Under DP, this share decreases from 69% ($k = 1$) to 23% ($k = 3$), and under UP, from 69% ($k = 1$) to 32% ($k = 3$). In total, 38% of the awarded bidders suffered a loss under DP and 42% under UP.

The theoretical benchmark outcomes in Table 5.3 are computed on the basis of the actual values of the experimental parameters. That is, for every single auction in the experiment, we compute the outcome for the realized c and the equilibrium bids for the realized signals x_i. The results of the comparison of experimental and theoretical benchmark data are shown in Table 5.4. For this, we conduct sign tests on matching group level, that is, for each treatment, we have 6 observations. The subjects achieved significant lower profits than their equilibrium profits for $k \in \{1, 2, 3\}$ under DP and for $k = 1$ under UP (Table 5.4). Only for the lowest competition level ($k = 3$) under UP, the subjects' profits are on the same level as the equilibrium profits. The results are similar for the share of losses (Table 5.4). For $k \in \{1, 2, 3\}$ under DP and for $k = 1$ under UP, the subjects perform significantly worse than in the corresponding equilibria. That is, for all $k \in \{1, 2, 3\}$ in the DP auction and for $k = 1$ in the UP auction, the subjects perform worse with respect to their profits and loss frequency than theory predicts.

Two observations attract attention. First, the differences between the experimental and benchmark outcomes diminish in k (see lower part of Table 5.3). The actual outcomes in the experiment get closer to the corresponding equilibrium outcomes if k increases, particularly in the UP auction. This also means that the subjects perform better with respect to their profit and the loss frequency for higher k than for lower k. Second, under DP the subjects deviate stronger from the equilibrium than under UP.

Hence, the question arises if the theoretical predicted differences between the pricing rules, according to Hypothesis 1 and 2, still apply. To test the effects of the treatment variables pricing rule and number of goods, we conduct two two-way ANOVAs, one with the bidders' profit in case of an award as dependent variable and one with the bidders' share of loss in case of an award (Table B.1 and B.2 in B.2). The ANOVAs neither support Hypothesis 1 nor Hypothesis 2. There is neither a effect of the pricing rule on awarded bidders' profits nor on the loss frequency, and there is no significant difference between UP and DP with respect to these two variables. However, there is a strong effect of k. For both auctions, DP and UP, awarded bidders' profit significantly increases with k and the loss frequency significantly decreases with k.

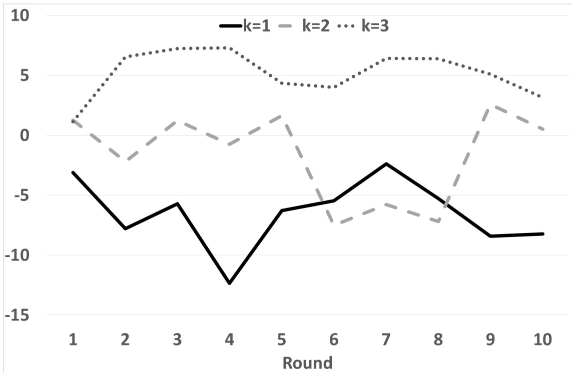
That is, the experimental results are inconsistent with the theoretical predictions of Hypothesis 1 and 2 but also with respect to the effect of k. In both auction, an increasing number of goods k leads to an increase in the awarded bidders' profits and a decrease in the frequency of losses. This is in line with the decreasing differences between the actual and benchmark outcomes in Table 5.3, as described before.

Next, we investigate whether the subjects increase their performance during the experiment. First, we compare the first and the last section, which have the same configuration, i.e., the same k. We do not find any significant improvement regarding bidders' profits and the loss frequency from the first and the last section across all six treatments.[16] Apparently, the experiences and observations within the first three sections do not help the subjects to increase their profits and to avoid losses.

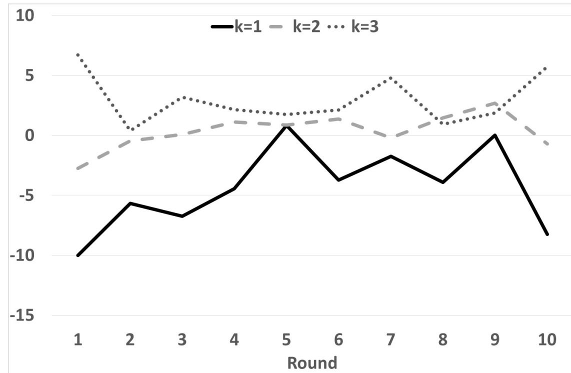
How do the subjects perform within the different sections with $k \in \{1, 2, 3\}$? Figure 5.1 shows the development of the average awarded bidders' profit and the share of awarded bids with a loss during the 10 rounds of the different sections. Apart from a slight increase in the profits in the first rounds in the UP auction for $k = 1$ and $k = 2$ (b), trends are not apparent. The conspicuous zigzag pattern in share of loss in the UP auction for $k = 1$ (d) is discussed in Section 5.4.3. Obviously, the subjects also do not learn to improve their outcome within the sections.

These observations are in line with experimental studies on CV auctions, in which typically a pervasiveness of losses is observed (Kagel and Levin, 2016).

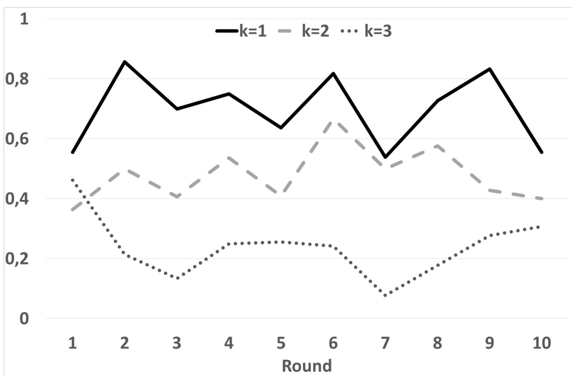
[16] The statistical test is presented in Table B.4 in B.2.



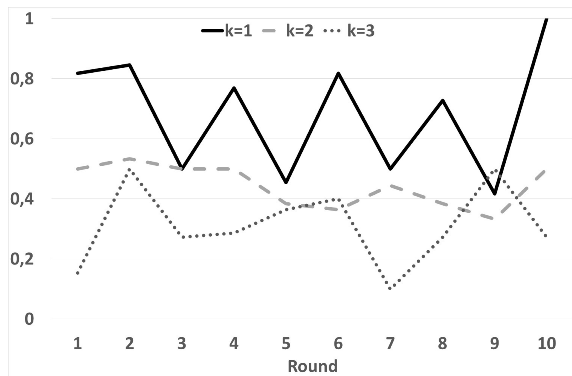
(a) Average awarded bidders' profit (DP)



(b) Average awarded bidders' profit (UP)



(c) Share of awarded bids with a loss (DP)



(d) Share of awarded bids with a loss (UP)

Figure 5.1: Development of the average awarded bidders' profit and the share of awarded bids with a loss during the 10 rounds of the sections with $k \in \{1, 2, 3\}$ in the DP auction and UP auction.

The following result summarizes our findings in this section.

Result 1. *(i) In all treatments, except for the UP auction for* $k = 3$ *and to a lesser extent also for* $k = 2$*, bidders' profits and, thus, the prices are lower and the loss frequencies are higher in the experiment than in the theoretical equilibrium. In the course of the experiment, there is no trend towards a change.*

(ii) The deviations from the equilibrium are larger in the DP auction than in the UP auction. There is no support for Hypothesis 1 and Hypothesis 2.

(iii) If the number of goods k increases, the differences between the experimental and the theoretical outcomes diminish and the subjects perform better with respect to their profit and the loss frequency, particularly in the UP auction.

5.4.2 Bidding behavior

To gain a better understanding of the findings in Section 5.4.1, we now investigate the bidding behavior. The distributions of the bids around the corresponding equilibrium bids are shown in Table 5.5 and in Figure 5.2. Generally, subjects underbid the equilibrium bid more often than they overbid, which is the main reason for the high frequency of losses in the experiment. This, however, differs between the DP auction and the UP auction and between the different competition levels $k \in \{1, 2, 3\}$. In the DP auction, significantly more bids are below than above the corresponding equilibrium bids for $k \in \{1, 2, 3\}$.[17] In the UP auction, this only applies to $k = 1$, while for $k = 2$ the higher frequency of below-equilibrium bids is not significant and for $k = 3$ the ratio is balanced. The case $k = 3$ in the UP auction is notable because the equilibrium bid is equal to the bidder's signal (Table 5.2), which is met by 14% of all bids. In this case we also observe a high share of "irrational bids" (>10%), which are lower than the lowest possible realization of C from a bidder's view, i.e., $b_i < x_i - \varepsilon$. These bids are mainly responsible for the relatively large negative value of the average deviation of the submitted bids from the equilibrium bids in this case. Obviously, the relatively high number of goods induces the subjects to make the typical error in second-price auctions to heavily underbid their signal to increase the award probability in the procurement auction, analogously to overbidding in second-price sales auctions (Kagel et al., 1987; Kagel and Levin, 1993; Harstad, 2000).

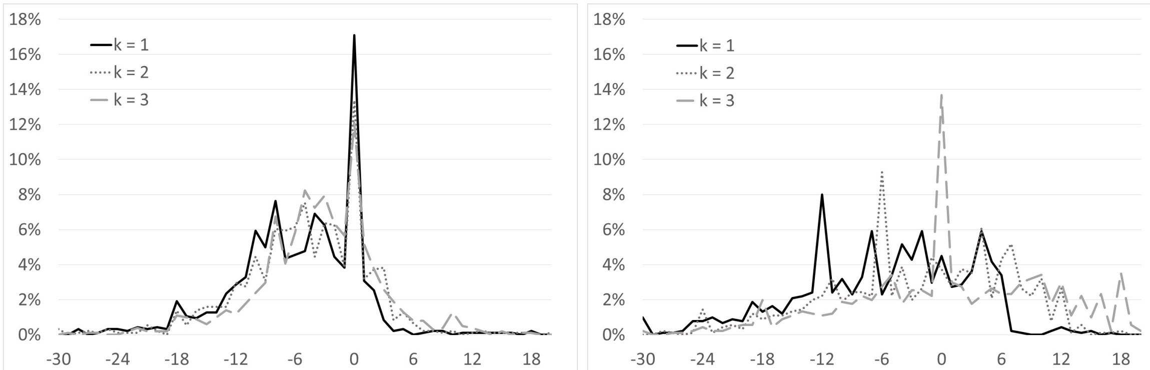
[17] The results of the corresponding sign test are presented in Table B.3 in B.2.

Table 5.5: Deviation of the submitted bids from the corresponding equilibrium bids.

	DP auction			**UP auction**		
Deviation of submitted bids from equilibrium bids	$k=1$	$k=2$	$k=3$	$k=1$	$k=2$	$k=3$
<0	74%	71%	66%	70%	54%	42%
$=0$	17%	13%	12%	4%	4%	14%
>0	9%	16%	22%	25%	42%	44%
Average deviation	-6.11	-5.37	-3.49	-7.20	-3.47	-4.72
$b_i < x_i - \varepsilon$ (irrational bids)	0.2%	0.4%	0.0%	2.1%	3.6%	10.2%

Let us take a closer look at the distributions of the bids around the corresponding equilibrium bids in Figure 5.2. While in the DP auction (a) the distributions of the different values of k look very similar, in the UP auction (b) the distributions are more diverse. The equilibrium bids in Table 5.2 provide an explanation. In the DP auction, the equilibrium bids for the different values of k differ only slightly. For low and medium values of c, they are even equal: the integer equilibrium bid is ε higher than the signal x_i, $b_i = x_i + \varepsilon$. The peak in 0 in the distributions for $k \in 1, 2, 3$ indicates that in the DP auction the equilibrium bid is submitted most frequently of all available bids. In the UP auction, the equilibrium bids for $k \in \{1, 2, 3\}$ differ, but they are independent of c. The peaks in the distributions in -12 for $k = 1$, -6 for $k = 2$, and 0 for $k = 3$ are caused by bids that are equal to the signal. For $k = 1$, the equilibrium bid is 12 higher than the signal, for $k = 2$, it is 6 higher than the signal, and for $k = 3$, it is equal to the signal (Table 5.2). That is, in the UP auction the individual and private signal is submitted most frequently.

We conclude that the high share of bids below the equilibrium is responsible for the high loss frequencies. But why do the subjects in the DP



(a) DP auction (b) UP auction

Figure 5.2: Distribution of the submitted bids around the corresponding equilibrium bids.

auction perform worse than in the UP auction with respect to profit and loss frequency relative to the equilibrium outcome (Table 5.3: Difference between experimental and benchmark outcome)? The different distributions of the bids around the equilibrium provide a first answer to this question, particularly the lower share of bids below and the larger share of bids above the equilibrium for $k = 2$ and $k = 3$ in the UP auction. This leads us to the question why in both auctions, DP and UP, the subjects' performance increases in k (Table 5.3). In both auctions, there is an upwards shift of the distributions of the bids in form of a larger share of bids above the equilibrium under higher values of k (Table 5.5). We refer to this as the *shift effect*. However, the shift effect is very weak in the DP auction (see also Figure 5.2 (a)) and, thus, it cannot fully account for the strong improvement from $k = 1$ to $k = 3$, that is, an increase of 11.5 in the average profit and a decrease of 46% in the share of loss, while theory predicts an increase of 5.3 and an increase of 1% (Table 5.3: Experimental outcome and Benchmark outcome). The same applies to the UP auction for the improvement from $k = 2$ to $k = 3$.

For this reasons, we investigate the submitted bids in more detail, particularly the deviations of the bids from the signals and the equilibrium

Table 5.6: Heterogeneous bidding behavior.

	DP auction			UP auction		
	$k=1$	$k=2$	$k=3$	$k=1$	$k=2$	$k=3$
Spearman rank correlation coefficient between signals and bids	0.79	0.75	0.82	0.63	0.62	0.58
Percentage of bids for the k-lowest signals among the k awarded bids	63%	74%	86%	45%	66%	77%
Average deviation of the ... from the equilibrium bid						
... 1st lowest bid ...	-13.56	-13.32	-7.98	-22.31	-23.83	-32.10
... 2nd lowest bid ...	-8.74	-6.44	-4.60	-8.91	-6.16	-7.62
... 3rd lowest bid ...	-6.74	-4.98	-4.09	-5.68	-3.91	-0.41
... 4th lowest bid ...	-5.14	-4.31	-2.98	-4.57	-0.34	1.17
... 5th lowest bid ...	-4.16	-3.19	-2.42	-2.92	0.69	4.24
... 6th lowest bid ...	0.71	0.15	0.94	2.31	11.33	12.48

bids (Table 5.6). The Spearman rank correlation coefficients indicate a significantly positive relationship between signal and bid.[18] However, since the rank correlation coefficients are (clearly) below 1, it is not surprising that not only the bids for the k-lowest signals are awarded, but also bids for higher signals (second block in Table 5.6).

Against this background, we analyze the deviation of the submitted bids from the equilibrium bids subject to the rank of the submitted bid. In an auction with k goods, the k-lowest bids are awarded, that is, the k bids with the lowest ranks. While Table 5.5 shows the average deviation from the equilibrium bids, Table 5.6 present the average deviation separately for the six ranks. These values, which are presented in the third block of Table 5.6, provide a clear picture. The lower the rank, the higher the underbidding compared to the equilibrium bid. With an increasing rank,

[18] Each rank correlation coefficient is calculated for more than 900 pairs of bids and signal. All correlations are significantly positive with p-values < 0.001***.

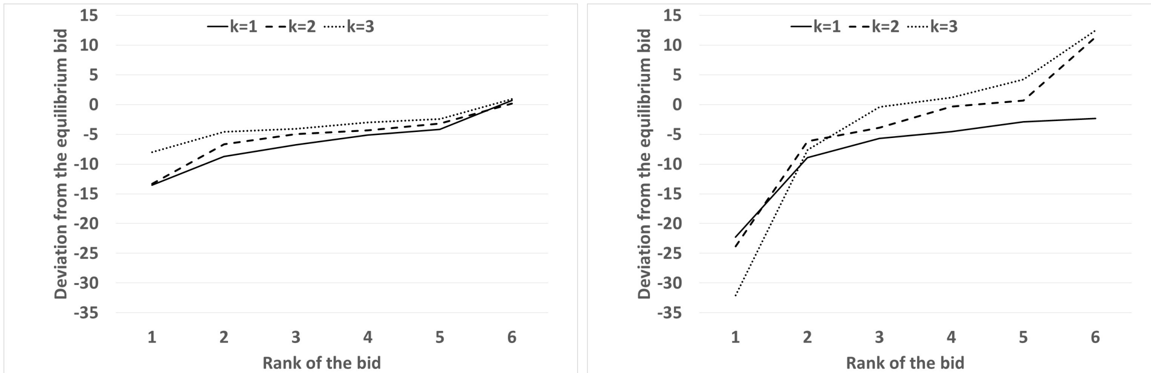
the submitted bids approach their equilibrium bids from below and even exceed them (see also Figure 5.3).[19] That is, the awarded bids undershoot the corresponding equilibrium bids at most. The high negative value of the first rank in the UP auction with $k = 3$ is mainly due to the high share of "irrational bids" (Table 5.5).[20]

The heterogeneity of the bids relative to the equilibrium in Table has the following effect. In the DP auction, an awarded bid determines its price. An increasing k implies that an additional bid is awarded, which on average is closer to the equilibrium bid than the lower awarded bids. Thus, an increasing k leads to an improvement of the average profit. In the UP auction this effect is even stronger because the price for all awarded bids is determined by the $(k+1)$-lowest bid. This bid increases relative to the equilibrium bid in k and even exceed it. As a consequence, the price and, thus, the awarded bidders' profits increase in k. In other words, the bidder who is awarded first, makes the biggest mistake, but the mistake becomes smaller with each additional awarded bidder. In the DP auction, the average profit increases and the loss probability decreases. If in the UP auction the number of awarded bids is high enough, the price is determined by a bidder who does not make a mistake or even overbid the equilibrium bid.

Concluding, behavioral heterogeneity seems to be mainly responsible for the experimental auction outcome getting closer to the equilibrium outcome if k increases and for the outcome in the UP auction being closer to the equilibrium than the DP auction for $k \in \{2, 3\}$. In support of this statement and as robustness check, we conduct Monte Carlo simulations with different bid distributions.

[19] For all $k \in \{1, 2, 3\}$ in the DP auction and the UP auction, the gradient of a linear regression of the difference between submitted bid and equilibrium bid on the rank of the bid is significantly positive with a p-value < 0.001***.

[20] Behavioral heterogeneity is a typical finding in experimental studies of CV auctions (Crawford and Iriberri, 2007; Kagel and Levin, 2016).



(a) DP auction (b) UP auction

Figure 5.3: Average deviation of the bids from the equilibrium bids subject to the rank of the bids.

Monte Carlo simulation

For the simulations, we implement different distributions of bids around the equilibrium bids, which are derived from the actual distributions in the experiment (Figure 5.2), so that the simulations approximate the characteristics of the actual distributions, particularly the values in the tables 5.5 and 5.6. For each auction, DP and UP, we implement three different distributions (Figure B.1 in B.3): (1) uniform distribution, (2) normal distribution, and (3) normal distribution with a peak in the equilibrium bid. For the DP auction, the latter reproduces the actual distributions (Figure 5.2 (a)) quite accurately. As a robustness check of our hypothesis that behavioral heterogeneity is mainly responsible for the different results under $k = \{1, 2, 3\}$, we compare the different values of k under the same distribution. That is, for each auction, DP and UP, we run three simulations, each with a different distribution. In each simulations, we compute and compare the results of $k \in \{1, 2, 3\}$ for the same distribution.[21] The setup and the results of the simulations are presented in Table B.6 in B.3.

[21] In the simulations, each sample unit is given by a draw of C from the uniform distribution of integers in the interval $[125, 325]$ followed by the draws of the six signals X_i from the uniform distribution of integers in the interval $[c - \varepsilon, c + \varepsilon]$ (Table 5.1). Then, each of the six bids b_i is determined by a random draw from the implemented distribution of bids around the equilibrium bid, which corresponds to x_i.

First, we compare the results of the simulations in Table B.6 with the theoretical equilibrium predictions in Table 5.2. In the latter, the average profit per awarded bid increases from $k = 1$ to $k = 3$ by 4.8 in the DP auction and in decreases by 1.7 in the UP auction. In the simulations, the average profit increases by nearly 7 in the DP auction, i.e., slightly more than theory predicts, while in the UP auction the average profit does not decrease but increases by around 5. This also applies to the loss probability (share of loss) in case of an award in the UP auction. While theory predicts an increasing loss probability, the simulations generate decreasing probabilities of losses.

Second, the comparison of the results of the simulations in Table B.6 with the experimental results in Table 5.3 reveals that simulations accurately reproduce the trends in the average profit and the share of loss. In all three simulations of both auctions, DP and UP, the average profit per award increases from a negative value for $k = 1$ to a positive value for $k = 3$, and the share of awarded bids with a loss decreases from $k = 1$ to $k = 3$, just as in the experiment. Since we compare the different values of k under the same distributions, we interpret this result as a clear indication for the impact of the behavioral heterogeneity on the different results for $k = \{1, 2, 3\}$, particularly on the bidders' better performance under higher values of k. We refer to this as the *heterogeneity effect*. However, the simulated changes are smaller than the actual, both for the profits and the losses. According to the tables 5.3 and B.6, in the DP auction, the average profit increases from $k = 1$ to $k = 3$ by 11.5 in the experiments and by just under 7 in the simulations, and in the UP auction, by 6.6 in the experiments and by around 5 in the simulations. In the DP auction, the share of loss deceases by 46% in the experiment and by 32% DP in the simulations, and in the UP auction by 37% in the experiment and

Table 5.7: Change in the bid relative to the signal subject to the outcome of the previous round.

	DP auction			UP auction		
Result previous round	Profit	Loss	**Total**	Profit	Loss	**Total**
Awarded (experienced)	0.58	4.66	2.10	1.87	8.79	5.01
Not Awarded (observed)	-1.82	-0.68	-1.27	-6.59	-0.54	-3.26
Total	-0.93	0.79	-0.16	-3.46	2.11	-0.41

by around 18% in the simulations. We suppose that the shift effect is responsible for this additional improvement.

The following result summarizes our findings in this section.

Result 2. *In both auctions, DP and UP, the subjects' better performance under an increasing k in form of higher profits per award, a lower share of losses, and outcomes closer to the equilibrium predictions are mainly caused by the heterogeneity effect and the shift effect, where the heterogeneity effect is supposed to be stronger.*

5.4.3 Behavior pattern

Finally, we try to identify behavior patterns, which may help to better understand the experimental results, particularly of the permanence of losses. For this, we analyze the change of the bids relative to their signals subject to the outcome of the previous round by distinguishing four cases in the previous round: (1) the bidder is awarded and gains a profit, (2) the bidder is awarded and suffers a loss, (3) the bidder is not awarded and observes that the awarded bidders gain a profit, and (4) the bidder is not awarded and observes that the awarded bidders suffer a loss.

In the DP auction and the UP auction we observe similar patterns (Table 5.7).[22] After being awarded in the previous round, bidders on

[22]The statistical significance of the effects result from the ANOVA in Table B.5 in B.2.

average increase their bid relative to their signal, where they increase their bid more in case of a loss in the previous period than in case of a gain. The modest increase in case of a previous gain can be interpreted as an attempt to increase the profit while not significantly reducing the award probability. The strong increase in case of a experienced loss apparently aims at preventing a further loss. After being not awarded, bidders reduce their bid relative to their signal if the awarded bidders gained a profit, whereas they rarely lower their bid if the awarded bidders suffered a loss. In the first case, non-awarded bidders' stronger bid reduction apparently aims at being awarded with a profit in the current round. In the second case, non-awarded bidders are more reluctant to lower their bid in the current round after the awarded bidders suffered a loss in the previous round.

The sequence of increasing the bid after an experienced loss and the lowering the bid after an observed gain is held responsible for the zigzag pattern in the UP auction for $k = 1$ (Figure 5.1 (d)) since in the majority of the groups the awarded bidder suffers a loss in the rounds with an even number.

Since the overall change of the bids relative to the signal is slightly negative (-0.14 and -0.41), it is not surprising that the subjects do not improve their profits and reduce the loss frequency during the experiment.

The observed bid adjustment has the character of myopic best reply behavior (e.g., Boylan and El-Gamal, 1992). The upward adjustment of the bids after being awarded and the downward adjustment after not being awarded in our experiment resembles the effects of winner's regret and of loser's regret in the study of Engelbrecht-Wiggans and Katok (2008), who examine the adjustment of bids in repeated first-price sealed bid auctions with private values under different information feedback conditions. This may be an indication that the subjects in our CV experiment tend to treat their signals as true cost and disregard the relationship between cost and signals, that is, the signals are randomly scattered around the true cost and the bidders, when submitting their bids, do not know whether they have low or high signals.

The following result summarizes our findings in this section.

Result 3. *Subjects adjust their bids relative to their signals according to a myopic best reply rule that accounts for their and the other bidders' success and failure in the previous round. On average, subjects do not increase their bids relative to their signals, which provides an explanation for the permanence of losses in the experiment.*

5.5 Conclusion

Based on a theoretical approach, we experimentally study sealed bid multi-unit procurement auction for homogeneous CV goods, in which single-unit supply bidders participate. We compare the DP auction with the UP auction under different demand levels (i.e., number of auctioned goods).

Beside the typical pervasiveness of losses in CV auction experiments, the theoretic predicted differences between DP and UP concerning bidders' profit and, thus, the price, and the frequency of losses (winner's curse) are not reproduced. The theoretical predicted advantages of DP over UP diminish, which is mainly caused by the fact that the subjects under DP deviate more from the equilibrium than under UP. However, in both auctions, DP and UP, the auction outcomes develop towards the equilibrium outcome as the number of goods increases. This improvement is essentially caused by a "mechanical effect" due to behavioral heterogeneity concerning the deviation of the submitted bids from the corresponding equilibrium bids. That is, a larger number of demanded goods mitigate the negative effects of aggressive bidding behavior for the awarded bidders, particularly in the UP auction. Subjects' bidding behavior can be quite well characterized by a myopic best reply rule depending on the own and the other bidders' previous performance. Since this myopic behavior does not include an average increase of the bids relative to the signals, it is not surprising that the high loss probabilities are persistent and do not diminish.

There are several implications for practical applications. First, the theoretical differences between the DP auction and UP auction do not necessarily apply to real world auctions. Instead, the competition level, i.e., the relationship between demand and supply, seems to have a stronger impact on the price and the occurrence of the winner's curse than the pricing rule. Also, theoretically complemented, the degree of uncertainty of the good's value resp. cost plays an important role. Against the background of the experimentally observed pervasiveness and the persistence of the winner's curse, which is mostly not in the auctioneer's interest either, the auctioneer should try to reduce degree of uncertainty as far as possible.

To gain further insights, the experimental study can be extended by also varying the number of bidders, i.e., testing different combinations of the supply and demand, by applying other cost and signal distributions, or by also implementing other auction formats, e.g., open English-style (ascending resp. descending) auctions, in which the bidders can learn about the other bidders' signals and, thus, about the CV.

Chapter 6

Conclusions and outlook

To mitigate climate change and to reach greenhouse gas emission reduction targets, the expansion of RE sources is inevitable. However, the energy transition impacts the everyday life of most people directly or indirectly and its implementation is therefore full of political, social, environmental and economical challenges. A farsighted and reliable political approach is, thus, all the more important.

Auctions have become the prevalent mechanism to promote REs in recent years. This development started in Latin America and Europe and by now auctions are implemented all over the world. In general terms, auctions are a suitable mechanism for the auctioneer to pursue several targets simultaneously. In the context of RE support, the support cost reduction, efficiency and the controlability of the expansion are the most frequently mentioned targets. However, as proved in this thesis, it is hard to pursue all those targets at the same time. Therefore, it is of utmost significance to prioritize the targets and design the auction accordingly.

6.1 Summary

This thesis enhances the knowledge of four relevant criteria regarding auctions for RE support. First, prequalification requirements are a significant design choice for auctions for RE support, yet their direct implications on the auction outcome in this specific field of application were analyzed in this thesis. Second, the participants in auctions for RE support are heterogeneous. For example, there might be regional or technological differences that might be accompanied by differences in the company structure of the bidders. This thesis analyzed how to include and utilize those differences in discriminatory auctions. Third, the implementation of auctions to promote REs is quite novel, thus, also the bidders are rather inexperienced. This thesis compared auction outcomes with the results of an ABM. Finally, REs usually involve CV and common cost components. This thesis theoretically and experimentally analyzed the effects of common costs in a realistic multi-unit auction setting.

In contrast to other governmental procurement auctions in most cases there is no long-term relationship between auctioneer and bidders in auctions for RE support. There is a huge heterogeneous set of bidders that participate in such auctions, from small cooperatives to international companies and some of them might participate the first or even the only time. That is, the auctioneer has neither information regarding the reliability of the bidders nor sanctioning possibilities like exclusion of future bid rounds. Therefore, there are usually auction design measures to guarantee serious participation, namely penalties, physical and financial prequalifications. Those measures also provide further benefits regarding the uncertainty in the auction.

This work analyzes the auction-theoretic implications of the different auction design elements and gives recommendations regarding an appropriate use of them. The trade-off in implementing prequalifications and penalties is between realization rates and support costs. Generally speaking, the higher the costs for prequalifications and potential penalty payments the higher the realization rates and the support costs. Therefore, it is a political decision on how much non-realization is acceptable or vice versa round, what price for a high realization rate is acceptable. However, physical prequalifications also benefit the bidders as they reduce the cost uncertainties and, thus, the risk of bad investments. The main problem with penalties that are only sanctioned after the auction is that the effects on the heterogeneous bidders may differ and, thus, be inefficient. For that reason, the recommendation derived in this thesis to design an efficient auction with a sufficiently high realization rate is requiring a high financial prequalification and an adjusted physical prequalification. The physical prequalification should not be too high in relation to the securities and also to limit the sunk costs effect. Furthermore, according to the result of the analysis, there is a preference for the first-price auction over the second-price auction.

The heterogeneity of bidders in auctions for RE support yields further implications. The auction design elements have different effects on different bidder groups. This is especially important as the current trend of auctions for RE support is to open the auction to different technologies or even to bidders from different countries. For example, a realization period of 18 months is sufficient for a PV plant, it may be not sufficient for building new wind turbines. There may be even structural cost differences between technologies. And, on the other hand, there are differences in the value of the electricity generated by variable REs. That is, the load profile of PV and wind differ in so far, that the electricity generated by wind may be more valuable than the electricity generated by PV or vice versa.

The differences in costs and values of different groups of RE projects result in different target settings of auctioneers. Possibilities to optimize the auction design include the value of the RE or the support costs. This thesis shows that the targets in different countries vary and are sometimes even ambiguous and contradictory. Further, this thesis presents two ways of implementing discriminatory design elements to achieve either one of the targets. This thesis compares three discriminatory design elements that yield theoretically the same result with respect to cost minimization but have practical differences especially with respect to robustness. Finally, it is important to note, that the introduction of discriminatory design elements can only improve the auction outcome if the auctioneer chooses them in accordance with the auction targets. To comply with this principle, the targets have to be set before the auction is designed.

This thesis also takes on the bidders' perspective in order to enhance the understanding of the German PV pilot auctions. In this first of its kind series of auctions in Germany the prices decreased more than the observable costs of PV plants. By utilizing an ABM this thesis could show that the assumption regarding the competition in the first auction round has major implications on further rounds. The actual outcome can be reconstructed if the bidders had a very low expectation regarding competition in the first round. Although auctions for RE support are not repeated auctions in the pure sense, the results of prior rounds still have an effect on all forthcoming rounds.

In the theoretical and experimental analysis of CV auctions, this thesis complements the existing literature by including multi-unit auctions and a systematical comparison between different competition levels and pricing rules. Although auctions for RE support are not pure CV auctions, there are major CV and common cost components in such auctions and this implies the risk of the – so called – *winner's curse*. In auctions for RE support the occurrence of the winner's curse, that is the project costs are higher than the project revenues, is usually accompanied by a project non-realization. However, as non-realization threads the achievement of expansion targets, it is in common interest to avoid the winner's curse when designing the auction.

While the theoretical findings suggest that there are major differences with respect to prices and loss probabilities between the two pricing rules DP and UP, the experimental results draw another picture. There are no significant differences between the two pricing rules. Under both pricing rules the participants in the experiment perform worse than theoretically predicted but on an equal level. The competition level, however, has significant influence on the auction outcome. A lower competition level results in a smaller probability of bidders suffering a loss.

6.2 Conclusions

The target of this thesis is to enhance the understanding of the implications of the auction design on the auction outcome in the specific field of auctions for RE support. Such auctions are necessary to achieve the RE expansion targets and to introduce REs to a competitive market. Naturally, since the auctioneer determines the auction design, the associated analyses focuses on the auctioneer's perspective. The four main sections of this thesis set priorities on different design options, however, there are recurring implications in all of them.

There are two main challenges when designing auctions for RE support. The first one is aligning auction targets and auction design. Second, the set of participating bidders is heterogeneous. This means that, on the one hand, there arise even more trade-offs and conflicts but, on the other hand, there are also more possibilities for the auction design. Overall, there is no one-size-fits-all auction design and every auction has to be designed specifically to its application.

For the auctioneer this means, that first and foremost the targets have to be set before deciding on the auction design. However, this is a very hard task and - if not done correctly - may lead to ambiguity and errors. This thesis illustrates that it is not possible to pursue all targets at the same time. Auctioneers who try it, certainly fail to design the auction appropriately. Therefore, any effort before the auction for a broad public discussion regarding the political targets of the promotion mechanism will be worth the effort. The same holds for any effort to gain insights into the market and the participants. The availability of these information is essential for an appropriate auction design.

If the information is obtained and the targets are set, an auctioneer can make use of the toolbox that is provided in this thesis to design the auction. There is a broad variety of auction design elements to tailor-fit the auction design to the targets but all of them induce trade-offs of some kind. Some between price and efficiency others between sunk costs and realization rate. This thesis not only highlights the impossibility of pursuing different targets with one auction but also the interdependency of auction design elements. The three main targets of auctions for RE support are cost reduction, efficiency and controllability of the RE expansion.

If either one of the targets is given priority, the auction design can never reach the other two targets at the same time. If the auctioneer chooses to design an auction in order to reduce the RE support costs as far as possible, the recommendations are to foster competition through low entry barriers and discrimination of strong bidders. That is, the auction should have low requirements regarding financial and physical prequalifications and discriminatory design elements that favor weaker bidders. Of course this may lead to inefficiencies and low realization rates.

If the latter one is the main target, the auction design must prioritize the reduction of cost uncertainties for the bidders and balance – if feasible – the auction volume between insufficient competitiveness and the risk of the winner's curse. Again, such an auction design neither results in efficiency nor lowest costs. To pursue the target of efficiency is insofar hard, that depending on the context, there is more than one definition of efficiency, e.g. efficiency from a value or cost perspective. In general terms, the auction should be a level playing field for all participants. However, this is easier said than done. Different bidder groups react differently to design elements like realization times and prequalification requirements making it virtually impossible to achieve this goal. And if there are separate auctions for the different bidder groups, efficiency is even more unlikely. Nevertheless, some general recommendations hold, e.g. the implementation of financial prequalifications and not penalties.

Those examples illustrate quite obviously that the pursuit of one auction target results in negative effects on other potential targets. Therefore, prioritizing targets and gaining of relevant information are the first and most important steps to implement an successful auction mechanism. With sufficient information and clear targets, this thesis provides recommendations to tailor fit the auction design to the targets.

6.3 Critical reflection and outlook

The whole energy sector is at a turning point from conventional energy sources to RE sources. This energy transition involves a more competitive environment for REs compared to only a few years ago. More and more countries implement auctions as a mechanism to promote REs but neither the development nor the auction design has settled yet. The research conducted in this thesis enhances the auction-theoretical knowledge of those auctions and facilitates the understanding of the implications of different auction design elements. As the dynamic development of auctions for RE support continuously results in additional research questions, this thesis is only a starting point for further analyses.

A topic already discussed in this thesis are prequalification measures as requirements to participate in the auction. While this research concentrates on the auctioneer's point of view, especially regarding realization rate and auction prices, future research might take a look on the bidders' perspective. That is, analyzing the costs and benefits for bidders of both mandatory and voluntary prequalification measures. A topic that was also addressed in this thesis, is the repeated nature of auctions for RE support. However, those are not sequential auctions as some bidders participate in multiple auctions while others do not. Further theoretical research could complement the ABM in this thesis. With more and more auctions for RE support conducted all over the world, more auction results will become available. Based on those results it will be possible to conduct econometric analyses to complement the theoretical and experimental results.

One essential requirement of a successful energy transition is the full integration of REs in the energy market. This long-term goal requires further research in various energy (economic) research areas from balancing power to grid infrastructure. The first step concerning auctions for RE support is the opening of the auctions to more bidder groups (technologies, countries, etc.). Thus, future research should focus on discriminatory instruments and asymmetric auctions. This could be complemented by experimental research. The research of this thesis and the further research to develop an energy market with fully integrated REs contributes to the important challenges associated with the energy transition which is – in turn – necessary to facilitate a sustainable energy supply.

Appendix A

Appendix to Chapter 3

A.1 Equivalence of quota, maximum prices and bonus

In a RE auction with a given demand D, participate the bidders of two technologies, A and B, with different cost structures, described by the increasing marginal cost functions MC_A and MC_B, where

$$MC_A(x) < MC_B(x) \text{ for all } x \geq 0\,. \tag{A.1}$$

A UP auction with LRB is applied. The auction is incentive compatible, that is, it is optimal to bid the support that exactly covers the costs (Weber, 1983). The supply functions are given by

$$S_k(p) = MC_k^{-1}(p),\ k \in \{A, B\}, \tag{A.2}$$

and increase in the price p. From (A.1), it follows that

$$S_A(p) > S_B(p) \text{ for all } p \geq MC_A(0)\,. \tag{A.3}$$

The elasticities of supply of the two technologies are defined as

$$\varepsilon_k(p) = \frac{S_k'(p)}{S_k(p)}p \text{ with } S_k'(p) = \frac{\mathrm{d}S_(p)}{\mathrm{d}p},\ k \in \{A, B\}\,. \tag{A.4}$$

In a free competition, the market clearing price p^* is determined by

$$S_A(p^*) + S_B(p^*) = D\,, \tag{A.5}$$

where $S_A(p^*) > S_B(p^*) \geq 0$. The auctioneer's total support costs are $K(p^*) = p^* D$.

Each of the three discriminatory instruments – quota, maximum price, and bonus – induces a supply shift from the A-bidders to the B-bidders, and different prices p_A and p_B, which lead to the supply volumes $S_A(p_A)$ and $S_B(p_B)$, with

$$S_A(p_A) + S_B(p_B) = D\,. \tag{A.6}$$

In these cases, the total support costs are

$$K(p_A, p_B) = p_A S_A(p_A) + p_B S_B(p_B)\,. \tag{A.7}$$

Incentive compatibility holds for a quota Q, which is effective if $Q > S_B(p^*)$, that is, if the B-bidders would not reach Q in a free competition. This leads to a volume shift

$$q^{\pm} = Q - S_B(p^*) \tag{A.8}$$

from the A-bidders to the B-bidders and to different award prices p_A and p_B, with

$$p_A = MC_A(D - Q) > p^* \;\text{ and }\; p_B = MC_B(Q) < p^*\,. \tag{A.9}$$

Incentive compatibility also holds for a maximum price $\hat{p}_A^{max}$, except for the A-bidders with higher costs than $\hat{p}_A^{max}$, who do not participate. The maximum price is effective if $\hat{p}_A^{max} < p^*$. Then, by (A.2) and (A.5), $p_A = \hat{p}_A^{max} < p^*$, $p_B > p^*$, $S_A(p_A) < S_A(p^*)$, and $S_B(p_B) > S_A(p^*)$.

With a bonus b^+, incentive compatibility applies to the A-bidders, whereas the B-bidders reduce their bids by b^+. The bonus also implies $p_A < p^* < p_B$ and supply volumes $S_A(p_A) < S_A(p^*)$ and $S_B(p_B) > S_B(p^*)$. Incentive compatibility holds for the bid bonus. Since the argumentation is the same as for the monetary bonus, the results also apply to the bid bonus.

Both the maximum price and the bonus imply volume shift (A.8) as the quota.

To analyze the effect of discriminatory instruments on the support costs, we state three conditions:[1]

(C1) $\varepsilon_A(p)$ and $\varepsilon_B(p)$ are non-increasing in p.

(C2) $S_B(p^*) > 0$.

(C3) $\varepsilon_A(p^*) < \varepsilon_B(p^*)$.

Let $\Delta(q^{\pm})$ denote the change in the support costs induced by $q^{\pm}$ compared to those in a free competition. Then, (A.7) and (A.9) imply

$$\begin{aligned}\Delta(q^{\pm}) = MC_A(S_A(p^*) - q^{\pm}) \cdot (S_A(p^*) - q^{\pm}) + MC_B(S_B(p^*) + q^{\pm}) \\ \cdot (S_B(p^*) + q^{\pm}) - K(p^*)\end{aligned}.$$

Differentiating $\Delta(q^{\pm})$ with respect to $q^{\pm}$, denoted by $\Delta'(q^{\pm})$, we obtain

$$\begin{aligned}\Delta'(q^{\pm}) &= -MC'_A(S_A(p^*) - q^{\pm})(S_A(p^*) - q^{\pm}) - MC_A(S_A(p^*) - q^{\pm}) \\ &\quad + MC'_B(S_B(p^*) + q^{\pm})(S_B(p^*) + q^{\pm}) + MC_B(S_B(p^*) + q^{\pm})\,.\end{aligned}$$

We first analyze the effect of discriminatory instruments on the support costs when the instruments become effective. Thus, we consider $\Delta(q^{\pm})$ at

[1] (C1) is a standard assumption and is supported by the RE literature (de Vries et al., 2007; Hoefnagels et al., 2011; Brown et al., 2016). (C2) requires that the B-bidders gain at least a small share in a non-discriminatory auction. There are many examples where wind and solar are awarded in multi-technology auctions, for example, in Mexico (IRENA, 2017) and Spain (Ministerio de Energia, Turismo y Agenda Digital, 2017), or are awarded in separate auctions but at similar prices, for example, in Germany (Bundesnetzagentur, 2017a,b). According to (C3), the B-bidders' price elasticity of supply at p^* is larger than that of the A-bidders, which is justified by the B-bidders' smaller supply volume in a non-discriminatory auction.

$q^{\pm} = 0$,

$$\begin{aligned}\Delta'(0) = &-MC_A(S_A(p^*)) - S_A(p^*)MC'_A(S_A(p^*)) + MC_B(S_B(p^*)) \\ &+ S_B(p^*)MC'_B(S_B(p^*))\,.\end{aligned}$$

By $MC_A(S_A(p^*)) = MC_B(S_B(p^*)) = p^*$, we obtain

$$\Delta'(0) = S_B(p^*)MC'_B(S_B(p^*)) - S_A(p^*)MC'_A(S_A(p^*)). \tag{A.10}$$

With $MC'_k(S_k(p)) = \frac{1}{S'_k(p)}$ for $k \in \{A, B\}$,

$$\Delta'(0) < 0 \quad \text{if} \quad \frac{S_A(p^*)}{S'_A(p^*)} > \frac{S_B(p^*)}{S'_B(p^*)} \Longleftrightarrow \frac{S'_A(p^*)}{S_A(p^*)}p^* < \frac{S'_B(p^*)}{S_B(p^*)}p^*\,,$$

which, by (A.4), holds because of (C3). Therefore, the support costs decrease if the quota Q becomes effective, that is, $q^{\pm}$ becomes positive, the maximum price $\hat{p}_A^{max}$ becomes effective – that is, $\hat{p}_A^{max} - p^*$ becomes negative –, or the bonus b^+ becomes positive.

We now show that, given (C1), (C2), and (C3), for each instrument there exists a unique support cost minimizing parameterization and the respective optima are equivalent. The minimization of the support costs

$$K(p_A, p_B) = p_A S_A(p_A) + p_B S_B(p_B) \;\text{ subject to }\; S_A(p_A) + S_B(p_B) = D \tag{A.11}$$

with regard to p_A and p_B yields the first order conditions

$$\frac{\partial K(p_A, p_B)}{\partial p_k} \;=\; S_k(p_k) + p_k S'_k(p_k) + \lambda S'_k(p_k) = 0,\; k \in \{A, B\}\,,$$

which lead to the condition

$$p_B - p_A = \frac{S_A(p_A)}{S'_A(p_A)} - \frac{S_B(p_B)}{S'_B(p_B)}\,. \tag{A.12}$$

For $Q \leq S_B(p^*)$, $p_B = p_A = p^*$ and, thus, the left-hand side of (A.12) is zero. $Q > S_B(p^*)$ implies $p_B > p^* > p_A$. As Q increases, p_B increases and p_A decreases and, thus, the left-hand side of (A.12) increases. (A.4) together with (C1), (C2), and (C3) imply that the right-hand side of (A.12) is positive at p^*. Thus, (A.12) does not hold for an ineffective quota $Q \leq S_B(p^*)$. By (C1), $\varepsilon_B(p_B)$ does not increase if p_B increases and $\varepsilon_A(p_A)$ does not decrease if p_A decreases. Thus, based on (A.4), the right-hand side of (A.12) decreases. Since the left-hand side of (A.12) increases in Q and the right-hand side of (A.12) decreases, there exists a unique $\hat{Q}$ that fulfills (A.12). Combined with the property that the support costs decrease when the quota becomes effective, this implies that $\hat{Q}$ is the unique cost minimizing quota. Thus, there exists a unique quota $\hat{Q} > S_B(p^*)$ that minimizes the support costs, where $\hat{Q}$, p_A, and p_B are determined by $\hat{Q} = S_B(p_B)$, $S_A(p_A) + S_B(p_B) = D$ and

$$p_B - p_A = \frac{S_A(p_A)}{S'_A(p_A)} - \frac{S_B(p_B)}{S'_B(p_B)}\,.$$

Analogously, this also applies to the maximum price and the bonus. Thus, there exists a unique maximum price $\hat{p}_A^{max} > 0$ that minimizes the support costs, where $\hat{p}_A^{max}$, p_A, and p_B are determined by $S_A(\hat{p}_A^{max}) + S_B(p_B) = D$ and

$$p_B - \hat{p}_A^{max} = \frac{S_A(\hat{p}_A^{max})}{S'_A(\hat{p}_A^{max})} - \frac{S_B(p_B)}{S'_B(p_B)}\,,$$

and there exists an unique bonus $\hat{b} > 0$ that minimizes the support costs, where $\hat{b}$ and the award price p are determined by $S_A(p) + S_B(p + \hat{b}) = D$ and

$$\hat{b} = \frac{S_A(p)}{S'_A(p)} - \frac{S_B(p+\hat{b})}{S'_B(p+\hat{b})}\,.$$

From these results, it follows directly that the quota $\hat{Q}$, the maximum price $\hat{p}_A^{max}$, and the bonus $\hat{b}$ lead to the same support-cost-minimizing outcome, that is, the prices (payments) and the supply volumes of the A-bidders and B-bidders are the same for $\hat{Q}$, $\hat{p}_A^{max}$, and $\hat{b}$.

A.2 Example with linear marginal costs

A.2.1 Linear marginal cost functions

In this appendix, we illustrate and discuss the principle of functionality of the three discriminatory instruments $\hat{Q}$, bonus $\hat{b}$ and maximum price $\hat{p}_A^{max}$ by means of a simplified model: the marginal costs of the bidders in class $k \in \{A, B\}$ are uniformly distributed over the interval $[a_k, d_k]$ with density m_k. Thus, $m_k(d_k - a_k)$ represents the number of bidders in $[a_k, d_k]$. This approach involves the linear marginal cost function

$$MC_k(x) = \frac{x}{m_k} + a_k \tag{A.13}$$

for $x \in [0, m_k(d_k - a_k)]$. By (A.2), the supply functions for $k \in \{A, B\}$ are

$$S_k(p) = \begin{cases} 0 & \text{for } p < a_k \\ m_k(p - a_k) & \text{for } p \geq a_k\,. \end{cases} \tag{A.14}$$

with

$$S_k'(p) = \frac{\mathrm{d}S_k(p)}{\mathrm{d}p} = m_k\,.$$

By (A.4), the elasticity of supply is given by

$$\varepsilon_k(p) = \frac{S_k'(p)}{S_k(p)}p = \frac{p}{p - a_k}\,. \tag{A.15}$$

It does not depend on m_k, which is due to the linear supply function (A.14), and is non-increasing in p,

$$\frac{d\varepsilon_k(p)}{dp} = -\frac{a_k}{(p - a_k)^2} < 0 \text{ for all } p \neq a_k\,.$$

For the following analysis, we express the characteristic parameters of the B-class a_B and m_B as multiples of the characteristic parameters of the A-class a_A and m_A: $a_A = a$, $m_A = m$, $a_B = \varrho a$, and $m_B = m/\lambda$ with $1 \gtreqless \lambda > 0$ and $\varrho > 1$, which follows from (A.1). Parameter ϱ describes the general cost ratio (strength) of the B-class and A-class, while λ indicates the ratio of the number bidders of the A-class and B-class.

We assume $d_B > d_A$. Thus, the marginal cost functions do not intersect, which is in line with Condition (A.1). Furthermore, we assume that d_B and d_A are sufficiently large so that in neither of the two classes the bidders with marginal cost at the upper boundary are awarded. This implies that d_A and d_B are irrelevant for the analysis.

The marginal cost functions (A.13) yield

$$\begin{aligned} MC_A(x) &= \frac{x}{m} + a \quad \text{ for } \; x \in [0, m(d_A - a)], \\ MC_B(x) &= \frac{\lambda x}{m} + \varrho a \; \text{ for } \; x \in [0, \frac{m}{\lambda}(d_B - \varrho a)]. \end{aligned}$$

The intercept and the slope of the marginal cost function MC_B are expressed as multiples of the intercept and the slope of the marginal cost function MC_A. While the case $\lambda < 1$ allows that MC_B is flatter than MC_A (more B-bidders than A-bidders), $\varrho > 1$ implies that the lowest marginal cost in the B-class are always higher than in the A-class.

The supply functions (A.14) then yield

$$S_A(p) = \begin{cases} 0 & \text{for } p < a \\ m(p - a) & \text{for } p \geq a\,, \end{cases}$$

$$S_B(p) = \begin{cases} 0 & \text{for } p < \varrho a \\ \frac{m}{\lambda}(p - \varrho a) & \text{for } p \geq \varrho a\,. \end{cases}$$

By (A.15), $\varepsilon_A(p) = \frac{p}{p-a}$ and $\varepsilon_B(p) = \frac{p}{p-\varrho a}$. Thus, due to $\varrho > 1$, $\varepsilon_A(p) <$

$\varepsilon_B(p)$.

In the free competition case, the equilibrium price and the supply volumes are

$$\begin{aligned} p^* &= \frac{D}{m}\frac{\lambda}{\lambda+1} + \frac{(\lambda+\varrho)a}{\lambda+1}\,, \\ S_B(p^*) &= \frac{D}{\lambda+1} - \frac{m(\varrho-1)a}{\lambda+1}\,, \\ S_A(p^*) &= \frac{D\lambda}{\lambda+1} + \frac{m(\varrho-1)a}{\lambda+1}\,, \end{aligned}$$

where $S_B(p^*) > 0$ requires $D > m(\varrho-1)a$. The total support costs yield

$$K(p^*) = Dp^* = (S_A(p^*) + S_B(p^*))p^* = \frac{\lambda D}{\lambda+1}\left(\frac{D}{m} + \left(1+\frac{\varrho}{\lambda}\right)a\right)\,. \tag{A.16}$$

The price and the support costs increase in ϱ and in λ. This is caused by the fact that a larger ϱ and a larger λ correspond to "weaker" B-bidders. That is, a larger ϱ corresponds to a higher cost level and a larger λ corresponds to a smaller number of B-bidders.

We keep λ as a variable parameter throughout this appendix. However, for illustration purposes, in the figures we set $\lambda = 1$, i.e., the same density of bidders in the two classes. In Figure A.1, the individual support costs $K_A(p^*)$ and $K_B(p^*)$ are visualized by the areas $p^*S_A(p^*)$ and $p^*S_B(p^*)$. The A-bidders receive a larger payment as their supply is greater.

We now consider the optimal quota $\hat{Q}$, bonus $\hat{b}$, and maximum price $\hat{p}_A^{max}$. As outlined in Appendix A.1, the optimal values of the three instruments are determined by the price difference

$$p_B - p_A = \frac{S_A(p_A)}{S'_A(p_A)} - \frac{S_B(p_B)}{S'_B(p_B)} = (p_A - a) - (p_B - \varrho a)\,,$$

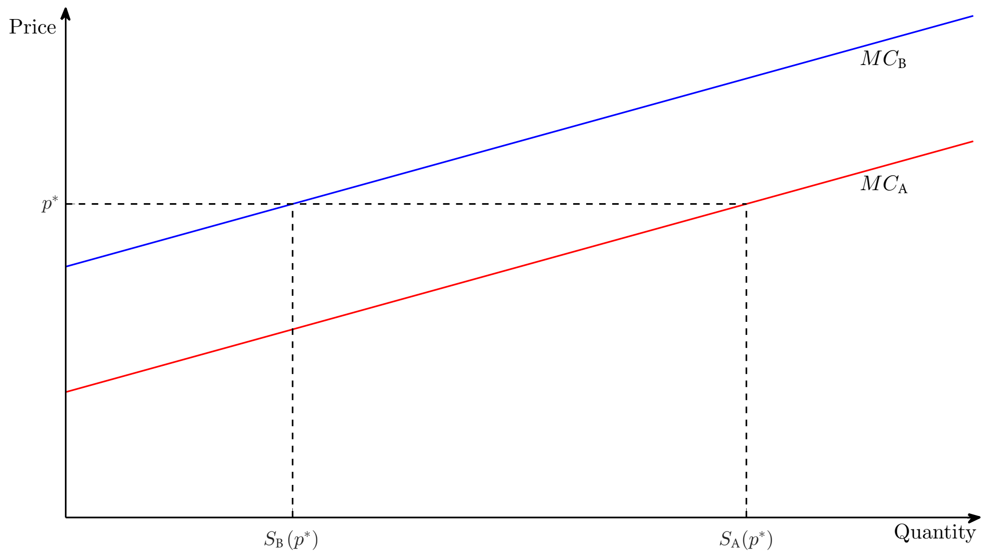


Figure A.1: Illustration of the linear marginal costs model with free competition.

which directly determines the optimal bonus $\hat{b}$,

$$p_B - p_A = \frac{(\varrho - 1)a}{2} = \hat{b}\,. \tag{A.17}$$

The optimal bonus $\hat{b}$ increases in ϱ and is independent of λ. This implies that the bonus increases if the cost difference between the A-bidders and the B-bidders increases. The optimal bonus does not react to different quantities of the two bidder classes.

With two different prices p_B and p_A the Condition (A.5) still holds, that is $S_A(p^*) + S_B(p^*) = S_A(p_A) + S_B(p_B) = D$ and, thus, with (A.17) we get

$$p_B = \frac{D}{m}\frac{\lambda}{\lambda+1} + \frac{a(\lambda+2\varrho+\lambda\varrho)}{2(\lambda+1)}\,, \tag{A.18}$$

$$p_A = \frac{D}{m}\frac{\lambda}{\lambda+1} + \frac{a(1+2\lambda+\varrho)}{2(\lambda+1)} = \hat{p}_A^{max}\,, \tag{A.19}$$

which also determines the optimal maximum price $\hat{p}_A^{max}$. That is, $\hat{p}_A^{max}$ depends on λ and ϱ and increases in both meaning that the A-bidders are less restricted if the B-bidders are weaker and/or less.

By (A.14), (A.18) and (A.19), the supply volumes and the optimal quota $\hat{Q}$ are

$$\begin{aligned} S_B(p_B) &= \tfrac{D}{\lambda+1} - \tfrac{m(\varrho-1)a}{2(\lambda+1)} &= \hat{Q}\,, \qquad (A.20)\\ S_A(p_A) &= \tfrac{D\lambda}{\lambda+1} + \tfrac{m(\varrho-1)a}{2(\lambda+1)} &= D - \hat{Q}\,, \qquad (A.21)\end{aligned}$$

which also depends on λ and ϱ and decreases in both.

With (A.20) and (A.21), the volume shift $q^{\pm} = \hat{Q} - S_B(p^*)$ to the B-bidders is

$$q^{\pm} = \frac{m(\varrho-1)a}{2(\lambda+1)}\,. \qquad (A.22)$$

The optimal bonus $\hat{b}$, the optimal maximum price $\hat{p}_A^{max}$ and the optimal quota $\hat{Q}$ induce the same volume shift $q^{\pm}$ from (A.22).

Comparing the total support costs $K(p_A, p_B)$ under the optimal quota $\hat{Q}$, bonus $\hat{b}$ and maximum price $\hat{p}_A^{max}$ with $K(p^*)$ in free competition (A.16) yields

$$\begin{aligned} K(p_A, p_B) &= p_B S_B(p_B) + p_A S_A(p_A)\\ &= \frac{D^2\lambda}{m(\lambda+1)} + \frac{aD(\lambda+\varrho)}{\lambda+1} - \frac{a^2 m(\varrho-1)^2}{4(\lambda+1)}\\ &= K(p^*) - \frac{a^2 m(\varrho-1)^2}{4(\lambda+1)} \;<\; K(p^*)\,.\end{aligned}$$

The support costs $K(p_A, p_B)$ are lower than $K(p^*)$ by $\frac{a^2 m(\varrho-1)^2}{4(\lambda+1)}$. This difference increases in ϱ and decreases in λ. As a result, discrimination is more effective, i.e., $\frac{a^2 m(\varrho-1)^2}{4(\lambda+1)}$ increases if the relative cost difference ϱ between A-bidders and B-bidders is greater. If, however, the ration between the number of B-bidders and A-bidders is lower, discrimination is less effective. Further, it shows that, given (A.3) and the conditions (C1), (C2), (C3) are met, the three instruments only reduce the price for a $\varrho > 1$. That is, to reduce support costs through discrimination, the lowest cost bidders of the two bidder classes must have different costs $MC_A(0) < MC_B(0)$. A pure difference in numbers is not sufficient.

In Figure A.2, the individual support costs are given by the areas $p_B S_B(p_B)$ and $p_A S_A(p_A)$. Compared to Figure A.1, the sum of the two areas, i.e., the total support costs, is smaller. Although the price increase for the B-bidders is equal to the price reduction for the A-bidders,[2] the overall costs for the auctioneer decrease as the number of bidders for which the price increases is lower than the number of bidders for which the price decreases.

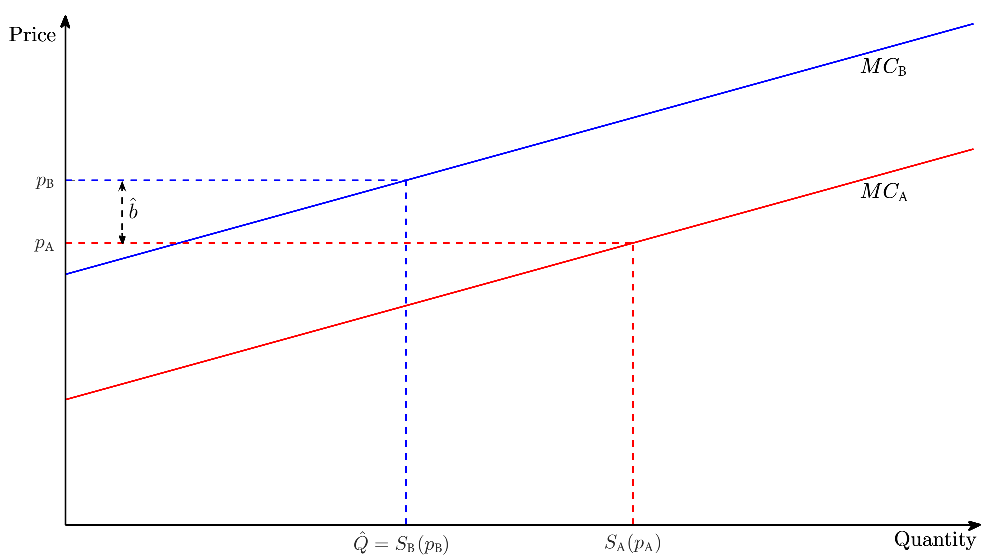


Figure A.2: Illustration of the linear marginal costs model with optimal discriminatory instruments $\hat{Q}$, $\hat{b}$ and $\hat{p}_A^{max} = p_A$.

[2]This equality is caused by the characteristics of the example because the marginal cost curves of both classes are parallel shifts of each other. This equality does not necessarily hold for other marginal cost curves.

A.2.2 Linear marginal cost functions with estimations of λ and ϱ

We analyze and compare the effects of interior misestimations, particularly on support costs, by applying the model with linear marginal cost functions from Appendix A.2.1.

Let us assume that the auctioneer knows the A-class parameters a and m but she does not know the B-class multipliers ϱ and λ.[3] The auctioneer's estimates for these two parameters are denoted by ϱ^e and λ^e. Let b^e , p_A^e, and Q^e denote the corresponding bonus, maximum price, and quota that are determined by (A.17), (A.19), and (A.20) under ϱ^e and λ^e:

$$b^e = \frac{(\varrho^e - 1)a}{2}, \tag{A.23}$$

$$r^e = \frac{D}{m}\frac{\lambda^e}{\lambda^e + 1} + \frac{a(1 + 2\lambda^e + \varrho^e)}{2(\lambda^e + 1)}, \tag{A.24}$$

$$Q^e = \frac{D}{\lambda^e + 1} - \frac{m(\varrho^e - 1)a}{2(\lambda^e + 1)}, \tag{A.25}$$

where $b^e = \hat{b}$, $r^e = \hat{e}$, and $Q^e = \hat{Q}$ for $\varrho^e = \varrho$ and $\lambda^e = \lambda$.

In the following, we investigates the effects of misestimations of λ and ϱ, i.e., $\lambda^e \neq \lambda$ and/or $\varrho^e \neq \varrho$, on the calibration of the discriminatory instruments and the support costs.

The first major difference between the instruments is that the maximum price r^e (A.24) and the quota Q^e (A.25) both depend on ϱ^e and λ^e, while the bonus b^e (A.23) only depends on ϱ^e but not on λ^e. Therefore, the bonus is robust to misestimations of λ but not of ϱ. Since b^e depends positively on ϱ^e, it holds that $b^e \gtreqqless \hat{b}$ for $\varrho^e \gtreqqless \varrho$ and all λ^e.

Things are different for the maximum price and the quota for the A-bidders. By (A.24), r^e depends positively on both λ^e and ϱ^e and the following hold: (i) $r^e \gtreqqless \hat{p}_A^{max}$ for $\varrho^e \gtreqqless \varrho$ and $\lambda^e = \lambda$; (ii) $r^e \lesseqqgtr \hat{p}_A^{max}$ for

[3] The results of the following analyses are qualitatively the same if we assume that the auctioneer knows the B-class parameters but not the A-class parameters.

$\lambda^e \gtreqless \lambda$ and $\varrho^e = \varrho$. The effects of misestimations are reverse for the quota. Since, by (A.25), the quota Q^e depends negatively on both λ^e and ϱ^e, the following hold: (i) $Q^e \lesseqgtr \hat{Q}$ for $\varrho^e \gtreqless \varrho$ and $\lambda^e = \lambda$; (ii) $Q^e \lesseqgtr \hat{Q}$ for $\lambda^e \gtreqless \lambda$ and $\varrho^e = \varrho$.

On the basis of ϱ^e and λ^e and the correspondingly calibrated instruments b^e, r^e, and Q^e, we now consider the price, supply, and cost effect of misestimations $\lambda^e \neq \lambda$ and $\varrho^e \neq \varrho$. That is, we calculate the prices and support costs under the condition that the actual parameters are ϱ and λ, but the instruments are calibrated under the assumption of ϱ^e and λ^e.

Bonus b^e (A.23) leads to the prices

$$\begin{aligned} p_A^{b^e} &= \frac{D}{m}\frac{\lambda}{\lambda+1} + \frac{a(2\lambda + 2\varrho - \varrho^e + 1)}{2(\lambda+1)}\,, \\ p_B^{b^e} = p_A^{b^e} + b^e &= \frac{D}{m}\frac{\lambda}{\lambda+1} + \frac{a(\lambda + 2\varrho + \lambda\varrho^e)}{2(\lambda+1)}\,, \end{aligned}$$

and the corresponding supply volumes

$$\begin{aligned} S_A(p_A^{b^e}) &= \frac{D\lambda}{\lambda+1} + \frac{am(2\varrho - \varrho^e - 1)}{2(\lambda+1)}\,, \\ S_B(p_B^{b^e}) &= \frac{D}{\lambda+1} - \frac{am(2\varrho - \varrho^e - 1)}{2(\lambda+1)}\,. \end{aligned}$$

Obviously, $p_A^{b^e}$ and $S_A(p_A^{b^e})$ negatively depend on ϱ^e, i.e., the higher the estimate, the lower the A-bidders' price and the supply, while the reverse applies for the B-bidders. The support costs are

$$K(b^e) = \frac{D^2\lambda}{m(\lambda+1)} + \frac{aD(\lambda+\varrho)}{\lambda+1} + \frac{a^2m(2\varrho - 2\varrho\varrho^e + \varrho^{e^2} - 1)}{4(\lambda+1)}\,.$$

Since b^e (A.23) does not depend on λ^e, nor of the above variables do. For analyzing the cost effect of ϱ^e we consider

$$\frac{\partial K(b^e)}{\partial \varrho^e} = \frac{a^2 m(\varrho^e - \varrho)}{2(\lambda + 1)}\,,$$

which is non-zero for all $\varrho^e \neq \varrho$. Thus, since $b^e = \hat{b}$ and K are minimized for $\varrho^e = \varrho$, the support costs K are higher if the estimation is incorrect.[4]

When analyzing the effects of misestimations for either a quota (A.25) or a maximum price (A.24), we additionally have to take λ^e into account. Since in our setting with linear marginal costs functions the effects of misestimations are the same for both instruments, we restrict our notation to r^e. Both instruments lead to the prices

$$\begin{aligned} p_A^{r^e} = r^e &= \frac{D}{m}\frac{\lambda^e}{\lambda^e + 1} + \frac{a(1 + 2\lambda^e + \varrho^e)}{2(\lambda^e + 1)}\,, \\ p_B^{r^e} &= \frac{D}{m}\frac{\lambda}{\lambda^e + 1} + \frac{a(\lambda + 2\lambda^e \varrho + 2\varrho - \lambda\varrho^e)}{2(\lambda^e + 1)}, \end{aligned}$$

and supply quantities

$$\begin{aligned} S_A(p_A^{r^e}) &= \frac{D\lambda^e}{\lambda^e + 1} + \frac{am(\varrho^e - 1)}{2(\lambda^e + 1)}\,, \\ S_B(p_B^{r^e}) = Q^e &= \frac{D}{\lambda^e + 1} - \frac{am(\varrho^e - 1)}{2(\lambda^e + 1)}\,. \end{aligned}$$

The prices and quantities for the A-bidders increase in ϱ^e and λ^e while the

[4] The derivative $\frac{\partial K(p_A^{b^e}, b^e)}{\partial \lambda^e}$ is equal to zero.

opposite holds for the B-bidders. The resulting support costs are

$$K(p_A^{r^e}, p_B^{r^e}) = \frac{1}{(\lambda^e+1)^2}\left(\frac{D^2(\lambda^{e^2}+\lambda)}{m}\right.$$
$$+ aD\left[\varrho(\lambda^e+1) - \lambda(\varrho^e-1) + \lambda^e(\lambda^e+\varrho^e)\right]$$
$$\left. + \frac{a^2 m(\varrho^e-1)\left[\varrho^e(\lambda+1) + 2\lambda^e(1-\varrho) - 2\varrho - \lambda + 1\right]}{4}\right). \tag{A.26}$$

Differentiating (A.26) with respect to ϱ^e and λ^e leads to

$$\frac{\partial K(p_A^{r^e}, p_B^{r^e})}{\partial \varrho^e} = \frac{1}{(\lambda^e+1)^2}\left(aD(\lambda^e-\lambda)\right.$$
$$\left. + \frac{a^2 m\left[(\varrho^e-\varrho) + (\varrho^e\lambda - \lambda^e\varrho) + (\lambda^e-\lambda)\right]}{2}\right), \tag{A.27}$$

$$\frac{\partial K(p_A^{r^e}, p_B^{r^e})}{\partial \lambda^e} = \frac{1}{(\lambda^e+1)^3}\left(\frac{2D^2(\lambda^e-\lambda)}{m}\right.$$
$$+ aD\left[(2\varrho^e\lambda - \lambda^e\varrho^e - \lambda^e\varrho) + 2(\lambda^e-\lambda) + (\varrho^e-\varrho)\right]$$
$$\left. - \frac{a^2 m(\varrho^e-1)\left[(\varrho^e-\varrho) + (\varrho^e\lambda - \lambda^e\varrho) + (\lambda^e-\lambda)\right]}{2}\right). \tag{A.28}$$

Both derivations (A.27) and (A.28) are non-zero for $\varrho^e \neq \varrho$ or $\lambda^e \neq \lambda$. Hence, analogous to the above argumentation, misestimations of the strength and/or number of the B-bidders lead to higher support costs than in the minimum.

There are three effects. First, if only λ is estimated incorrectly ($\lambda^e \neq \lambda$ and $\varrho^e = \varrho$), implementing a bonus still yields the optimal result, while implementing a maximum price or a quota does not.

Second, if only ϱ is estimated incorrectly, i.e., $\varrho^e \neq \varrho$ and $\lambda^e = \lambda$, all three instruments yield the same non-minimal support costs, i.e., $K(b^e) = K(r^e)$. However, the prices and the supply volumes are not equal. The same support costs are achieved through different combinations of prices and quantities, all of which are non-optimal. As mentioned above, $p_A^{b^e}$ and $S_A(p_k^{b^e})$ decrease in ϱ^e, while $p_A^{r^e}$ and $S_A(p_A^{r^e})$ increase in ϱ^e. Thus, when implementing the bonus b^e, an underestimation (overestimation) of the B-bidders' strength, i.e., $\varrho^e > (<)\ \varrho$, leads to a lower (higher) than optimal price and supply volume for the A-bidders, whereas under the maximum price r^e and quota q^e an underestimation (overestimation) of the B-bidders' strength leads to a higher (lower) than optimal price and supply volume for the A-bidders. The reverse applies for the B-bidders. That is, depending on whether a bonus or a maximum price (quota) is implemented, a wrong estimation of the B-bidders' strength leads to opposing privileges through higher prices and supply volumes of the two bidder classes.

Third, if both parameters are estimated incorrectly, i.e., $\lambda \neq \lambda^e$ and $\varrho \neq \varrho^e$, we have to distinguish two cases. If both estimates are wrong in the same direction, i.e., both the relative strength and number of B-bidders are underestimated ($\varrho^e > \varrho$ and $\lambda^e > \lambda$) or overestimated ($\varrho^e < \varrho$ and $\lambda^e < \lambda$), the bonus yields a better result than maximum price and quota. However, if the estimates are wrong in opposing directions, i.e., $\varrho^e > \varrho$ and $\lambda^e < \lambda$ or $\varrho^e < \varrho$ and $\lambda^e > \lambda$, the result is ambiguous and the maximum price and the quota might even yield a better result than the bonus.

To summarize, since the bonus does not depend on λ^e for linear marginal cost functions, it dominates the maximum price and the quota for misestimations of λ. The bonus is also more robust to misestimations of ϱ and λ as long as those misestimations do not neutralize each other. Although the support costs are equal under all three instruments if only ϱ is misestimated, one should keep in mind that the two bidder classes are privileged differently, depending on whether a bonus or a quota (maximum price) in implemented.

Appendix B

Appendix to Chapter 5

B.1 Derivation of the equilibrium bids in the CV model

Uniformly distributed common cost The common cost C is the same for all k goods and drawn from a uniform distribution on $[\underline{c}, \bar{c}]$. Given $C = c$, bidders' signals $X_1, X_2, \ldots, X_n$ are independent draws from a uniform distribution on $[c - \varepsilon, c + \varepsilon]$. We restrict our analysis to signals in the interval $[\underline{c} + \varepsilon, \bar{c} - \varepsilon]$. The distribution function of a signal X given $C = c$ is

$$F(x|c) = \begin{cases} 0 & : \ x < c - \varepsilon \\ \frac{x-c+\varepsilon}{2\varepsilon} & : \ c - \varepsilon \leq x \leq c + \varepsilon \\ 1 & : \ x > c + \varepsilon \end{cases} \tag{B.1}$$

and the density function is

$$f(x|c) = \begin{cases} \frac{1}{2\varepsilon} & : \ c - \varepsilon \leq x \leq c + \varepsilon \\ 0 & : \ \text{otherwise.} \end{cases} \tag{B.2}$$

From the perspective of a bidder with signal x, C is uniformly distributed on $[x - \varepsilon, x + \varepsilon]$.

Derivation of the UP equilibrium bid (5.1): $\beta^{UP}_{(k,n)}(x) = x + \frac{n-2k}{n}\varepsilon$ According to Ehrhart and Ott (2019),

$$\beta^{UP}_{(k,n)}(x) = E[C \,|\, X_i = x, Y_k = x]\,, \tag{B.3}$$

where Y_k denotes the k-lowest signal of the $n-1$ opponents. By (5.5),

$$E[Y_k \,|\, C = c] = c + \frac{n-2k}{n}\varepsilon$$

and, thus,

$$E[Y_k] = E[C] - \frac{n-2k}{n}\varepsilon\,,$$

which implies

$$E[C \,|\, Y_k = x] = x + \frac{n-2k}{n}\varepsilon\,,$$

which with $E[C \,|\, X_i = x, Y_k = x] = E[C \,|\, Y_k = x]$ and (B.3) verifies (5.1).

Derivation of the DP equilibrium bid (5.2): $\beta^{DP}_{(k,n)}(x) = x + \varepsilon - \frac{k+1}{n+1}\varepsilon \cdot \exp\left(-\frac{n(\bar{c}-\varepsilon-x)}{2k\varepsilon}\right)$
Let $G_{(k,n)}(z|c)$ denote the distribution of the kth order statistics of $n-1$ signals conditional on v, where for $k < n$ (e.g., Ahsanullah et al., 2013)

$$G_{(k,n)}(z|c) = \sum_{j=0}^{n-k-1} \binom{n-1}{j} F(z|c)^{n-1-j}(1-F(z|c))^j, \tag{B.4}$$

$$g_{(k,n)}(z|c) = \frac{(n-1)!}{(k-1)!(n-k-1)!} f(z|c)F(z|c)^{k-1}(1-F(z|c))^{n-k-1}\,. \tag{B.5}$$

Under the assumption that the other $n-1$ bidders apply the strictly increasing bidding strategy $\beta \equiv \beta^{DP}_{(k,n)}$, the expected profit of the bidder with signal x when bidding $\beta(z)$ is

$$\Pi(x,z) = \int_{x-\varepsilon}^{x+\varepsilon} (\beta(z) - x)(1 - G_{(k,n)}(z|c))dc\,, \tag{B.6}$$

With (B.1), (B.2), (B.4), and (B.5), the first order condition for maximizing (B.6) yields

$$
\begin{aligned}
0 \stackrel{!}{=} \frac{\partial \Pi(x,z)}{\partial z} &= \int_{x-\varepsilon}^{x+\varepsilon} \beta'(z) - \beta'(z) G_{(n,k)}(z|c) - \beta(z) g_{(n,k)}(z|c) \\
&\quad + c g_{(n,k)}(z|c) dc \\
&= 2\varepsilon\beta'(x) - \int_{x-\varepsilon}^{x+\varepsilon} \beta'(z) G_{(n,k)}(z|c) dc - \int_{x-\varepsilon}^{x+\varepsilon} \beta(z) g_{(n,k)}(z|c) dc \\
&\quad + \int_{x-\varepsilon}^{x+\varepsilon} c g_{(n,k)}(z|c) dc \\
&\stackrel{z=x}{=} 2\varepsilon\beta'(x) - \beta'(x)(\frac{1}{2\varepsilon})^{n-1} \sum_{j=0}^{n-k-1} \binom{n-1}{j} \int_{x-\varepsilon}^{x+\varepsilon} (x-c+\varepsilon)^{n-1-j} \\
&\quad \cdot (\varepsilon - x + c)^j dc \\
&\quad - \beta(x) \frac{(n-1)!}{(k-1)!(n-k-1)!} (\frac{1}{2\varepsilon})^{n-1} \int_{x-\varepsilon}^{x+\varepsilon} (x-c+\varepsilon)^{k-1} \\
&\quad \cdot (\varepsilon - x + c)^{n-k-1} dc \\
&\quad + \frac{(n-1)!}{(k-1)!(n-k-1)!} (\frac{1}{2\varepsilon})^{n-1} \int_{x-\varepsilon}^{x+\varepsilon} c(x-c+\varepsilon)^{k-1} \\
&\quad \cdot (\varepsilon - x + c)^{n-k-1} dc \\
&= 2\varepsilon\beta'(x) - \beta'(x)(\frac{1}{2\varepsilon})^{n-1} \sum_{j=0}^{n-k-1} \frac{(n-1)!}{j!(n-j-1)!} \cdot \frac{(n-j-1)!j!}{(n-1)!} \frac{1}{n} (2\varepsilon)^n \\
&\quad - \beta(x) \frac{(n-1)!}{(k-1)!(n-k-1)!} (\frac{1}{2\varepsilon})^{n-1} \cdot \frac{(k-1)!(n-k-1)!}{(n-1)!} (2\varepsilon)^{n-1} \\
&\quad + \frac{(n-1)!}{(k-1)!(n-k-1)!} (\frac{1}{2\varepsilon})^{n-1} \cdot \frac{(k-1)!(n-k-1)!}{(n-1)!} (2\varepsilon)^{n-1} \\
&\quad \cdot (x + \varepsilon - \frac{2k\varepsilon}{n}) \\
&= 2\varepsilon\beta'(x) - \beta'(x)\frac{2\varepsilon}{n}(n-k) - \beta(x) + x + \varepsilon - \frac{2k\varepsilon}{n} \,.
\end{aligned}
$$

The first integral was calculated by using $n-j-1$ partial integration, where for the second and third integral $k-1$-times partial integration was used. Rearranging the first order condition yields the differential equation

$$x+\varepsilon-\frac{2k\varepsilon}{n}=\beta(x)-\frac{2k\varepsilon}{n}\beta'(x)\,.$$

The solution of the differential equation with the initial condition $\beta(\bar{c}-\varepsilon)=\bar{c}-\frac{k+1}{n+1}\varepsilon$, which yields an expected profit of zero, is given by

$$\beta^{DP}_{(k,n)}(x)=x+\varepsilon-\frac{k+1}{n+1}\varepsilon\cdot\exp\left(-\frac{n(\bar{c}-\varepsilon-x)}{2k\varepsilon}\right)\,. \tag{B.7}$$

For $x\in[\bar{c}-\varepsilon,\bar{c}+\varepsilon)$, the equilibrium bid is $\beta^{DP}_{(k,n)}(x)=\bar{c}-\frac{(\bar{c}+\varepsilon-x)(k+1)}{2(n+1)}$, which also yields an expected profit equal to zero and is derived under the initial condition $\beta^{DP}_{(k,n)}(\bar{c}+\varepsilon)=\bar{c}$ (cf. Ehrhart and Ott (2019) for sales auctions).

B.2 Supplementary statistical analyses

In the following three two-ways ANOVAs, the independent factors are the pricing rule p with the levels DP and UP and the number of goods k with the levels 1, 2, and 3. The depend variable in the first ANOVA is the awarded bidders' profit (Table B.1) and in the second the share of loss (Table B.2). The depend variables are the averages of each subject for each treatment in which the subject is awarded at least once or at least suffer a loss, respectively. Hence, there are at maximum four observations per subject in a data set. In total, the are 525 observations in the data set of the first and second ANOVA and 340 observations in the data set of the third ANOVA.

Table B.1: Two-way ANOVA on bidders' profits in case of an award.

$n = 525$	DF	F-value	Pr($> F$)	
Overall	5	24.63	< 0.001	***
p	1	0.135	0.713	
k	2	58.746	< 0.001	***
$p : k$	2	2.766	0.064	

	Estimate	t-value	Pr($> \|t\|$)	
(Intercept)	-4.48	-5.184	< 0.001	***
$p = UP$	0.73	0.564	0.573	
$k = 2$	4.19	3.685	< 0.001	***
$k = 3$	10.04	9.070	< 0.001	***
$p = UP : k = 2$	0.11	0.066	0.947	
$p = UP : k = 3$	-2.94	-1.814	0.070	

Table B.2: Two-way ANOVA on the share of loss in case of an award.

$n = 340$	DF	F-value	Pr($> F$)	
Overall	5	22.60	< 0.001	***
p	1	0.444	0.505	
k	2	55.488	< 0.001	***
$p : k$	2	0.791	0.454	

	Estimate	t-value	Pr($> \|t\|$)	
(Intercept)	0.64	14.903	< 0.001	***
$p = UP$	0.04	0.571	0.569	
$k = 2$	-0.17	-2.964	0.003	**
$k = 3$	-0.43	-7.847	< 0.001	***
$p = UP : k = 2$	-0.06	-0.680	0.497	
$p = UP : k = 3$	0.03	0.416	0.677	

Table B.3: Sign tests on the difference between submitted bids and equilibrium bids.

Majority of differences between submitted bids and equilibrium bids		**DP auction**				**UP auction**			
		Total	$k = 1$	$k = 2$	$k = 3$	**Total**	$k = 1$	$k = 2$	$k = 3$
< 0	*matching group*	**18**	6	6	6	**15**	6	5	4
	individual[1]	**260**	90	89	81	**191**	82	63	46
> 0	*matching group*	**0**	0	0	0	**3**	0	1	2
	individual	**50**	13	15	22	**121**	23	43	55
p-value	*matching group*	<**0.001***	0.031*	0.031*	0.031*	**0.008**	0.031*	0.219	0.688
	individual	< 0.001***	< 0.001***	< 0.001***	< 0.001***	<**0.001***	< 0.001****	0.064	0.426

Table B.4: Two-way ANOVA on bidders' learning behavior w.r.t. profit.

$n = 351$	DF	F-value	$\Pr(> F)$	
Overall	1	0.03	0.954	
learn	1	0.03	0.954	

	Estimate	t-value	$\Pr(> \|t\|)$	
(Intercept)	0.42	2.022	0.044	*
$learn = 1$	0.02	0.057	0.954	

Table B.5: Two-way ANOVA on bidding behavior compared to previous round.

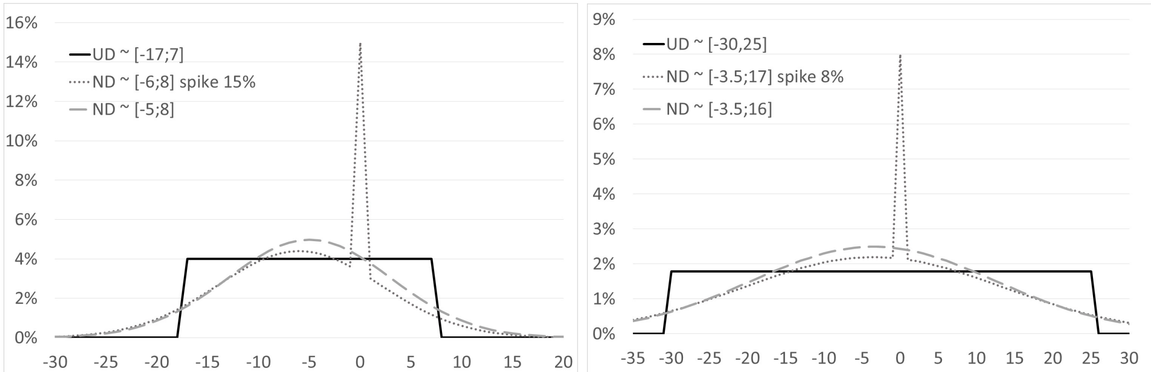
$n = 3368$	DF	F-value	$\Pr(> F)$	
Overall	7	20.06	< 0.001	***
pr.round	3	39.19	< 0.001	***
p	1	2.62	0.11	
$pr.round : p$	3	6.75	< 0.001	***

	Estimate	t-value	$\Pr(> \|t\|)$	
(Intercept)	4.66	4.141	< 0.001	***
$pr.round = A - P$	-4.08	-2.871	0.004	**
$pr.round = NA - L$	1.40	0.460	0.646	
$pr.round = NA - P$	-6.11	-4.992	< 0.001	***
$p = UP$	4.13	2.596	0.009	**
$pr.round = A - P : p = UP$	-2.84	-1.362	0.173	
$pr.round = NA - L : p = UP$	-9.99	-2.960	0.003	**
$pr.round = NA - P : p = UP$	-6.72	-3.803	< 0.001	***

B.3 Monte Carlo simulation

Table B.6: Monte Carlo simulation.

	DP auction			UP auction		
	$k=1$	$k=2$	$k=3$	$k=1$	$k=2$	$k=3$
Uniform distribution						
Distribution of the bids relative to the equilibrium bids	Uniform distribution on $[-17, 7]$			Uniform distribution on $[-30, 25]$		
Number of samples	10,000,000			10,000,000		
Average profit per award	-3.29	0.39	3.31	-3.75	-0.74	1.73
Share of awarded bids with a loss	66%	46%	34%	63%	51%	41%
Average deviation of the ... from the equilibrium bid						
... 1st lowest bid ...	-10.45	-10.48	-10.52	-19.41	-19.40	-19.40
... 2nd lowest bid ...	-7.32	-7.36	-7.42	-12.69	-12.69	-12.69
... 3rd lowest bid ...	-5.61	-5.64	-5.68	-5.98	-5.98	-5.98
... 4th lowest bid ...	-4.41	-4.40	-4.39	0.98	0.98	0.98
... 5th lowest bid ...	-2.68	-2.64	-2.58	7.69	7.69	7.69
... 6th lowest bid ...	0.47	0.53	0.59	14.41	14.41	14.41
Normal distribution						
Distribution of the bids relative to the equilibrium bids	Normal distribution with $\mu = -5$ and $\sigma = 8$			Normal distribution with $\mu = -3.5$ and $\sigma = 16$		
Number of samples	1,000,000			1,000,000		
Average profit per award	-3.87	-0.00	3.02	-3.96	-1.43	0.42
Share of awarded bids with a loss	67%	48%	35%	63%	54%	46%
Average deviation of the ... from the equilibrium bid						
... 1st lowest bid ...	-11.39	-11.41	-11.48	-20.54	-20.53	-20.53
... 2nd lowest bid ...	-7.61	-7.64	-7.70	-11.85	-11.85	-11.85
... 3rd lowest bid ...	-5.71	-5.77	-5.80	-6.08	-6.10	-6.11
... 4th lowest bid ...	-4.29	-4.28	-4.27	0.91	0.91	0.89
... 5th lowest bid ...	-2.39	-2.36	-2.31	4.86	4.86	4.88
... 6th lowest bid ...	1.42	1.47	1.54	13.55	13.53	13.53
Normal distribution with spike in equilibrium bid						
Distribution of the bids relative to the equilibrium bids	Normal distribution with $\mu = -6$, $\sigma = 8$, and 15%-spike in 0 (equilibrium bid)			Normal distribution with $\mu = -3.5$, $\sigma = 17$, and 8%-spike in 0 (equilibrium bid)		
Number of samples	1,000,000			1,000,000		
Average profit per award	-4.08	-0.19	2.82	-3.92	-1.18	0.76
Share of awarded bids with a loss	67%	47%	35%	62%	53%	45%
Average deviation of the ... from the equilibrium bid						
... 1st lowest bid ...	-11.67	-11.69	-11.75	-21.25	-21.24	-21.24
... 2nd lowest bid ...	-7.65	-7.69	-7.75	-11.78	-11.74	-11.76
... 3rd lowest bid ...	-5.80	-5.81	-5.84	-5.71	-5.70	-5.72
... 4th lowest bid ...	-4.46	-4.46	-4.45	-0.57	-0.55	-0.51
... 5th lowest bid ...	-2.77	-2.73	-2.69	5.18	5.21	5.19
... 6th lowest bid ...	0.55	0.60	0.67	14.30	14.31	14.30



(a) DP auction (b) UP auction

Figure B.1: Distributions of bids around the equilibrium bid in the Monte Carlo simulation.

B.4 Experimental instructions

Welcome to the Experiment!

You are participating in an economic experiment. Please read the following instructions carefully. The instructions state everything you need to know about your participation in the experiment. Please note:

- **For arriving on time to the experiment, you will receive a show-up fee of 5 EUR. You will receive this payment independent of the result of the experiment.**
- From this moment on, during the whole experiment, **you are not allowed to communicate** with other participants. Please do not surf the Internet. If you have any questions, please raise your hand silently.
- **All decisions are anonymous**. This means none of the other participants will learn about the identity of any other decision maker.
- **In this experiment, you can earn additional money**. The exact amount depends on your decisions as well as on the decisions of the other participants. The total amount of money you will have earned

during the experiment plus the show-up fee will be paid out in **cash** at the end. The payment will be **individual and anonymous** that means no one learns about the payments of the other participants. This experiment uses the currency "Monetary Units" (GE). **5 GE correspond to one EUR**, or 1 GE corresponds to 0.20 EUR.

- For this experiment, you have a **starting balance of 30 GE**.

The Experiment

The experiment consists of **40 rounds**. In each round, you form a **group of six** with five other, randomly selected participants. The composition of your group is unknown and changes each round. In each round, you have **exactly one decision** to take.

PROCEDURE OF THE EXPERIMENT

In each of the 40 rounds, you compete against the other five members within your group for the award of **one or several assignments** each for the delivery of one unit of a good. The 40 rounds are divided into **four sections** of 10 rounds each: Section 1 with rounds 1-10, Section 2 with rounds 11-20, Section 3 with rounds 21-30 and Sections 4 with rounds 31-40.

The particular sections only differ in how many **units of the good** are demanded in the respective rounds. The number of units of demand is either one, two or three. This means that in all rounds of a section either **one, two or three** units of the good are demanded. The number of units of demand per round is announced at the beginning of each section.

DECISION

In all 40 rounds, you represent a company which produces **one unit of a certain good** with the intention to sell. All members within your group of six (i.e. their companies) produce one unit of the same good and compete for selling their good only by their offer prices. In each round, **the cost**

of producing a unit of the good is the same for all members of your six member group. The costs change each round and are **drawn randomly**. However, the production costs are **unknown**. Therefor you and each other group member receive an **individual estimated value** for these costs.

In each of the 40 rounds, you can produce and sell one unit of the good with the valid production costs for this round. Your decision consists of **submitting an offer price for selling the unit**.

If your offer is accepted, you will earn the **profit in the amount of the sales price less the actual production costs**. If your offer is rejected, you will not receive any payment and you will not incur any costs as you do not produce the goods. Thus your profit is equal to zero.

PROCEDURE OF A ROUND

Each of the 40 rounds is structured as follows:

(1) Random group composition

In each round you and five other **randomly selected** participants form a group of six. You do not know who the other members of your group are.

(2) Demand and accepted offers

In Section 1 and 4 **one unit** is demanded, in Section 2 **two units** are demanded and in Section 3 **three units** are demanded. Accordingly, in each round either the **lowest offer** or **the two lowest offers** or **the three lowest offers** are accepted.

(3) Cost of production

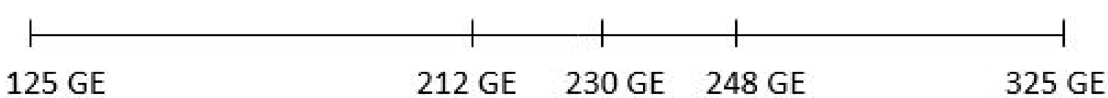
In each round, the cost of production for one unit of the good **are the same for all members within a group of six**. The cost of production are defined at the beginning of each round as a random **integer between 125 GE and 325 GE**, where each whole number between 125 GE and 325 GE is **equally probable**. However, at the beginning of a round, you do not know the cost of production; you only learn them after the round is finished.

(4) Individual cost estimations

At the beginning of each round your individual cost **estimation for the cost of production** is announced to you. This cost estimation is an **integer** and **deviates from the cost of production by maximum 18 GE**. Each cost estimation is **randomly** defined, where each whole number between the cost of production minus 18 GE and the cost of production plus 18 GE is **equally probable**. The individual cost estimations of the members within your group can differ. You only know your individual cost estimation.

Example for (3) and (4):

In this example, let the randomly defined – as described in (3) – cost of production be 230 GE. Consequently, each member of your group of six obtains an individual cost estimation between 230 GE – 18 GE = 212 GE und 230 GE + 18 GE = 248 GE.



Let the six cost estimations of your group be defined as described in (4) and be given by: 219 GE, 236 GE, 230 GE, 242 GE, 227 GE and 215 GE. That is, your individual cost estimation can be smaller, equal or greater than the cost of production.

(5) Decision

You **decide about your offer** for a unit of the good produced by your firm. **Simultaneously**, the other members within your group of six take their decisions about their offers. All participants only know their own offer and are **unaware** of the others' offers. Your offer consists of one **offer price**. This offer price is only allowed to be **between 100 GE and 350 GE**.

(6) Award price

If your offer is accepted, the award price will be determined by your offer price:

award price = offer price

If your offer is accepted, the award price will be determined by the lowest not accepted offer in your six member group:

award price = lowest not accepted offer in your six member group

Thus all accepted offers of one round obtain the same award price. If one unit is demanded, than the second lowest offer will determine the award price. If two units are demanded than the third lowest offer will determine the award price and so on.

(7) Result

If your offer is accepted, your profit equals your offer price less the cost of production:

profit = offer price − cost of production

If your offer is not accepted, you receive no payment, the cost of production do not accrue and thus your profit is zero.

In the end of each round you are informed about the **result of the round**. This information includes, if your offer was accepted and if

yes, at which award price you sell your unit of the goods and what your profit was in that round.
In addition, the **cost** of production, the anonymized order of all **offers** with the corresponding **individual cost estimations** and **profits** within your group of six are announced.

The particular rounds **only differ in Paragraph (2)**, i.e. the number of units of demand or the number of accepted offers. The **Paragraphs (1) and (3) – (7) are equal for all 40 rounds**.

NOTICE

In case of equal offer prices, awards are determined by a random mechanism.

YOUR PAYMENT

For your payment in the end of the experiment **three (out of ten) rounds of each of the four Sections are randomly chosen**, where all rounds are equally probable. The results of the other rounds are not paid. Your profits of these 12 randomly chosen rounds are added up and amount together with your starting balance of 30 GE to your total payment. If the sum of your profits is negative, i.e. result in a loss, this loss will be deducted from your starting balance; a negative total payment is not possible, however. This means: If your loss out of the 12 randomly chosen rounds exceeds 30 GE, your total payment will be 0 GE. Your total payment will be converted into EUR (5 GE correspond to 1 EUR).

Your payment is the sum of your total payment (in EUR) and your show-up fee (5 EUR).

B.5 Experimental questionnaire

Welcome to the Experiment!

You are participating in an economic experiment. Please read the following instructions carefully. The instructions state everything you need to know about your participation in the experiment. Please note:

- **For arriving on time to the experiment, you will receive a show-up fee of 5 EUR. You will receive this payment independent of the result of the experiment.**
- From this moment on, during the whole experiment, **you are not allowed to communicate** with other participants. Please do not surf the Internet. If you have any questions, please raise your hand silently.
- **All decisions are anonymous**. This means none of the other participants will learn about the identity of any other decision maker.
- **In this experiment, you can earn additional money**. The exact amount depends on your decisions as well as on the decisions of the other participants. The total amount of money you will have earned during the experiment plus the show-up fee will be paid out in **cash** at the end. The payment will be **individual and anonymous** that means no one learns about the payments of the other participants. This experiment uses the currency "Monetary Units" (GE). **5 GE correspond to one EUR**, or 1 GE corresponds to 0.20 EUR.
- For this experiment, you have a **starting balance of 30 GE**.

The Experiment

The experiment consists of **40 rounds**. In each round, you form a **group of six** with five other, randomly selected participants. The composition of your group is unknown and changes each round. In each round, you have **exactly one decision** to take.

PROCEDURE OF THE EXPERIMENT

In each of the 40 rounds, you compete against the other five members within your group for the award of **one or several assignments** each for the delivery of one unit of a good. The 40 rounds are divided into **four sections** of 10 rounds each: Section 1 with rounds 1-10, Section 2 with rounds 11-20, Section 3 with rounds 21-30 and Sections 4 with rounds 31-40.

The particular sections only differ in how many **units of the good** are demanded in the respective rounds. The number of units of demand is either one, two or three. This means that in all rounds of a section either **one, two or three** units of the good are demanded. The number of units of demand per round is announced at the beginning of each section.

DECISION

In all 40 rounds, you represent a company which produces **one unit of a certain good** with the intention to sell. All members within your group of six (i.e. their companies) produce one unit of the same good and compete for selling their good only by their offer prices. In each round, **the cost of producing a unit of the good is the same for all members of your six member group**. The costs change each round and are **drawn randomly**. However, the production costs are **unknown**. Therefor you and each other group member receive an **individual estimated value** for these costs.

In each of the 40 rounds, you can produce and sell one unit of the good with the valid production costs for this round. Your decision consists of **submitting an offer price for selling the unit**.

If your offer is accepted, you will earn the **profit in the amount of the sales price less the actual production costs**. If your offer is rejected, you will not receive any payment and you will not incur any costs as you do not produce the goods. Thus your profit is equal to zero.

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At the beginning of each round your individual cost **estimation for the cost of production** is announced to you. This cost estimation is an **integer** and **deviates from the cost of production by maximum 18 GE**. Each cost estimation is **randomly** defined, where each whole number between the cost of production minus 18 GE and the cost of production plus 18 GE is **equally probable**. The individual cost estimations of the members within your group can differ. You only know your individual cost estimation.

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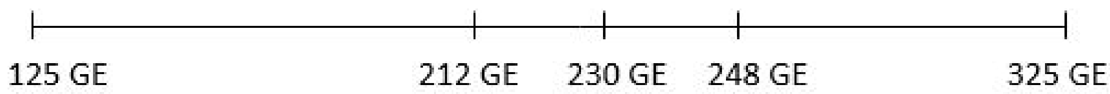

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You **decide about your offer** for a unit of the good produced by your firm. **Simultaneously**, the other members within your group of six take their decisions about their offers. All participants only know their own offer and are **unaware** of the others' offers. Your offer consists of one **offer price**. This offer price is only allowed to be **between 100 GE and 350 GE**.

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If your offer is accepted, the award price will be determined by your offer price:

$$\textbf{award price} = \textbf{offer price}$$

If your offer is accepted, the award price will be determined by the lowest not accepted offer in your six member group:

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If your offer is accepted, your profit equals your offer price less the cost of production:

profit = offer price – cost of production

If your offer is not accepted, you receive no payment, the cost of production do not accrue and thus your profit is zero.

In the end of each round you are informed about the **result of the round**. This information includes, if your offer was accepted and if yes, at which award price you sell your unit of the goods and what your profit was in that round.

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For your payment in the end of the experiment **three (out of ten) rounds of each of the four Sections are randomly chosen**, where all rounds are equally probable. The results of the other rounds are not paid. Your profits of these 12 randomly chosen rounds are added up and amount together with your starting balance of 30 GE to your total payment. If the sum of your profits is negative, i.e. result in a loss, this loss will be deducted from your starting balance; a negative total payment is not possible, however. This means: If your loss out of the 12 randomly chosen rounds exceeds 30 GE, your total payment will be 0 GE. Your total payment will be converted into EUR (5 GE correspond to 1 EUR).
Your payment is the sum of your total payment (in EUR) and your show-up fee (5 EUR).

B.6 Participants and payments

Pricing rule	**Section order**	**Session**	**Payment [EUR]**	**Average Payment [EUR]**[2]
UP	1-3-2-1	29.03.2017, 11:00	201.60	10.09
UP	3-1-2-3	24.03.2017, 14:00	215.20	11.12
DP	3-2-1-3	24.03.2017, 11:00	481.60	13.22
DP	1-3-2-1			
DP	2-3-1-2	22.03.2017, 14:00	465.40	12.65
DP	2-1-3-2			
UP	2-3-1-2	22.03.2017, 11:00	477.80	13.13
UP	2-1-3-2			
DP	1-2-3-1	15.03.2017, 16:00	466.00	12.25
DP	3-2-1-3			
UP	1-2-3-1	15.03.2017, 13:30	379.20	10.12
UP	3-2-1-3			

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