Market Design for Renewable Energy Auctions: An Analysis of Alternative Auction Formats

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Abstract

Auctions are widely used to determine the remuneration for renewable energies. They typically induce a high concentration of renewable energy plants at very productive sites far-off the main load centres, leading to an inefficient allocation as transmission line capacities are restricted but not considered in the allocation, resulting in an inefficient system configuration in the long run. To counteract these tendencies effectively, we propose a combinatorial auction design that allows to implement regional target capacities, provides a simple pricing rule and maintains a high level of competition between bidders by permitting package bids. By means of extensive numerical experiments we evaluate the combinatorial auction as compared to three further RES auction designs, the current German nationwide auction design, a simple nationwide auction, and regional auctions. We find that if bidders benefit from high enough economies of scale, the combinatorial auction design implements system-optimal target capacities without increasing the average remuneration per kWh as compared to the current German auction design. The prices resulting from the combinatorial auction are linear and anonymous for each region whenever possible, while minimal personalised markups on the linear prices are applied only when necessary. We show that realistic problem sizes can be solved in seconds, even though the problem is computationally hard.

Keywords: renewable energy auction, combinatorial auction, market design

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1. Introduction

Auctions are widely used in Europe and even worldwide to determine the remuneration for renewable energy sources (RES). Numerous countries have implemented auction systems to determine feed-in tariffs (FITs) and -premiums (FIPs), deductions or other subsidies for electricity from renewable power plants, among them Brazil, China, Denmark, France, Germany, South Africa and the United Kingdom, to name but a few.

Compared to fixed FITs and FIPs, auctions – if designed and implemented appropriately – have the potential to reduce remuneration and thus avoid overcompensation (de Vos & Klessmann, 2014; del Río & Linares, 2014; Mora et al., 2017). Renewable energy auctions are often considered economically efficient, since the resulting remuneration is competitively determined, close to the bidders' true cost and capacity expansion can be steered more effectively (Cozzi, 2012; del Río & Linares, 2014; Held et al., 2014; Kreiss et al., 2017; Mora et al., 2017). However, this typically induces a high concentration of renewable energy power plants at the most productive (i.e. windy or sunny) sites, which are often located far from the main load centres (Gerlach et al., 2015; Ibrahim et al., 2011; IRENA and CEM, 2015).

To counteract these tendencies, some countries, e.g. Germany or Uruguay, have established mechanisms that modulate support levels according to the location of a RES plant to induce a broader regional distribution of plants, in particular closer to main load centres (IRENA and CEM, 2015; Federal Ministry for Economic Affairs and Energy, 2016). Yet such location-specific auction mechanisms frequently fail to account for relevant aspects like potential network congestion arising from renewables expansion. Overall, the German mechanism, the reference yield model (Referenzertragsmodell, REM), has been criticised to reduce incentives to build wind power plants at efficient sites, while it also does not provide an effective means to steer generation capacity to particular target regions: the capacities awarded under the current German wind auction design with the REM are far from the envisaged targets in the individual regions (Güsewell, 2016; Jürgens, 2017).

In this paper, we build on advances in auction design to assess the potential of combinatorial auctions to induce efficient locational choices for RES and thereby reach the aforementioned efficiency goals. Combinatorial auction designs have already been successfully applied in transportation, logistics and for spectrum sales (Bichler & Goeree, 2017). In particular, combinatorial auctions allow to determine target capacites for each region and, at the same time, maintain a sufficient level of competition between bidders. Moreover, bidders can express their economies of scale across projects in one or more regions via package bids.

On the downside, package bids typically do not allow for linear and anonymous prices. Non-linear and personalised package prices, used e.g. in spectrum auctions, are often perceived as unfair (Bichler & Goeree, 2017). For our analyses, we therefore leverage the fact that RES auctions are large and the resulting non-convexities in the associated optimisation problems small. Our proposed auction design computes linear and anonymous prices whenever possible, and minimal mark-ups for the winning bidders on top of these anonymous linear prices when exact linear and anonymous prices are

impossible. The overall design draws on theoretical insights from the literature on pricing in combinatorial auctions (Adomavicius et al., 2012; Bichler et al., 2017, 2010; Guo et al., 2012). Even though the allocation pricing is computationally hard, we can solve realistic problem sizes in minutes, as we will show.

With this in mind, the focus of this paper is to assess and evaluate the impact of different RES auction designs on the resulting allocative efficiency and subsidy payments, i.e. the cost for the taxpayer. The short time span since most RES auction schemes are in place and the limited data availability renders an empirical evaluation of different RES auction designs infeasible. Moreover, since combinatorial auctions have not been used for this purpose in practice, a counterfactual analysis of different auction designs with field data is impossible. We therefore conduct extensive numerical experiments, with our analyses based on the case of RES auctions in Germany.

Germany constitutes an excellent starting point for our study, as both comprehensive market data as well as information on system-optimal RES locations are available to calibrate the numerical model. Following the European Commission's guidelines to use auction schemes for RES support (European Commission, 2014), Germany's renewable energies support scheme was revised in 2017. Since then, the capacities and the remuneration of all renewable energy plants exceeding 750 kilowatt (kW) capacity are determined via auctions (see section 22 Renewable Energy Sources Act, EEG, 2017). Pre-defined capacities are auctioned off to the lowest remuneration rates asked for in up to four auctions per technology a year (see section 32 EEG, 2017). Like in most countries with RES auctions, winning bidders are awarded a sliding FIP per kilowatt-hour (kWh), i.e. a subsidy covering the difference between the current electricity market price and the awarded bid price, if the market price lies below the awarded bid price (Wigand et al., 2016).

In our numerical study, we focus on onshore wind auctions, as onshore wind power is the capacity-wise largest renewable energy technology in Germany (section 28 EEG, 2017; Federal Ministry for Economic Affairs and Energy, 2018). We compare the current design, a nationwide auction with REM, to (i) a simple nationwide auction design, (ii) a regional auction design that implements the desired regional capacities and (iii) a combinatorial auction design that implements the desired regional target capacities but maintains a sufficient level of competition. The regional target capacities are taken from a study by Grimm et al. (2017), who determine the optimal RES locations in Germany accounting for the location of load centres and available network capacities.

We find that for reasonable synergies among projects, the proposed combinatorial auction design implements the system-optimal regional target capacities without considerably increasing the resulting remuneration compared to the current German auction design. This is surprising, given that the combinatorial auction exactly implements regional target capacities at less productive sites closer to demand centres, while the current nationwide auction design does not face those constraints. Notably, this remunerations does not even include long-run cost savings resulting from lower redispatch and network investment requirements when regional target capacities are met, the cost for which easily exceed a billion Euro per year (e.g. \in 1.5bn in 2017) and are largely caused by the regional mismatch of supply and demand (Federal Network Agency and

Federal Cartel Office, 2019). Grimm et al. (2017) show that a system-optimal allocation of RES in Germany enables efficiency gains of up to $\in 2.6$ bn p.a. Although we focus on a particular application to the current German wind auctions, key insights can be obtained for RES auctions in general.

Our research builds on several strands of the literature. Building on experiences with RES auctions in various countries and on insights from auction theory, there is large consent on the importance of certain design elements for the general success of renewable energy auctions. An overview and discussion is provided in e.g. Cramton (2010), IRENA and CEM (2015), Klemperer (2004), Maurer & Barroso (2011) or del Río et al. (2015). In particular, several studies stress the need for enforceable penalties to preclude project non-realisation, and advise in this regard to additionally include financial securities, fixed construction deadlines as well as prequalification criteria that require projects to be in an advanced planning stage, i.e. to conduct 'late auctions' (Anaya & Pollitt, 2015; de Jager & Rathmann, 2008; del Río & Linares, 2014; Maurer & Barroso, 2011; Mora et al., 2017; Toke, 2015). Several contributions point to a significant trade-off between cost-efficient support levels, reaching capacity expansion targets and actor diversity (del Río, 2017; Grashof, 2013; Hauser et al., 2014; Hauser & Kochems, 2014).

The optimal allocation of RES capacity remains largely untouched in the literature on RES auctions. While traditionally, under fixed feed-in tariffs, locational choice for renewable energy plants only depended on site specific weather conditions, several recent studies, among them Benz et al. (2015) and Grimm et al. (2017), illustrate the systemic optimality of a decentralised allocation of generation capacity that additionally accounts for existing network infrastructure and potentially arising network constraints. They show that closer proximity to main demand centres can significantly reduce prospective network congestion and, ultimately, the need for transmission line expansion. Ackermann et al. (2001) and Amado et al. (2017) support this notion and show that especially renewable energies are very well suited for distributed generation and smart grids.

Current studies using numerical experiments and simulations to compare or devise auction designs in an energy-related context have so far mainly focused on day-ahead auctions (e.g. Contreras et al., 2001; Fernandez-Blanco et al., 2014; Kardakos et al., 2013), local reserve energy markets (e.g. Rosen & Madlener, 2013), inter-grid power auctions (e.g. Zhang et al., 2014), carbon allowance auctions (e.g. Tang et al., 2017), energy contract auctions (e.g. Barroso et al., 2011) or an agent-based comparison of payas-bid vs. uniform price wind auctions (Anatolitis & Welisch, 2017). To our knowledge, we are the first to combine the findings on RES auction design and a system-optimal distribution of generation capacity to analyse whether minor adjustments to an existing auction design can lead to an improved regional distribution of generation capacities and compare several auction mechanisms with regard to the resulting FIPs.

The remainder of the paper is structured as follows: Section 2 illustrates the current situation and wind auction design in Germany, before we describe our model and the analysed auction designs in Section 3. Section 4 provides information on the data and experimental design, while we present our results in Section 5. Section 6 concludes.

2. Onshore wind auctions: A discussion based on the German case

As outlined above, the aim of our study is to conduct a counterfactual analysis of different auction designs to assess the effects of implementing system-optimal RES locations on the resulting level of remuneration.

To make the effects quantifiable, we conduct the analysis using data from the German onshore wind auctions. Germany is an ideal example to illustrate the comparative performance of different auction designs, as not only comprehensive market data is available for calibration, but also information on system-optimal RES locations (see Section 4.1). We therefore start from the current German wind auction design, before we discuss and evaluate alternative auction designs. Although we focus on a particular application to the current German wind auctions, key insights can be obtained for RES auctions in general.

As a starting point to motivate and outline the structural background of our model, this section provides a brief description of the legal framework for wind auctions in Germany, the currently implemented reference yield model (REM), insights on the systemoptimal allocation of RES in Germany as well as a discussion of alternative RES auction designs. Building on this, we specify our model and report our results in the subsequent sections.

2.1. Legal framework and results

In Germany, the EEG 2014 introduced RES auctions for the first time. Since 2017, the annual auction volume for onshore wind energy has been 2.8 Gigawatt (see section 28 EEG 2017). It is divided into four auctions, which take place quarterly. The rules for each single tender auction are as follows: (1) For each tender, the Federal Network Agency defines an exact auction volume of onshore wind capacity to be installed; (2) subsequently, bidders compete on the remuneration per kWh of fed-in electricity; (3) the bidders offering the lowest remuneration per kWh win, until full capacity is reached; remuneration per kWh or (4.b) receive the highest remuneration per kWh if they are a so-called 'citizen energy cooperative'.

Citizen energy cooperatives (Buergerenergiegesellschaften, BEG) are local communities that intend to build a wind power plant (Deutsche WindGuard, 2017). In order to foster local acceptance and regional value added, the legislator has granted BEG some simplifications in the auction procedure. Most importantly, while institutional bidders face a pay-as-bid auction, BEG are subject to a uniform price auction and receive the tariff of the highest accepted bid in the same round (sections 3(51) and 36g(5) EEG 2017).¹

The final FIP paid to each winner then results from the awarded remuneration per kWh minus the average monthly electricity market price, which is called a "sliding FIP"

¹ In addition, BEG also face a lower required collateral and penalty fees, are allowed a longer realisation period and do not need to submit an approval according to the Federal Immission Control Act (BImSchG) three weeks prior to the auction date (see sections 36 and 36g EEG).

(annex to section 23a EEG). Since the final FIPs and thus the subsidy payments by the regulator depend on the hourly electricity market price, which we do not simulate in our model, we focus our analysis and discussion on the offered and awarded remuneration per kWh, and not the resulting FIPs. Note that this does not limit the interpretation of our results: the difference between the remuneration levels resulting from the various auction designs corresponds exactly to the difference in subsidy payments by the regulator.

In 2017, a price ceiling of 7 ^{ct}/_{kWh} was set, above which bids were not accepted. This price ceiling was lowered to 6.3 ^{ct}/_{kWh} in the 2018 and to 6.2 ^{ct}/_{kWh} for the 2019 auctions (see sections 36b and 85(1) EEG and Federal Network Agency 2019a). Except for the BEG, who can submit at most six bids for no more than 18 MW in sum, there are no restrictions on maximum awarded capacity or number of bids. To ensure a high realisation rate, bidders must submit approval according to the Federal Immission Control Act (BImSchG) three weeks prior to the auction date (sections 36 and 104(8) EEG),² as well as a bid bond of 30 [€]/_{kW} installed capacity (15 [€]/_{kW} for BEG, with another 15 [€]/_{kW} due upon winning). Failure to commission a plant within the prescribed deadline of 24 months (48 months for BEG) results in a penalty fee of 10 [€]/_{kW} after 24 (48), 20 [€]/_{kW} after 26 (50) and 30 [€]/_{kW} after 28 (52) months. After a delay of 30 (54) months or a default on the security payments, an awarded tender is withdrawn. Table 1 provides a condensed overview of the main design elements of the German onshore wind auctions.

Auction design element	Implementation
Product	Installed capacity (MW)
Pricing rule	Pay-as-bid and uniform price sealed-bid auction (for BEG)
Туре	Price-only multi-item auction
Auctioned volume	2800 MW per year, i.e. 700-1000 MW per round
Remuneration scheme	Energy-related remuneration (capacity is tendered, electricity is remunerated)
Price ceiling	7 ^{ct} / _{kWh} in 2017; from 2018: average of highest accepted bid in the last three
	rounds, increased by 8% (6.3 ^{ct} / _{kWh} in 2018, 6.2 ^{ct} / _{kWh} in 2019)
Pre-qualification requirements	Bid bond of 30 €/kw of installed capacity (for BEG: 15 €/kw, secondary bid
	bond of 15 ϵ/kw upon winning)
	BImSchG-approval 3 weeks before auction
Frequency	3 to 4 auctions a year (every 2-4 months)
Concentration rules	Min. 750 kW
	Max. 6 bids for max. 18 MW in total for BEG
Penalties	$10 \in /_{kW}$ after 24 (48)
	$20 \in /kw$ after 26 (50) months of delay (for BEG)
	$30 \in /_{kW}$ after 28 (52)
Form of support	Sliding FIP per kWh
Support duration	20 years

Table 1: Design elements of the German onshore wind auction design

Source: Own elaboration.

 $^{^2}$ This encompasses a very thorough examination of compliance with building and environmental regulation and can take up to 3 months. The approval process is detailed in section 10 BImSchG.

2.2. The reference yield model

Another important element of the German onshore wind auctions is the reference yield model ('Referenzertragsmodell, REM) (see annex 2 EEG). The motivation for its introduction was to foster a more even distribution of wind power plants across Germany to relieve the already heavily loaded transmission lines (Federal Ministry for Economic Affairs and Energy, 2016).

To provide incentives for plant operators to also build wind power plants in less windy areas, and not only in the particularly windy north, a lower site quality of potential plant locations is compensated by a higher remuneration: The expected electricity yield of a wind power plant at its planned location is put into proportion with the so-called reference yield, i.e. the hypothetical electricity yield this particular wind power plant would generate at a pre-defined reference site, thereby arriving at a relative site quality factor. At an 80 percent site, for instance, the expected yield is 20 percent less than at the reference site, and at a 120 percent site, it is 20 percent higher. For many current wind power plant types, the reference yield is provided by Foerdergesellschaft Windenergie und andere Dezentrale Energien (FGW) (2017).

Having this in mind, bidders have to submit the bids for their onshore wind projects as if they were to be built at the reference site, so as to make bids for drastically different locations comparable regarding the wind conditions and site quality. The FIP that winning bidders then actually receive is their ask price adjusted by a correction factor based on the aforementioned relative site quality factor, i.e. for a less windy site the remuneration is adjusted upwards, while it is adjusted downwards for a windier one. The correction factor for various site quality levels is shown in Table 2.

Table 2: Site quality and correction factors for German onshore wind auctions

Site quality factor	70~%	80~%	90~%	100~%	110 $\%$	120~%	130~%	140~%	150~%
Correction factor	1.29	1.16	1.07	1.00	0.94	0.89	0.85	0.81	0.79
Source: Own elaboration based on section 36h EEG.									

2.3. System-optimal RES capacity allocation

RES support mechanisms typically do not accurately account for important factors that determine the optimal spatial allocation of RES generation capacities, since the minimisation of subsidies is typically the main target criterion and indicator. While the minimisation of subsidies implies that renewable energy plants should be built at the most productive locations, we follow Grimm et al. (2019; 2018; 2016; 2017) and expand on the definition of allocative efficiency by additionally considering existing load centres as well as potential congestion of the network infrastructure that would, in the medium term, induce costs for network expansion in case of regionally concentrated RES locations. This concept naturally implies a closer proximity of generation capacity to load centres. We call the resulting allocation of generation capacity "system-optimal". Grimm et al. (2017) determine this system-optimal RES allocation for Germany using a comprehensive energy market model. Their multi-level optimisation model takes into account long run (investment) decisions on network and generation capacity as well as short run decisions on production, consumption and redispatch. In this framework, there is a trade-off between the concentration of RES capacities at productive sites (which implies high transmission investment and redispatch cost) and RES capacity locations closer to load centres (which comes at lower RES productivity but also lower network expansion and redispatch cost). In one of their scenarios, Grimm et al. (2017) determine the system-optimal RES locations for the current German market design and show that optimal RES locations imply yearly welfare gains of at least $\in 2.6$ billion compared to the status quo in Germany.

A precise control of capacity locations via auctions is highly difficult, since capacity expansion and the final locational choice depend on the bidders. However, appropriately designed auction mechanisms can at least steer an allocation in the desired direction and incentivise bidders to build their plants at system compatible sites. We therefore employ the system-optimal onshore wind capacity allocation (MaxW) presented in Grimm et al. (2017) to assess the extent to which it can be achieved with adjustments to the current German wind auction design.

2.4. Alternative auction designs

The previous sections have illustrated several aspects concerning the spatial allocation of RES that are important for auction design. A very basic national auction without any locational steering mechanism would allocate RES at the most productive locations and thus yield the cost-minimal remuneration. However, it would ignore additional costs arising from redispatch and prospectively necessary network expansion. Thus, overall system cost from the induced RES expansion would be inefficiently high.

The undesirable concentration of RES at productive sites that are often far from load centres could be mitigated by using mechanisms like the REM, which compensates the disadvantage of less productive sites using correction factors on bids. However, determining the correction factor only based on site productivity and disregarding other important aspects like load proximity limits the effectiveness of the approach. It is only by chance that such a mechanism would induce an almost system-optimal RES allocation.

An alternative approach to ensure a desirable regional distribution is to set regional target capacities. To implement such target capacities, a straightforward approach is to conduct regional instead of national auctions. The corresponding regional target capacities are then tendered in each state or region, thereby exactly implementing the desired regional distribution of capacity. Under appropriate auction rules, within each region, the most productive sites are chosen first. Even though such a regional auction design implements the desired regional distribution of generation capacities, it is vulnerable to market power. In fact, competition within each region is the lower the smaller the regions are, i.e. the more tailored the mechanism is to induce an optimal regional distribution. To ensure a sufficient level of competition in regional auctions, they should be conducted less frequently (e.g. only once a year) and thus, for higher volumes. Note also that separate regional auctions would impose challenges on bidders that consider sites in different regions as substitutes or complements.

As a superior option, a single national auction with predetermined regional capacity quotas or targets could be considered, which allows bidders to place package bids for RES sites in multiple regions. This allows to ensure a sufficient level of competition, both within and between regions. Moreover, such a mechanims exploits the scope for further cost reductions by allowing for package bids that enable bidders to reflect synergies between different projects. Such 'combinatorial' auctions have already been used in industrial procurement, logistics as well as spectrum auctions to increase competition and leverage economies of scale and scope, which could be equally beneficial for the procurement of renewable energies (Bichler et al., 2006; Kokott et al., 2018; Sheffi, 2004; Bichler & Goeree, 2017).

In the remainder of the article we compare the auction formats sketched in this section using numerical experiments on the basis of data for the German electricity market.

3. Model

Let us now introduce the model for our numerical simulations. We first detail our assumptions on project costs and bidder types, before we precisely specify hoe we implement the analysed auction designs and their respective allocation and pricing rules.

3.1. Project cost

Bidders place bids on individual projects, with a project j describing a wind park of capacity y_j in kW, which can consist of multiple wind power plants at the same location. In order for these projects to operate profitably, bidders need to cover at least their investment costs over the remuneration period of 20 years. Based on regionally differentiated investment costs for onshore wind power plants in ϵ/kw and site-specific wind power generation per installed kW, we derive the break-even rate c_j in ct/kwh for a project j over the remuneration period of 20 years and divide this by the respective wind efficiency w_j at a project's location in kWh/kw. Investment costs include all administrative fees and costs for land improvement, while operating costs are assumed to be negligible. To allow for project-dependent variations, we randomly vary the underlying project costs by up to $\pm 5\%$.

The corresponding project capacity y_j is drawn randomly from a PERT distribution with a minimum 0.75 MW, a maximum of 25 MW and a region specific mean. The distributional assumptions are based on the submitted project capacities in 2018 (Federal Network Agency, 2019b). We choose a PERT distribution as it fits the empirical data best. For every auction, we consider an individual number of projects per region relative to its size, i.e. at least six projects per region and at most 100 projects in the largest region. The amount of projects is set such that the capacity requirements from both the German network development plan ('Netzentwicklungsplan', NEP, ÜNB 2017), which describes the capacity expansion path currently aimed for by German politics and the German auction system, as well as the MaxW allocation (Grimm et al., 2017) can be satisfied. As the largest of the 16 German states, Bavaria would thus be assigned 100 projects. However, due to its strict legal constraints regarding permissible wind park locations, the number of available projects is reduced to $40.^3$

3.2. Bidder types

We assume price taking behaviour of bidders in all our experiments. This allows for a transparent comparison among different auction formats. While renewable energy auctions on a national basis are large markets, we are aware of the fact that strategic behaviour could play a role if separate regional auctions were implemented. Strategic behaviour would be an additional drawback of regional auctions.

In our model there are two types of bidders, namely institutional and BEG bidders. As BEG are small local bidders, they are active in only one region. Each BEG is assigned one project in its respective region, with a capacity $y \leq 18$ MW. Based on the status quo of four auctions per year, we generate up to six BEG bidders per German state and auction, leading to a total of 384 BEG bidders for 2018. Analogously, we consider 120 institutional bidders for 2018, who are each randomly assigned 0-4 projects per auction, i.e. 0-16 projects in 2018. The number of BEG and institutional bidders is based on the 2018 auction data and adjusted such that the capacity requirements in all regions can be met. Bidders participate in every subsequent auction unless all their projects won in earlier auctions.

Since institutional bidders can place bids on multiple projects, they can realise synergies via economies of scale. There are numerous ways how such synergies can come into play, which we try to accommodate by integrating different synergy concepts in our experiments and checking the consistency of our results across these. We account for synergies that arise if a bidder is awarded multiple projects, either subsequently or in a single auction. In particular, we distinguish between synergies for projects within one region (regional synergy), for projects in neighbouring regions (cross-regional synergy), and for all projects in Germany (national synergy). Since BEG are small, local bidders that only place one bid in a single region, they do not realise synergies. An overview of the type as well as number of bidders and synergies is given in Table 3.

Bidder type	Number of bidders	Projects per bidder	Synergy concept	Synergy levels
BEG	384	1	None	None
Institutional	120	0-16	$\{\text{regional, cross-regional, national}\}$	[0, 0.5]

Table 3: Overview of bidder types and synergy concepts

Consequently, a project bundle B_i of bidder *i* can be partitioned into *k* sets of synergy groups S_k . A synergy group thus contains all projects of a bidder that, depending on the synergy concept, would create scale economies if awarded. Consider e.g. four projects assigned to *i* from the following regions: R_1, R_1, R_2 and R_3 , where R_1 and R_2 are neighbouring regions. In the regional synergy concept, the two projects in R_1 would be in one

 $^{^{3}}$ The so-called '10H' rule requires wind power plants to have a distance of at least ten times the wind power plant's hub height to residential areas, see section 82 of the Bavarian Building Law (2007).

synergy group, the other two each in a separate one, i.e. $S_1 = \{R_1, R_1\}, S_2 = \{R_2\}, S_3 = \{R_3\}$. For cross-regional synergies, the groups would be $S_1 = \{R_1, R_1, R_2\}, S_2 = \{R_3\}$; while for national synergies all four projects would be in one group. In this respect, the more regions enter a single synergy group, the 'wider' the corresponding synergy concept, i.e. the cross-regional concept is wider than the regional one. The unit cost of each project j in a synergy group S_k is then adjusted by a factor $\lambda \in [0, 1]$ to

$$\tilde{c}_j(S_k) = c_j \cdot (1 - (\lambda \cdot \frac{|S_k| - 1}{|S_k|})).$$
(1)

 λ describes the share of cost savings achieved via synergies. For $\lambda = 0$ there is no synergy. With each additional project in S_k , the marginal effect of synergy decreases. To compute the unit cost of a project bundle, $\bar{c}(B_i)$, we consider the synergy-adjusted unit costs of all individual projects $j \in B_i$ weighted by their respective capacity y_j and wind efficiency w_j , i.e.

$$\bar{c}(B_i) = \frac{\sum_{k=1}^K \sum_{j \in S_k} \tilde{c}_j(S_k) \cdot y_j \cdot w_j}{\sum_{j \in B_i} y_j \cdot w_j}$$
(2)

An example calculation of synergy-adjusted project and bundle unit costs is given in Appendix B.

3.3. Analysed auction designs

For our analyses, we examine only one year, and we assume that the regulator intends to expand generation capacity proportionately to the final allocation. Based on the respective installed capacity, it is possible to periodically define regional capacity expansion quotas to achieve some target capacity for e.g. 2035. To answer the question whether a certain auction design enables an effective steering of generation capacity expansion according to such quotas, it thus suffices to analyse only one period. More specifically, we do not calibrate our model to most closely match the results of all past auctions.⁴ Instead, we aim to provide a sound counterfactual comparison of different auction designs based on their outcome with the administrative parameters given for 2018, the first year during which onshore wind auctions were conducted subject to the current regulatory framework in Germany. In particular, we assess the allocative efficiency of four auction designs, whose allocation mechanisms and pricing rules are described in the following.

3.3.1. Single-lot auction designs

In the single-lot auction designs, one bid always corresponds to a single project j.

⁴ Since the start of the auction scheme in 2017, the corresponding legal framework has been subject to change in late 2017. Therefore, the available auction data is difficult to interpret. As a matter of fact, only limited information is provided on the auction results. The only available data are on an aggregate level or simple averages and thus do not allow an intricate empirical analysis.

National

The *National* auction design with four auctions a year constitutes our benchmark for comparison, as it implements the cost-minimal outcome.

A bid in the *National* auction design contains the ask price b_j and the capacity y_j for a project j. After all bids are submitted, they are sorted in ascending order by ask price. Bids are accepted as long as the cumulative capacity of accepted bids is smaller than the tendered capacity. Successful BEG bidders receive the remuneration per kWh of the last accepted bid (uniform-price), while institutional bidders receive the remuneration per kWh they asked for (pay-as-bid). This procedure is also shown in pseudo-code below.

ALGORITHM 1: Allocation and pricing rule for *National, National REM* and *Regional* auction designs

Data: Submitted bids, represented by tuples of ask price b_j and capacity y_j for a project j **Result:** Set of winning bids W, allocated remuneration p_j Determine tendered capacity D; Sort submitted bids in ascending order by ask price b_j ; In case of a tie: sort in ascending order by capacity y_j ; **while** D > 0 **do** $\begin{vmatrix} assign j \text{ to } W; \\ p := b_j; \\ \text{ if } project not a BEG$ **then** $<math>\mid p_j := b_j; \\ end \\ D := D - y_j; \\ end \\ To all projects in <math>W$ without price, assign $p_j = p;$

National REM

The National REM auction design essentially describes the current design of the German wind auctions. A total of 2710 MW (the total wind auction volume in 2018 in Germany, see Federal Network Agency, 2019b) is auctioned off in four auctions. Bidders place bids according to the REM for a reference site (see section 2.2), which are then tendered as in the National auction design. Successful bidders receive a remuneration adjusted by the correction factor corresponding to their bids relative site quality factor as shown in Table 2.

Regional

The *Regional* auction design exactly implements the regional target capacities of MaxW. In particular, we analyse individual auctions for each of the 16 German states, with one auction per state per year, since the auction volumes would be very small for four auctions per region and year. All 16 regional auctions are conducted simultaneously each year. In each state, the total capacity to be built in 2018 according to MaxW is tendered. Within each region, the most productive and wind-efficient sites are chosen first. The allocation and pricing procedure for *Regional* is identical to the *National* auction design.

3.3.2. Combinatorial auction design

While all previous auction designs allow bids only for single projects, we now propose an auction design that allows to submit package bids: the *Combinatorial* auction design. As in the *Regional* auction design, annual target capacities for every region are set according to MaxW, but auctioned off simultaneously in a single auction. Bids are awarded such that the resulting allocation is as efficient and subsidy-minimising as possible. BEG are local and can only place bids in one region, while institutional bidders can place package bids for projects in multiple regions. In the following, we introduce the corresponding allocation and pricing rule. When discussing unit prices, we are referring to remuneration per kWh in our context.

For each bidder $i \in I$, we determine whether a bundle of projects $B_i \subseteq P_i$ has been allocated or not by a decision variable $z_i(B_i)$. For an allocated bundle B_i , its unit cost in ct/kwh is denoted by $\bar{c}(B_i)$, its total capacity in kW at node (i.e. a region) $n \in N$ by $y_n(B_i)$, and its average wind efficiency in ${}^{\mathrm{kWh}}/{}_{\mathrm{kW}}$ at node n by $w_n(B_i)$. Table 4 summarises the necessary notation.

Table 4: Notation

Sets	
Ι	Set of bidders
P_i	Set of projects of bidder $i \in I$
$B_i \subseteq P_i$	Set of projects in a bundle bid of bidder $i \in I$
N	Set of nodes or regions, i.e. states in Germany
Decision Variables $z_i(B_i)$	Assign bundle B_i to bidder $i \in I$
Parameters	
$y_n(B_i)$	Capacity (size) of bundle B_i in node $n \in N$ (in kW)
$w_n(B_i)$	Average wind efficiency at the generation sites
	in a bundle B_i (in $^{kWh}/_{kW}$)
$\bar{c}(B_i)$	Unit cost of bundle B_i in ct/kWh
d_n	Demanded capacity in node $n \in N$ (in kW)
p_n	Unit price in node $n \in N$ (in ^{ct} / _{kWh})

The sum of the allocated capacities of all accepted bundles must be larger or equal to the tendered capacity d_n for each node $n \in N$ (demand constraint), while each bidder can win at most one of her bundles (supply constraint). The objective of the problem is to select the most efficient projects while minimising excess capacities. To do so, we consider a bundle's unit cost times its capacity. The dual variable of the demand constraint can then be interpreted as the impact of an increase in the demanded capacity d_n of one kW on the objective function, which leads to a price in ^{ct}/_{kWh}.

$$\underset{\text{s.t.}}{\text{Min}} \sum_{i \in I} \sum_{B_i \subseteq P_i} z_i(B_i) \cdot \bar{c}(B_i) \cdot \sum_{n \in N} y_n(B_i)$$
(AP)

$$\sum_{i \in I} \sum_{B_i \subseteq P_i} z_i(B_i) \cdot y_n(B_i) \ge d_n \qquad \forall n \in N \qquad (Demand)$$

$$\sum_{B_i \subseteq P_i} z_i(B_i) \le 1 \qquad \qquad \forall i \in I \qquad (Supply)$$

$$z_i(B_i) \in \{0, 1\}$$
 $\forall i \in I, B_i \subseteq P_i$ (Binary)

This binary linear program used for the allocation problem of a multi-unit combinatorial procurement auction can be seen as a multidimensional knapsack problem, which is known to be NP-hard (Bichler, 2017, p. 100). We can solve the problem sizes in our analysis to near optimality (integrality gap < 1%) with standard solvers (Gurobi version 8.1) on commodity hardware within minutes in our experiments.

There is a large literature on pricing in multi-object markets, and more specifically in combinatorial auctions (Bichler, 2017). Let us briefly introduce and discuss some basic considerations for our pricing rule. It is well-known that the Vickrey-Clarke-Groves (VCG) mechanism is incentive-compatible and implements an efficient outcome (Krishna, 2010). However, bidders' payments under VCG are personalised and nonlinear. This means that prices for a package of objects can differ from the sum of the prices of individual objects in the package (non-linear), while prices for a package can also vary across bidders (personalised) (Bichler & Goeree, 2017). Moreover, the VCG outcome might not be in the core, i.e. there could be incentives for individuals or coalitions of bidders to deviate (Ausubel & Milgrom, 2006). As argued by Milgrom (2004), discriminatory pricing fails to promote the law of one price and thus may be hard for some people to accept.

Walrasian markets yield linear item-level, anonymous competitive equilibrium prices, but are not incentive-compatible (Hurwicz, 1972). However, Walrasian mechanisms are strategy-proof in the large (Azevedo & Budish, 2019). In other words, such markets are robust to strategic manipulation if there are many bidders who then become price takers. The RES market is relatively large (> 100 bidders and projects, Federal Network Agency, 2019b, thereby justifying the use of linear and anonymous prices. Such prices are widely used, e.g. in day ahead electricity markets, as well as easy to understand and interpret. Unfortunately, with indivisible goods such as projects in RES auctions, Walrasian prices do not always exist. The types of valuations (e.g. substitutes valuations) for which Walrasian equilibria exist are in fact rather limited (Baldwin & Klemperer, 2019).

In the RES market, linear prices exist if the linear programming relaxation of the allocation problem (AP) is integral. In other words, if the last set of constraints $z_i(B_i) \in \{0,1\}$ were relaxed to $z_i(B_i) \in [0,1]$ and the result were still integral, with all $z_i(B_i) \in \{0,1\}$, then the dual variables of the Demand constraint (p_n) would have a natural interpretation as Walrasian prices. This well-known observation follows from strong duality in linear programming (Bichler, 2017, p. 144ff). The linear programming

relaxation of AP is rarely integral, but the integrality gap of the linear programming relaxation, i.e. the difference between the objective function value of the integer program and its relaxation, is small (on average less than 1% in our experiments). This is due to the large number of bidders and bids. We leverage this observation for the pricing rule we introduce in this paper: due to the small integrality gap, also the dual variables of the linear programming relaxation are 'close' to Walrasian prices.

Although the integrality gap is small, market prices cannot simply be derived from the dual linear program, as we show next. To see this, let us first introduce the dual (DAP) of the linear programming relaxation of AP:

$$\begin{aligned}
& \underset{s.t.}{\operatorname{Max}} \sum_{n \in N} d_n p_n - \sum_{i \in I} \pi_i \\
& \sum_{n \in N} y_n(B_i) p_n - \pi_i \leq \bar{c}(B_i) \sum_{n \in N} y_n(B_i) \\
& \forall B_i \subseteq P_i, \forall i \in I \\
& \pi_i, p_n \geq 0 \\
\end{aligned} \tag{DAP}$$

Note that the objective function value of **DAP** is less than or equal to **AP** such that prices will be too low on average, unless we have integrality of the linear programming relaxation. As a result, the prices will be below the bids and bidders can make a loss. To avoid this, we introduce a modified version **MDAP** of the dual linear program to compute prices. MDAP deviates from anonymous prices via a markup only if necessary, and ensures that bidders do not make losses (Individual Rationality, IR). Simultaneously, prices for losing bidders should be below their costs (NOENVY). This approach is akin to pseudo-dual prices as proposed for ascending combinatorial auctions (Bichler et al., 2009).

Let us introduce **MDAP** more formally. If we reverse the inequality in **DAP** and minimise the objective, we get the lowest possible linear and anonymous prices for the winners, such that all winners $W \subseteq I$ can recover their costs, while we also ensure that prices for the losers $L \subseteq I$ are below their costs with $W \cup L = I$ and $W \cap L = \emptyset$. As this is not always possible, we introduce a slack variable, $\delta(B_i)$, for each winner's winning bundle, describing a personalised markup for this bidder. The bidder's payment then exactly covers their costs.

$$\underset{\text{s.t.}}{\text{Min}} \sum_{n \in N} d_n p_n + \sum_{B_i \in W} \delta(B_i) \cdot M$$
(MDAP)

$$\sum_{n \in N} y_n(B_i) w_n(B_i) (p_n + \delta(B_i)) \ge \bar{c}(B_i) \sum_{n \in N} y_n(B_i) w_n(B_i)$$
(IR)
$$\forall i \in W, B_i \subseteq P_i : z(B_i) > 0$$
$$\sum_{n \in N} y_n(B_i) w_n(B_i) p_n < \bar{c}(B_i) \sum_{n \in N} y_n(B_i) w_n(B_i)$$
(NOENVY)
$$\forall i \in L, B_i \subseteq P_i$$
$$p_n \ge 0 \quad \forall n \in N$$
$$\delta(B_i) \ge 0 \quad \forall i \in W, B_i \subseteq P_i : z(B_i) > 0$$

The resulting prices from **MDAP** are anonymous and linear for the losers while no winning bidder can make a loss (IR). Markups on the anonymous prices, $\delta(B_i)$, are introduced only when necessary. A penalty term M keeps these deviations as small as possible. In large auctions with small integrality gaps, the price computation in **MDAP** strikes a balance between different design goals.

4. Data and experimental design

In this section we briefly summarise the data used to parametrise our numerical experiments and outline our experimental design.

4.1. Data

We use a variety of historical data sets and data based on authorative forecasts to calibrate our model. In particular, we employ data on various aspects and areas that are relevant for bidders in wind auctions.

To begin with, we use data on existing and planned renewable energy generation capacity in each German federal state. Information on the installed capacity of onshore wind power plants is taken from Deutsche WindGuard (2018).

In order to generate an amount of projects satisfying the capacity expansion targets in our different treatments, we use data from scenario B 2035 in the NEP (ÜNB, 2017) and on MaxW (Grimm et al., 2019, 2018, 2017, 2016). Both the NEP and MaxW allocations provide capacity targets for 2035, with the planned capacity expansion underlying each allocation corresponding to the difference between the target capacity in 2035 and the current stock. Since we consider only one year in our analysis, we calculate the necessary yearly expansion assuming a linear expansion until 2035.

Table 5 shows the corresponding regional distribution of capacity envisaged according to the NEP (second column) and MaxW (third column). For comparative purposes, the distribution of the capacity awarded in the 2018 auctions is shown in the first column of Table 5.

Table 5: Distribution of awarded capacity in 2018 and capacity expansion paths by state and allocation

State	2018	NEP	MaxW
Schleswig-Holstein (SH)	7.7~%	10.2~%	0 %
Mecklenburg-West Pomerania (MV)	8.8~%	16.6~%	7.8~%
Hamburg (HH)	0 %	0 %	0 %
Bremen (HB)	0.2~%	0.1~%	0 %
Lower Saxony (NI)	12.1~%	19.0~%	0 %
Saxony-Anhalt (ST)	6.2~%	8.8~%	0 %
Brandenburg (BB)	16.9~%	5.4~%	0 %
Berlin (BE)	0 %	0 %	0.5~%
North Rhine-Westphalia (NW)	13.9~%	4.9~%	11.5~%
Saxony (SN)	1.3~%	8.1~%	4.9~%
Thuringia (TH)	3.3~%	9.2~%	0 %
Hesse (HE)	8.0~%	2.8~%	16.2~%
Rhineland-Palatinate (RP)	10.2~%	7.2~%	6.7~%
Saarland (SL)	0.3~%	0 %	3.5~%
Bavaria (BY)	5.2~%	0 %	35.2~%
Baden-Wuerttemberg (BW)	6.7~%	7.7~%	13.7~%
Sum	100~%	100~%	100~%

Note: 0% in the 2018 column means that no capacity was awarded to projects in these states in 2018. 0% in the NEP and MaxW columns indicates that no further capacity expansion is necessary in these states to reach the respective capacity targets, i.e. the optimal capacity in these states subject to the target allocation has already been reached.

Source: Own elaboration based on data from the Federal Network Agency (2019b), Grimm et al. (2017) and ÜNB (2017).

The auctioned capacity in each bidding round in the *National REM* auction design is defined according to the specifications in section 28 EEG. Based on the resulting annual electricity generation, we determine the respective capacity that needs to be tendered in the *National*, *Regional* and *Combinatorial* auction designs to arrive at the same annual electricity generation. We do so since the reference parameter for RES capacity expansion is generally the annual amount of electricity generation.

Moreover, following Grimm et al. (2017), we account for regional differences in site quality in Germany and within the 16 states by creating 15 classes of technical potential per state to allow for a differentiated simulation of bidding decisions. To generate the classes, we employ data from the Bundesverband WindEnergie (2012). In a next step, we allocate both the existing installed capacity by the end of 2017 and the target capacities for 2018 into the 15 classes in descending order up to their maximum capacity, starting with the best. For our analysis, we assume that within each region new capacity is bid on in the best available class of technological potential first, and in lower classes only once the better ones have reached full capacity. Analogously, we use data on hourly wind power generation per installed kW in kWh/kW by state and class of technological potential taken from Grimm et al. (2017).

To adequately model investors' cost structures, we use information on investment costs for wind power plants in 2018 based on Prognos (2013). Since only investment

cost data for 2013 and 2035 is given in Prognos (2013), we use linear interpolation to arrive at investment cost values for 2018. Furthermore, we assume spatially differentiated plant configurations and investment costs to account for the varying conditions in the German states. In less windy areas, comparably larger and thus more expensive wind power plants with greater rotor diameter have to be built to generate an amount of electricity per installed kW equal to that in very windy states.

For each of the configurations, we calculate an approximation of the reference yield per installed kW using data on reference yields of comparable existing wind power plants provided by FGW (2017). To be precise, we choose wind power plants whose configurations most closely match those of our four onshore wind categories, extrapolating their reference yields given by FGW (2017) by adjusting for slight differences in hub height or rotor diameter, if necessary. For an overview of the comparative values and wind power plants used for each wind category see Table A.1 in Appendix A. This allows us to simulate the current auction system including the REM. Table 6 provides an aggregated overview.

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	Category	Investment costs $[\in/kW]$	Plant configuration	Reference yield p.a. [MWh/MW]
	Onshore Wind 1 (HB, HH, MV, SH)	1,355	Hub height 95 m, 3 MW, 100 m rotor diameter	2,321
x	Onshore Wind 2 (BB, BE, NI, NW, ST)	1,456	Hub height 105 m, 3 MW, 100 m rotor diameter	2,376
201	Onshore Wind 3 (BW)	1,630	Hub height 120 m, 2.5 MW, 110 m rotor diameter	3,915
	Onshore Wind 4 (BY, HE, RP, SL, SN, TH)	1,732	Hub height 130 m, 2.5 MW, 115 m rotor diameter	4,065

Table 6: Investment costs for wind power plants

Source: Own elaboration based on Prognos (2013) and FGW (2017).

4.2. Synergies and cost computations

Institutional bidders can develop multiple projects and realise synergies. We are not aware of real-life estimates of such synergies, as bidders tend to be secretive about details of their cost functions. Nevertheless, economies of scale are almost always an issue for large bidders. In our study, synergies are a central treatment variable; understanding at which synergy level combinatorial auctions yield lower costs than alternative auction designs that do not consider target capacities is thus of great interest. In our numerical experiments, institutional bidders bid their cost for a project j while they consider synergies arising from previously won projects. They do not speculate on potential synergy effects by winning multiple items in order to avoid making losses. In the *Combinatorial* auction design, which allows bids on bundles of projects, institutional bidders bid their cost for any possible project bundle $B_i \in P_i$ accounting for possible synergy effects, i.e. they bid $\bar{c}(B_i)$. Bidders in the *National, National REM* and *Regional* auction designs consider only synergies from projects that they already won. When placing bids on individual projects, they do not lower their bids by speculating on winning multiple projects. Else, they would risk making losses.

In the National REM auction design, as described in Section 2.2, bidders place bids as if their projects were to be built at the reference site. Therefore, each project's individual site-specific wind efficiency w_j in ${}^{\rm kWh}/{}^{\rm kW}$ is put into proportion with the corresponding reference yield w_j^{REM} from Table 6, i.e. ${}^{w_j}/{}^{w_j^{REM}}$, which leads to the respective correction factor as shown in Table 2. The final bid results in the break-even costs c_j divided by the correction factor, anticipating that the final remuneration p_j will result from the ask price multiplied by the correction factor.

4.3. Experimental design and focus variables

As described in Section 3.3, we analyse the outcome of four auction designs for three different synergy concepts and various synergy levels. An overview of these treatment variables and their possible combinations is given in Table 7.

Treatment variable	Value
Auction design	{National, National REM, Regional, Combinatorial}
Synergy concept	{regional, cross-regional, national}
Synergy level	$\{0, 0.1, 0.2, 0.3, 0.4, 0.5\}$

Table 7: Preview of experimental design

To make sure that our results are robust, we analyse ten iterations per treatment combination. With four different auction designs, three synergy concepts, six synergy levels and ten iterations per treatment combination, we thus evaluate a total of 1,800 experimental auctions.⁵ More specifically, we assess our results based on the following focus variables:

- 1. The average remuneration per kWh \bar{p} , in ct/kWh
- 2. The allocative quality δ in %, measured as the percentage of capacity allocated to regions with capacity demand under MaxW. Naturally, $\delta = 100\%$ in the *Regional* and *Combinatorial* auction designs.
- 3. The actor diversity η in %, measured as the share of capacity won by BEG bidders.

5. Results

Based on our experiments, we report the effect of the four auction designs on the three primary focus variables: average remuneration per kWh (\bar{p}) , allocative quality (δ) and actor diversity (η) . In addition, we report the total payments p.a. $(\theta, \text{ in } \in \mathbf{m})$ and the bidders' average cost per kWh (\bar{c}) for the interested reader. As stated above, the *National* auction design serves as a benchmark for comparison.

⁵ 1,800 auctions = $[2(National, National REM) \cdot 4(February, May, August, October) + 2(Regional and Combinatorial)] \cdot 10(iterations) \cdot 3(synergy structures) \cdot 6(synergy levels)$

5.1. Synergies

We first compare different auction designs for various synergy levels. A synergy level of 0.2 indicates that a bundle of projects in a synergy group (e.g. a region) can cost up to 20% less than the sum of the individual projects. The more projects are in that group, the closer the cost reduction will be to 20%.

Result 1 (Synergies). A given synergy level has a stronger (negative) impact on the remuneration to be paid in the Combinatorial auction than in the National and National REM auction. The lowest impact of synergies on the remuneration is observed in the Regional auction design.

Dep. variable: avg remuneration \bar{p}	Coef.	SE	t	P > t
Intercept	6.5436	0.0280	233.51	0.0000
National REM	0.4597	0.0368	12.49	0.0000
Regional	0.8488	0.0368	23.06	0.0000
Combinatorial	0.8878	0.0368	24.12	0.0000
Cross-regional synergy	-0.3447	0.0180	-19.17	0.0000
National synergy	-0.3990	0.0180	-22.19	0.0000
National \times syn. level	-2.2605	0.0860	-26.29	0.0000
National REM \times syn. level	-2.5355	0.0860	-29.49	0.0000
Regional \times syn. level	-0.0102	0.0860	-0.12	0.9059
Combinatorial \times syn. level	-3.7501	0.0860	-43.62	0.0000
R^2	0.93			
N	720			

Table 8: Remuneration effects of design variables

Table 8 presents the effects of our experimental design elements on the average remuneration per kWh \bar{p} obtained from an OLS regression. The wider the synergy concept (regional < cross-regional < national), the lower the remuneration, as synergy groups become larger and the potential for economies of scale increases. However, the difference in effect size between cross-regional and national synergies is small (-0.3447 ^{ct}/_{kWh} vs. -0.3990 ^{ct}/_{kWh}), indicating that synergies are most profitably realised for projects in neighbouring or close regions.

The synergy level has the strongest impact on the remuneration per kWh in the *Combinatorial* auction design: an increase of 0.1 in the synergy level decreases the average remuenration by 0.38 ^{ct}/_{kWh}. In comparison, it leads to a decrease of only 0.23 ^{ct}/_{kWh} in the *National* auction design. Since bidders cannot explicitly account for synergies in the *Regional* auction design, they have no effect on the average price level. This is due to the fact that only one regional auction takes place per year so that bidders cannot account for projects won in ealier auctions when bidding in later auctions. Averaging across synergy concepts, the *Combinatorial* auction design yields the same average price as in the National auction design for a synergy level of 0.59.

5.2. Allocative quality and average remuneration per kWh

In a next step, we evaluate allocative quality and the corresponding average remuneration in the four auction designs.

Result 2. The National REM auction design yields a higher allocative quality compared to the National auction at the expense of a higher average remuneration per kWh. However, the resulting allocation still differs substantially from the desired MaxW. Both the Regional and the Combinatorial auction designs implement MaxW precisely, but at a higher average remuneration. For synergies of 0.4, the Combinatorial auction design yields the average remuneration per kWh of the National REM design. In case of synergies, among all auction formats, the Combinatorial auction design yields by far the lowest bidder margins.

Auction design	Synergy	$ar{m{p}}(rac{ct}{kWh})$	$oldsymbol{\delta}(\%)$	$oldsymbol{\eta}(\%)$	$\boldsymbol{\theta} (\in m$	$ar{m{c}}(rac{ct}{kWh})$
	level $(\boldsymbol{\lambda})$				p.a.)	
National	0	6.25	49	24	366	6.11
National REM	0	6.70	89	27	389	6.60
Regional	0	7.14	100	19	421	7.11
Combinatorial	0	7.17	100	18	417	7.13
National	0.2	5.81	46	15	332	5.43
National REM	0.2	6.23	74	11	355	5.86
Regional	0.2	7.14	100	19	413	6.52
Combinatorial	0.2	6.34	100	5	362	6.14
National	0.4	5.20	45	8	294	4.51
National REM	0.4	5.48	70	7	308	4.79
Regional	0.4	7.14	100	19	407	5.95
Combinatorial	0.4	5.50	100	5	310	5.04

Table 9: Comparison of auction design outcomes

Table 9 shows the outcome of the four action designs with respect to the focus variables. We focus on allocative quality (δ) and the average remuneration (\bar{p}) first. Since there is no information on scale economies for German wind auction bidders in reality, we report our results for both no synergies and cross-regional synergies with $\lambda = 0.2$ and $\lambda = 0.4$.

Allocative quality, average remuneration and bidders' costs increase when applying the REM. Without synergies, 89% of the subsidised capacity in *National REM* are allocated to regions with a positive capacity demand under MaxW. This is 40 percentage points more than in the *National* auction design. As synergy increases, these shares as well as their difference decrease, the latter from 40 to 28 ($\lambda = 0.2$) and 25 ($\lambda = 0.4$) percentage points. This is mostly due to a decline in allocative quality in the *National REM* design, since a higher cross-regional synergy supports a wider distribution of projects. For a graphical illustration of the resulting allocations, see Figures ??, ??, ?? and ?? in Appendix C. Meanwhile, the average remuneration per kWh in the National REM design is 7.2% $(\lambda = 0.0, 0.2)$ and 5.4% $(\lambda = 0.4)$ higher than in the National auction design. Note that while the REM slightly increases allocative quality, bidders lack incentives to search for efficient sites when it is applied.

Irrespective of the synergy level, allocative quality is at 100% in both the *Regional* and *Combinatorial* auction designs, as we only allow bidding in regions with positive capacity demand under MaxW. But this comes at a cost: without synergies, the average remuneration per kWh in both designs increases by 14.4% and 14.7% compared to the *National* design, respectively, which can be considered a surcharge for forcing the system-optimal allocation of MaxW. Note that, considering no synergies, the *Regional* auction design leads to slightly lower prices than the *Combinatorial* auction designs. The reason for this is that the *Regional* auction design only minimises prices while the *Combinatorial* auction design minimises prices and overcapacity, leading to lower total cost (θ).

However, the average remuneration per kWh in the *Combinatorial* auction design becomes similar to that of the currently applied *National REM* design in the presence of synergies, and remains only 9.1% ($\lambda = 0.2$) and 5.8% ($\lambda = 0.4$) higher than in the *National* auction design. In other words, for only moderate synergies, the *Combinatorial* auction design implements the system-optimal allocation without any surcharge compared to the current German auction design, while maintaining incentives to search and bid on the most efficient sites.

It is also notable that in case of synergies the *Combinatorial* auction design reduces bidders' margins substantially as compared to all other auction designs: from 0.38 (0.37, 0.62) ^{ct}/_{kWh} in the *National* (*National REM, Regional*) auction design to 0.20 ^{ct}/_{kWh} for $\lambda = 0.2$ and from 0.69 (0.69, 1.19) ^{ct}/_{kWh} to 0.46 ^{ct}/_{kWh} for $\lambda = 0.4$.

5.3. Bidder diversity

Result 3. The higher the synergies, the more institutional bidders benefit from economies of scale and the less capacity is allocated to BEG bidders.

The fifth column of Table 9 reports the share of awarded capacity won by BEG bidders, $\eta(\%)$. Without synergies, this ranges from as much as 27% in the *National REM* auction design to 18% in the *Combinatorial* design. With increasing synergy levels, institutional bidders gain a competitive advantage; consequently, the share of successful BEGs decreases substantially and generally lies below 10% for $\lambda = 0.4$. Since the *Regional* auction design is unaffected by synergies, the share of BEG bidders stays at 19%.

5.4. Computational cost

Result 4. All auction formats can be computed in seconds with realistic problem sizes. It takes significantly longer to compute the allocation and remuneration per kWh for the Combinatorial auction design than for the other auction designs, on average 5 seconds. The average time required to solve the allocation and corresponding pricing problems in each auction design is provided in Table 10. Note that we are solving real-world problem sizes. The computation times would not constitute a practical problem.

Auction design	Mechanism	mean (std) in sec.
National	Allocation	0.013 (0.000)
National REM	Allocation	$0.014\ (0.000)$
Regional	Allocation	$0.021 \ (0.000)$
Combinatorial	Allocation	4.47(0.045)
National	Pricing	0.003 (0.000)
National REM	Pricing	$0.005\ (0.000)$
Regional	Pricing	$0.019\ (0.000)$
Combinatorial	Pricing	$0.816\ (0.054)$

Table 10: Computation times

5.5. Summary

Forcing the system-optimal allocation of MaxW comes at the cost of an average increase in remuneration of about 14% compared to the *National* auction design. This changes in the presence of synergies: for $\lambda = 0.2$ and $\lambda = 0.4$ the average remuneration is only 9.1% and 5.8% higher, respectively, all the while maintaining the system-optimal capacity allocation of MaxW.

The percentage of capacity won by BEG bidders decreases with stronger synergy effects, as institutional bidders gain a comaprative advantage. Note that maintaining a steady and moderate share of successful BEG bidders can also be a policy goal. This could easily be implemented with additional allocative constraints in the *Combinatorial* auction design.

6. Conclusion

Many countries are using auctions to determine the remuneration for RES, which is however often accompanied by a high concentration of renewable energy power plants at very productive sites far-off the main load centres. To counteract these tendencies, we introduce a combinatorial auction design that allows to implement regional target capacities, provides a simple pricing rule and maintains a high level of competition between bidders by permitting package bids.

The aim of this paper was to assess and evaluate the impact of four different RES auction designs on allocative efficiency and subsidy payments by means of extensive numerical experiments. Based on the case of onshore wind auctions in Germany, we compare the current nationwide auction design with the REM to a simple nationwide auction design, a regional and our proposed combinatorial auction design.

We find that for only moderate synergies, the *Combinatorial* auction design implements the system-optimal wind capacity allocation presented by Grimm et al. (2017) without considerably increasing the average remuneration per kWh compared to the current German auction design, while maintaining incentives to search and bid on the most efficient sites. Grimm et al. (2017) estimate the potential savings resulting from a system-optimal allocation of RES in Germany to be at least $\in 2.6$ billion a year for a 2035 scenario. Current cost experiences for redispatch and feed-in management measures often range above a billion Euro per year and are mainly caused by the high concentration of onshore wind power plants in northern Germany, far from the main load centres in southern Germany. This indicates a high potential for savings resulting from our proposed Combinatorial auction design.

The prices resulting from the Combinatorial auction are linear and anonymous for each region whenever possible, while minimal personalised markups on the linear prices are applied only when necessary to prevent winning bidders from making losses. At the same time, prices are set such that no losing bidder would want to produce at those prices. Due to the size of the problem instances (i.e. the tendered capacity and number of bids), the personalised markups are minimal.

Combinatorial auctions come at the cost of computational complexity for the auctioneer since the allocation problem that needs to be solved is an NP-hard combinatorial optimisation problem. In our experiments, we show that realistic problem sizes can be solved in seconds due to the large number of relatively small bidders. For bidders, combinatorial auctions are strategically simpler than having to bid in a sequence of auctions. In particular, institutional bidders can bring their scale economies to bear with package bids, which reduces costs.

Overall, the combinatorial auction design proposed in this paper is a viable alternative to location-specific auction mechanisms like the German REM. Furthermore, it constitutes a candidate design for renewable energy auctions not only in Germany, but also in other countries worldwide where auctions are used to support the expansion of renewable energy capacity.

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Appendix A.

Category	Parameter	Configuration	Comparative value	Plant type	Reference yield p.a. $\left[\frac{MWh}{MW}\right]$
	Rotor diameter (m)	100	100.5		
1	Hub height (m)	95	99	eno 100	3,195.36
	Nominal capacity (MW)	3	2.2		
	Rotor diameter (m)	100	100.5		
2	Hub height (m)	105	99	eno 100	3,195.36
	Nominal capacity (MW)	3	2.2		
	Rotor diameter (m)	110	112		
3	Hub height (m)	120	119	Vestas V112	2,965.89
	Nominal capacity (MW)	2.5	3.3		
	Rotor diameter (m)	115	112		
4	Hub height (m)	130	140	Vestas V112	$3,\!192.87$
	Nominal capacity (MW)	2.5	3.3		

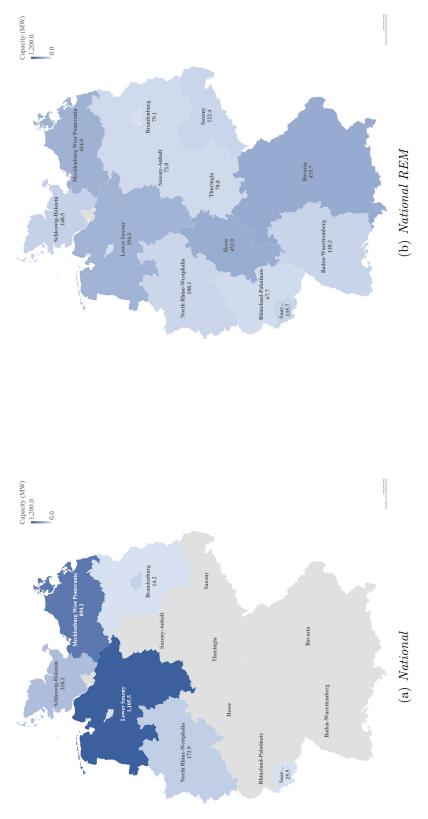
Table A.1: Comparative values for reference yield calculation

Source: Categories based on Prognos (2013), comparative values taken from FGW (2017).

Appendix B.

Example 1. A bidder *i* has $P_i = \{P1, P2, P3, P4, P5, P6\}$ projects, represented by tuples of (region, cost). Those are: ('BW',10), ('BW',10), ('BY',10), ('RP',10), ('BB',10), ('BE',10). Assuming there are no synergies, the unit cost for each project is: $\tilde{c}_j(S_k) = c_j = 10 \frac{ct}{kWh}, \forall j \in P_i$ and all partitions S_k of P_i .

Assume synergies are considered to be $\lambda = 0.5$ for projects within a region. The sets of projects in the same synergy groups are $S_1 = \{P1, P2\}, S_2 = \{P3\}, S_3 = \{P4\}, S_4 = \{P5\}, S_5 = \{P6\}$. When winning S_k , the respective unit cost for each project in S_1 is given by: $\tilde{c}_j(S_1) = 10 \cdot (1 - 0.5 \cdot \frac{1}{2}) = 7.5 \frac{ct}{kWh}$. The unit cost for all other k > 1 is $\tilde{c}_j(S_k) = 10 \frac{ct}{kWh}$.





Appendix C.

