Energy Policy 166 (2022) 112982

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

How to design efficient renewable energy auctions? Empirical insights from Europe

Vasilios Anatolitis [a,b,*], Alina Azanbayev [a,c], Ann-Katrin Fleck [d,e]

[a] Fraunhofer Institute for Systems and Innovation Research ISI, Breslauer Str. 48, 76139, Karlsruhe, Germany
[b] University of Freiburg, Faculty of Environment and Natural Resources, Tennenbacher Str. 4, 79106, Freiburg, Germany
[c] Goethe University Frankfurt, Theodor-W.-Adorno-Platz 4, 60323, Frankfurt, Germany
[d] Takon GmbH, Schwalbenweg 5, 95445, Bayreuth, Germany
[e] Karlsruhe Institute of Technology, Institute of Economics, Neuer Zirkel 3, 76131, Karlsruhe, Germany

A R T I C L E I N F O

Keywords:
Renewable energy auctions
Panel data analysis
Auction design elements
Efficiency
Support costs

A B S T R A C T

An increasing number of countries use auctions to allocate support for renewable energies. One major objective of policymakers when designing auctions is support cost efficiency, i.e., achieving low awarded prices. Based on a holistic database with auction outcomes from Europe covering the years 2012–2020, we conduct a fixed effects panel data regression to assess the effects of several auction design elements on the awarded prices. According to our results, policymakers aiming for low prices in renewable energy auctions should avoid restricting auctions to small-scale projects, implement ceiling prices, and ensure high levels of competition. Multi-technology auctions can also lead to higher efficiency, while quotas should be avoided. While PV tends to achieve lower prices in auctions restricted to small-scale projects, onshore wind performs better in auctions open to large-scale projects. Feed-in premia, multi-criteria auctions and allowing bidders to deviate from their awarded project capacity show no significant impact. The introduction of financial prequalification requirements and the length of the realisation period should be chosen carefully, as their effects are interrelated. While our results for individual design elements are largely in line with existing literature, we are able to produce new insights on the interdependencies between various auction design elements.

1. Introduction

It is widely acknowledged that the share of renewable energy sources (RES) in energy consumption needs to increase to mitigate the negative effects on the global climate (e.g., European Commission, 2014b). One major pillar in the struggle against the climate crisis is the European Green Deal (European Commission, 2019), which intends to decrease carbon emissions to establish a carbon-neutral Europe by 2050 (European Commission, 2019). The Renewable Energy Directive (European Parliament and European Council, 2018) sets an ambitious target of a 32% share of RES in the European Union's (EU) gross final consumption of energy in 2030. Although generation costs, i.e., levelised cost of electricity (LCOE), for renewable technologies have decreased over the last years (Akella et al., 2009; IRENA, 2021), there are still arguments in favour of support mechanisms, e.g., ensuring a predictable investment framework and tackling issues such as the cannibalisation effect of RES (Held et al., 2019). In the EU, support levels and support recipients need to be determined via a "competitive bidding process", i.e., an auction (European Commission, 2014b, 2022; European Parliament and European Council, 2018). Thus, it is not surprising that in the last decade more and more auctions for RES support have been conducted in the EU. A major objective for policymakers is hereby the static efficiency of auctions (del Río et al., 2015b). In this paper, we use the term "(static) efficiency" in the sense of "support cost efficiency", i.e., minimising the support expenditures, which manifests in low awarded auction prices (Ehrhart et al., 2019).[1] Another, similarly important objective is effectiveness (del Río et al., 2015b), i.e., deploying a certain amount of RES and achieving a certain target. In auction-based project selection, effectiveness also means achieving high realisation rates of awarded capacity (Matthäus, 2020).

Parallel to a steadily growing amount of theoretic literature on RES auctions (see Section 2), an increasing number of empirical literature

* Corresponding author. Fraunhofer Institute for Systems and Innovation Research ISI, Breslauer Str. 48, 76139, Karlsruhe, Germany.
E-mail addresses: vasilios.anatolitis@isi.fraunhofer.de (V. Anatolitis), ann-katrin.fleck@kit.edu (A.-K. Fleck).

[1] Please note that this is not necessarily the same as "allocative efficiency", which means awarding bidders with the lowest (generation) cost (LCOE).

https://doi.org/10.1016/j.enpol.2022.112982
Received 11 November 2021; Received in revised form 16 March 2022; Accepted 11 April 2022
Available online 12 May 2022

analyses efficiency and effectiveness of RES auctions through country-level case studies. Examples from Europe include, e.g., Germany (e.g., Tiedemann, 2015; Sach et al., 2019), Denmark (e.g., Kitzing and Wendring, 2015; González and Kitzing, 2019), Greece (e.g., Anatolitis, 2020), the UK (e.g., Fitch-Roy and Woodman, 2016; Woodman and Fitch-Roy, 2019), or the Netherlands (e.g., Noothout and Winkel, 2016; Jakob et al., 2019). Outside of Europe, e.g., auctions in Canada (Menzies and Marquardt, 2019), Brazil (Bayer, 2018; Bayer et al., 2018), and Argentina (Menzies et al., 2019) have been analysed.

Furthermore, a whole strand of literature examines RES auction design with agent-based modelling (e.g., Anatolitis and Welisch, 2017; Welisch, 2018, 2019; Lundberg, 2019). They simulate bidding behaviour to examine the impact of different design elements on auction outcomes, e.g., in the German solar photovoltaic (PV) auctions (Welisch and Kreiss, 2019).

Several articles conduct an empirical cross-country assessment of auctions. Shrimali et al. (2016) analyse 20 auctions from India and elsewhere to test effects of auction design on effectiveness, and to derive knowledge to design India's auctions for RES support accordingly. They find that auctions are almost always more efficient, in the sense of reducing support levels, compared to administratively-set feed-in-tariffs. Winkler et al. (2018) empirically compare the effectiveness and efficiency of RES auctions in five countries to non-auction based support schemes. They conclude that auctions can have an impact on both effectiveness and efficiency, although not as a general trend. In a similar vein, Bayer et al. (2018) conduct a comparative assessment of auction outcomes in Brazil, France, Italy and South Africa from the years 2009–2015.

Quintana-Rojo et al. (2020) point out that econometric literature looking deeper into effectiveness and efficiency of auctions is still lacking. While some articles employ econometric techniques to assess the impact of support schemes on effectiveness, they usually include auctions merely as an explanatory variable. For instance, Kilinc-Ata (2016) who employs a fixed effects panel regression with data from the EU and the US, finds that auctions as a policy instrument have a significant effect on RES deployment. Another example is Bersalli et al. (2020), who examine a similar question and come to the same conclusion by conducting a panel data analysis using data from Europe and Latin America.

In contrast, to the best of our knowledge, only a few articles employ econometric techniques to assess the effects of RES auction design on auction outcomes. Cassetta et al. (2017) analyse the Italian auctions for onshore wind between 2012 and 2016 using standard ordinary least squares (OLS) regressions. Their results show that auction design factors, more specifically the induced competition and the age of environmental permits, have a significant decreasing effect on the awarded prices. Batz Liñeiro and Müsgens (2021) investigate the solar PV auctions in Germany, in particular with regard to efficiency, effectiveness, as well as actor diversity. Probst et al. (2020) econometrically investigate the effect of local content requirements (LCRs) on awarded prices in solar PV auctions in India. Using an OLS and Heckman regression model, they were able to show that LCRs increase the awarded prices significantly. Another example is the paper of Matthäus (2020), which is closest to our work. Using a Tobit regression model, he statistically analyses results from RES auctions based on a dataset of 94 auctions from 42 countries worldwide between 1990 and 2017. Nevertheless, the focus of his work is on the effects of certain auction design elements on effectiveness, i.e., the awarded projects' realisation rates, thus not including the awarded prices in his analysis. While Matthäus (2020) finds strong, positive effects for prequalification criteria and penalties on the realisation rates, he could not find statistical significance for technology banding and the pricing rule.

Our work adds to this literature substantially by investigating the effects of specific auction design elements on awarded prices using econometric methods and taking into account 220 auction rounds from 16 European countries. First, based on existing literature, we identify the design elements that should have an impact on support cost efficiency, i.e, the objective that an auction results in low awarded prices (Ehrhart et al., 2019), and their actual effects on the prices. We then statistically test these theoretical predictions with a panel data regression. To overcome the issue of "differences in auction prices between countries [being] attributable to a multitude of factors" (Bayer et al., 2018), we include country and time fixed effects, as suggested in Winkler et al. (2018). Our statistical findings are an important contribution for policymakers aiming to design auctions for optimal results in terms of support cost efficiency. Furthermore, we include interaction terms for different design elements, which is only slightly touched upon in Matthäus (2020) (and only with regard to effectiveness) and to our knowledge not used in other econometric papers analysing RES support mechanisms.

The rest of the paper is structured as follows. Section 2 analyses design elements important for a panel regression by a vigorous literature review. Section 3 gives an overview of our dataset, while Section 4 introduces our model and methodology. In Section 5 we present and discuss our results. Finally, in Section 6, we conclude with our policy recommendations.

2. Theoretical considerations of auction design elements

An auction is a complex mechanism to allocate supply and demand. Auctions for RES support can be designed in many different ways with manifold design elements. Results of those auctions include prices, awarded bidders, and realisation rates, to only name a few. Not all results of an auction are equally important to the auctioneer, who in most cases is a government or an auction-conducting authority. In most auctions for RES support, the effects measured are efficiency and effectiveness (see Section 1). In this paper we focus on efficiency, as many European countries have not (yet) disclosed the realisation rates of their projects. In this context, an efficient auction leads to the lowest average awarded prices (e.g., Maskin et al., 2001) compared to other possible auction outcomes. Some design elements in theory do not influence auction results, while any variation of others can have manifold effects (Hochberg and Poudineh, 2018; Kreiss et al., 2017b). We therefore analyse the literature on RES auctions to identify the elements assumed to be important for an econometric analysis on auction prices.

The first decision, which is independent of the choice for an auction as the mechanism to determine award, is the number of projects the auctioneer wants to support. The *auction volume* thus determines the size of an auction, since in larger auctions the competition level decreases and more (and also more expensive) projects are awarded. Standard economic theory (e.g., Mankiw, 2020) as well as RES related literature (e.g., del Río and Linares, 2014; Shrimali et al., 2016; Gephart et al., 2017) predict higher prices for those auctions since they are more likely to have lower levels of competition. Similarly, an auctioneer can decide on the *maximum project size* to participate in the auction, which has an impact on awarded prices (Haelg, 2020; Álvarez and del Río, 2022). IRENA (2017) argue that favouring/limiting auctions to small-scale projects can impede economies of scale, which leads to higher awarded prices. Thus, opening the auction for more (large-scale) projects by increasing the maximum project size can have a decreasing effect on auction prices, either via lower generation costs (economies of scale) or through a higher level of competition (IRENA and CEM, 2015; del Río et al., 2015a).[2]

Also, the way how bidders are remunerated is central for an auction for RES support. Before the use of auctions, remuneration/support levels were set by regulatory authorities (IRENA, 2013), but still could be paid out in different forms. The most common (generation-based) *remuneration schemes* are the feed-in-tariff (FIT), the one-sided sliding feed-in-premium (FIP) and the two-sided sliding feed-in premium, which is also called Contract for Difference (CfD) (del Río et al., 2015a).[3] In a FIT-scheme, the bidder receives a fixed amount of money per kWh from the regulator/government, but without the possibility to sell the electricity on the market, i.e., they do not receive any additional revenues apart from the FIT payments (Gawel and Purkus, 2013). In contrast, generators under premium schemes (FIP and CfD) are obligated to sell the generated electricity on the market and receive a support payment on top. This premium equals the difference between a certain strike price (in our case, the awarded bid price) and the electricity market revenue (Gawel and Purkus, 2013). In case the electricity market revenues are lower than the awarded price, the premia of a FIP and a CfD do not differ. In case the electricity market revenues surpass the awarded price, generators can retain these additional revenues under a FIP, while under a CfD, generators need to transfer the additional revenue to the government. Typically, policymakers introduce a certain proxy for the electricity market revenue, namely the reference market value, which is usually the average electricity market price of a technology in a certain time period (Anatolitis and Klobasa, 2019). Due to the marketing obligation, the premium-based schemes entail two additional risks compared to the FIT, namely the (electricity market) price and balancing risks. A higher risk usually translates to higher cost of capital and thus to higher LCOE. Hence, we can state that a FIT leads to the lowest LCOE, while the LCOE under a FIP are at least as high as under a CfD. Based on this relation, we can derive a first indication of the submitted bid prices. In a competitive auction, we can assume bidders to submit their LCOE under a FIT-scheme. In contrast, if average market values are expected to be higher than the LCOE, bidders under a FIP have the incentive to bid below their LCOE, even down to zero (see, e.g., Kreiss et al., 2017a; Neuhoff et al., 2018). Under the same conditions, bidders under a CfD will submit a price somewhere between their LCOE and the expected market value. Thus, expecting sufficiently high market values, we expect to observe the lowest bids under a FIP, then FIT, then CfD (Neuhoff et al., 2018). In case of low expected market values in the future, we presume bids to be lowest under a FIT, while CfD and FIP to result in the same bid prices. Thus, it becomes clear that the exact relation between bid prices under these three schemes is highly dependent on expectations on future market values.

Closely related to the remuneration scheme is the support *duration*, i.e., the time period during which an awarded bidder is entitled to the support payments. A longer support duration can lead to lower awarded prices due to lower financing costs (del Río and Linares, 2014), and the spread of the necessary total support sum over a longer period of time. In a CfD scheme with a high level of competition and expected high market values, a shorter support duration can lead to lower awarded prices. After the end of the support duration, bidders can retain the additional market revenues, which would have to be transferred to the government. These revenues are then factored in when calculating their bid.

In a typical auction for RES support, bidders submit a combination of price and a certain volume as their bid (del Río et al., 2015a). Auctioneers can set a maximum price, the *ceiling price*, which defines the maximum acceptable bid. The ceiling price can thus prevent excessive bids in case of low competition and can thus ensure low awarded prices (del Río, 2017). The auctioneer then determines awarded bidders according to an a-priori announced set of rules. In *multi-criteria auctions*, the award criterion is usually a combination of prices and other components like local content, environmental compatibility, etc., which are then weighted by the auctioneer (GIZ, 2015). More award criteria lower the relative influence of bid price, thus giving bidders with higher bid prices a chance of being awarded (e.g., IRENA and CEM, 2015; Wigand et al., 2016; del Río, 2016; Mora et al., 2017b). Hence, this design element is expected to lead to higher auction prices compared to a *price-only* award criterion (e.g., GIZ, 2015; del Río, 2017).

Also, for some single large projects, e.g., offshore wind farms, it can be sensible to conduct *single-unit auctions* (Haufe and Ehrhart, 2016; Hochberg and Poudineh, 2018), i.e., an auction where only one pre-developed project is awarded. Compared to this, *multi-unit auctions* usually include both small- and large-scale projects (Haufe and Ehrhart, 2016; Hochberg and Poudineh, 2018), and thus, *multi-unit auctions* can lead to higher prices (del Río, 2017).

Another decision the auctioneer has to make is on the *auction type*, i.e., the way bidders submit their bids. There are two types of auctions: static and dynamic auctions (Haufe and Ehrhart, 2018). In static auctions, bidders submit one sealed-bid without knowledge of other competitors' bids while in dynamic auctions bidders have the chance to learn other bidders' behaviour and adapt their bids in the course of the auction (Haufe and Ehrhart, 2018). Standard auction theory predicts the same revenues for both auction types (under certain assumptions) (Weber, 1983; Krishna, 2009). Still, experiments have shown that this is not always the case in real-world applications, amongst others due to bidders' risk assessments (Kagel, 1990).

Not only how technologies are auctioned is important, but also whether there is direct competition between the technologies or not. We distinguish between *multi-technology* and *technology-specific* auctions. While multi-technology auctions, i.e., auctions with more than one technology competing, can help to award projects with the lowest costs, and thus can lead to lower awarded prices (Kreiss et al., 2021; IRENA and CEM, 2015; GIZ, 2015), technology-specific auctions can help to promote immature technologies (del Río and Linares, 2014) and create a diversified technology mix (IRENA, 2013).

Also, the question which *technology* results in lower awarded prices has not been fully answered yet. While not a design element in the traditional sense, policymakers face the decision which technologies to support and thus to allow to participate in the auctions. The existing empirical literature focuses mostly on the technologies' LCOE (e.g., IRENA, 2021; Lazard, 2021; Timilsina, 2021) or investigates the awarded auction prices of only one technology, e.g., onshore wind (Cassetta et al., 2017; Grashof et al., 2020) or PV (Batz Liñeiro and Müsgens, 2021). Although recent publications show the LCOE of onshore wind and (utility-scale) solar PV to be in a similar range (IRENA, 2021; Lazard, 2021; Timilsina, 2021), it is not clear whether this holds automatically for awarded prices, as well. LCOE can be assumed to have an impact on bid prices, yet, especially under premium-based remuneration schemes (CfD and FIP), awarded prices depend strongly on the expected market revenues and thus on the technologies' production profiles. In

[2] A higher maximum project size can lead to more large-scale projects winning in the auctions, and fewer awarded small-scale projects, which can discourage smaller bidders from participating in future auctions. Thus, in the mid-to long-term, competition might suffer and thus awarded prices might increase. Nevertheless, in this study, we focus on the short-term effects of the maximum project size, which is why we expect to observe lower awarded prices with a higher maximum project size.

[3] Due to comparability issues, we do not consider the fixed FIP and the investment grant in our study.

addition, auction-related conditions, such as the (expected) level of competition can influence bid prices. For instance, Timilsina (2021) observes a disconnect between record-low awarded prices and LCOE in non-European solar PV auctions, which she explains by potential direct and implicit forms of subsidies. Due to these influences, no clear prediction with regard to awarded prices of the two technologies can be made based on the existing literature on LCOE.

To participate in the auction, bidders often have to fulfill certain *prequalification* criteria (Haufe and Ehrhart, 2018). These can roughly be divided into two categories: financial prequalifications, e.g., payments to ensure financial liquidity, mostly in the form of bid bonds, and material prequalifications, e.g., building permits to ensure seriousness of bids (del Río et al., 2015a). The literature here is not totally aligned in its predictions regarding effects of prequalifications on efficiency. Since bidders have to pay to fulfill the requirements, participation in the auction is costly for bidders. Kreiss et al. (2017b) and Kruger and Eberhard (2018) argue, that these costs lead to higher bids, resulting in higher prices. On the other hand, standard economic theory suggests that sunk costs should not be included in the bid after their occurrence (e.g., Menezes and Monteiro, 2000). Thus, bid prices could decrease as well, since (material) prequalifications reduce uncertainty regarding future costs (Shrimali et al., 2016; Kreiss et al., 2017b).[4]

Closely related to financial prequalifications, *penalties* are often introduced to increase incentives for a punctual contract fulfillment, as they accrue when a project is delayed or not realised (e.g., Held et al., 2014; GIZ, 2015). This can either be a payment to the auctioneer or other punishments like exclusion from future auctions (GIZ, 2015). Thus, penalties increase bidders' risk and lead to higher prices (e.g., del Río and Linares, 2014; IRENA, 2017; Mora et al., 2017a; Gephart et al., 2017; Hochberg and Poudineh, 2018). On the other hand, they also ensure more serious bids, excluding too inexperienced bidders (USAID, 2020).

Since for penalties it is important to determine the project deadline, i.e., how long the developer has time to install the project, the different *realisation periods* of an auction are included in the analysis. For bidders, a longer realisation period is favourable since they face lower risks of delays as well as possibly decreasing technology costs (Dobrotkova et al., 2018). This can lead to lower bids (IRENA and CEM, 2015; Hochberg and Poudineh, 2018). From an auctioneer's point of view, a timely fulfillment of contract is desirable to reach expansion targets. Still, a too short period may lead to higher prices due to increased bidding risk as well as sunk costs (e.g., Gephart et al., 2017; del Río and Linares, 2014).

Flexibility measures are introduced in auctions to give bidders the possibility to slightly change their awarded volume (IRENA and CEM, 2015), i.e., within certain boundaries the bidders can change their project's installed capacity after being awarded. This decreases the risk stemming from uncertainties regarding, e.g., future technology costs. Since reduced risk for bidders has a decreasing effect on prices in general auction theory (e.g., Krishna, 2009), its effect will be tested in this paper.

The last auction design element included in this analysis is *quota*. Quotas are often used in multi-technology auctions to ensure a maximum or minimum award capacity for one technology, or in technology-specific auctions to limit regional disparities (e.g., Kreiss et al., 2017b; del Río et al., 2015a). Quotas can lead to higher prices due to the award of projects with higher costs, but are from a technology or region where the quota is not yet fulfilled (Sach et al., 2019). Still, under certain conditions, overall auction payments for the auctioneer can also be reduced through quotas (Kreiss et al., 2021).

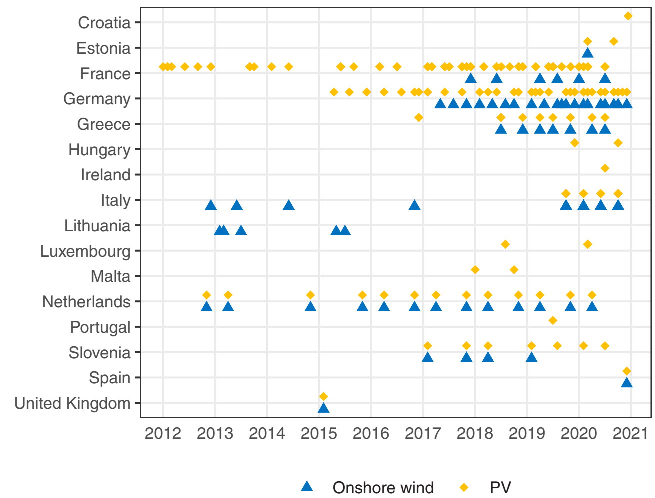

Fig. 1. Overview of auctions in the dataset. Observations are presented per technology and auction date. Source: Own illustration based on AURES II (2020)

Table 1
Descriptive statistics of final sample.

	Obs.	Mean	St. dev.	Median	Min	Max
Dependent variable						
Avg_price	250	83.83	35.96	72.29	20.3	229
ln_price	250	4.35	0.38	4.28	3.01	5.43
Control variables						
RES_share	250	0.26	0.1	0.23	0.08	0.54
Competition	250	0.78	0.42	1	0	1
Design variables						
Multi-technology	250	0.32	0.47	0	0	1
Technology_PV	250	0.7	0.46	1	0	1
Project_small	250	0.2	0.4	0	0	1
Ceiling	250	0.95	0.22	1	0	1
Fin_prequalification	250	0.75	0.44	1	0	1
Multi-criteria	250	0.36	0.48	0	0	1
Quota	250	0.1	0.3	0	0	1
Remuneration(=CfD)	250	0.41	0.2	0	0	1
Remuneration(=FIP)	250	0.43	0.78	0	0	1
Remuneration(=FIT)	250	0.42	0.75	0	0	1
Realisation	250	26.07	8.71	24	6	48
Flexibility	250	0.65	0.48	1	0	1

3. Data

The main data source for our analysis is the AURES II Auction Database (AURES II, 2020), which consists of data on auction design and auction outcomes from all EU member states and the UK. The database consists of 408 auction rounds yielding 713 observations[5] from 20 countries and covering the years 2011–2020. Of those, only 373 auctions (643 observations) were concluded with the remaining being either cancelled, planned, or still ongoing and thus not useable for our analysis. Then, we deleted all observations without information on the awarded price. Furthermore, we kept only the observations that

[4] For these theoretical considerations, a moderate level of prequalification is assumed as proposed in Del Río et al. (2015a). Too high prequalifications are excluding a large number of potential bidders, leading to lower levels of competition, and thus, higher auction prices in the long term.

[5] One auction round can have several observations. This stems from the fact that some auctions are multi-technology auctions, i.e., more than one technology competes for the support. To provide as much information as possible in the database, the researchers decided to split up multi-technology auctions into several observations, one for each technology involved.

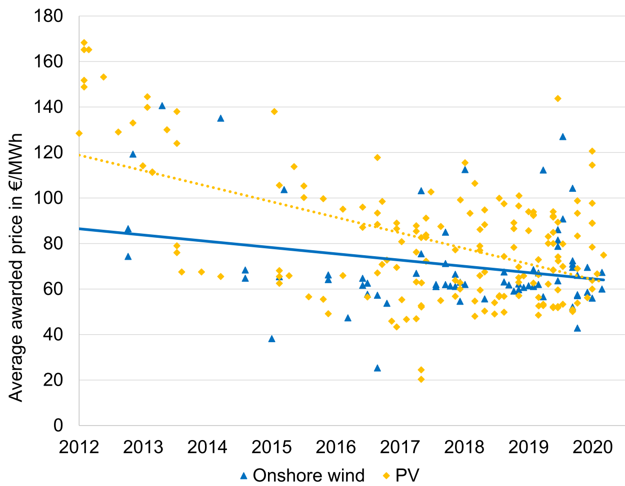

Fig. 2. Awarded prices in RES auctions. This figure presents the average awarded price in each observation broken down by technology. The continuous and dotted lines represent the linear trend of average awarded prices for onshore wind and PV, respectively. Source: Own illustration based on AURES II (2020).

included either PV or onshore wind and excluded auction rounds that had fixed FIP and investment grant as remuneration schemes,[6] trimming the dataset to 259 observations. As we only use observations that are complete concerning the variables in focus, our final sample consists of 250 observations from 220 auctions that have taken place in 16 countries from 2012 to 2020.

The auction data is highly unbalanced, which is due to the fact that the number of auctions held and their time frame differ between countries. This is illustrated in Fig. 1 which shows for each country in which years and for which technologies auctions were conducted.

To provide a deeper understanding of the data used in the analysis, the following subsection includes a short description of the used variables, while summary statistics of the variables are presented in Table 1.

3.1. *Dependent variable: average awarded price*

Our dependent variable is the logarithmic transformation of the nominal average awarded price of each auction round, which is expressed in €/MWh.[7]

Regarding the variable of interest, the average awarded price, the average over all observations is 78.0 €/MWh. The lowest price in a single auction round was achieved in Portugal in 2019 for PV, where bidders were awarded on average 20.3 €/MWh, while the highest price in our dataset is 168.3 €/MWh from a French PV auction in 2013. Fig. 2 visualises the development of the average awarded price over the years distinguished by technology. Here, it is evident that the prices decline steadily over the years (compare IRENA, 2021).

3.2. *Explanatory variables: auction design elements*

Furthermore, we present the list of explanatory design elements derived from the literature in Section 2.

The auction design variables can be distinguished between continuous and dummy variables. *Realisation* is continuous and captures the time period in months, which bidders have to complete their projects without accruing a penalty payment or losing their award/support. In case the penalties in a country occur step-wise, we chose the shortest penalty-free period for our analysis.

The first dummy variable of our model, *Technology_PV* indicates whether the technology in the auction round/observation was PV (=1) or onshore wind (=0). *Project_small* takes the value 1 if the maximum allowed project size in the auction is up to 1 MW, a threshold value introduced e.g., in the recent auctions in Italy (AURES II, 2020). This allows only small-scale projects to participate. The value 0 occurs if the maximum size is above 1 MW[8] or non-defined. *Ceiling* takes the value 1 if a ceiling price is in place in the auction round, and 0 otherwise. Similarly, *Fin_prequalification* takes the value 1 if either a bid bond or a performance bond (or both) is required as financial prequalification to participate in the auction. *Multi-criteria* becomes 1 if not only the price is taken into account in the award procedure, but rather a multitude of criteria, such as the project design or the age of the building permit. *Quota* becomes 1 if any sort of quota is implemented in the auction, such as a maximum restriction for a specific technology or for projects in a certain region. *Flexibility* indicates that the auction rules allow bidders to deviate from their awarded project capacity, which in our dataset ranges between −30% and +25% of the awarded capacity. For simplification purposes, we define *Flexibility* as a dummy variable, which takes the value 1 when this option is in place, and 0 otherwise. *Remuneration* can have three expressions: the support can be paid out as a CfD (the baseline), as a sliding FIP or as a FIT. The variable *Multi-technology* takes the value 1 if more than one technology competes in the auction, in contrast to a technology-specific one (value of 0).

Six potential explanatory variables that were mentioned in Section 2 could not be included in the analysis, mainly due to a lack of variability in each country. As Wooldridge (2010) states, "time-constant explanatory variables" cannot be included in a fixed effects panel regression, while it is sufficient that an explanatory variable "varies over time for some cross-section units" (countries in our analysis). This is the case for *auction type*, as countries in our sample stick either to static or dynamic auctions throughout the entire observed period. Similarly, countries either choose to demand *material prequalifications* or not.[9] Furthermore, we faced the same challenge with *penalties*, *multi-unit auctions*, and support *duration*.

Although we have sufficient data and variability for the *auction volume*, we omitted the variable due to a lack of comparability: three kinds of auction products are found in the dataset (capacity, electricity, and budget) that describe the auction volume, thus a comparison between the different auction volumes is rather difficult.

3.3. *Control variables*

We decided to include the share of renewables (*RES_share*) in the electricity system as a control variable, as it has been shown that experience in the deployment of RES reduces the projects' LCOE and thus potentially the awarded prices (Egli et al., 2018). The control variable is measured per country and year and is obtained from Eurostat's SHARES 2019 summary results data (Eurostat, 2020). Eurostat reports the RES shares as the proportion of electricity generated from

[6] This was due to the fact that fixed FIP and investment grant are not directly comparable to the major remuneration schemes of sliding FIP, CfD, and FIT. Furthermore, in our dataset only 5 observations had investment grant and only 11 observations had fixed FIP as their remuneration scheme.

[7] More information on the exchange rates used to calculate the awarded prices in countries not using as currency can be found in AURES II (2020).

[8] We chose this threshold, as according to European Commission (2014b), all support to RES projects above 1 MW needs to be allocated via auctions. It should be noted that this threshold applies to all RES technologies except onshore wind energy, where the threshold is at 6 MW or 6 generation units (European Commission, 2014b). Nevertheless, we decided to assign the threshold for 1 MW for onshore wind as well, as in our dataset the next highest maximum size for onshore wind projects after 1 MW was at 10 MW.

[9] Spain is an exception to this, but the relevant three auction rounds were not included in the analysis, since investment grant was used as the remuneration scheme.

renewable sources compared to the total electricity generation in a country. As Eurostat (2020) provides only values up to 2019, we projected the RES shares for 2020 using the growth rates from the years 2018 and 2019.

Furthermore, we control for the level of competition in each auction round, as literature regards it as one of the main determinants of awarded prices in auctions (e.g., IRENA and CEM, 2015; Mora et al., 2017a; Winkler et al., 2018; Gephart et al., 2017; Haufe and Ehrhart, 2018). *Competition* thus indicates whether there was a sufficient level of competition in the auction, taking the value 1 if the auction was oversubscribed, i.e., the ratio of submitted and auctioned capacity was above 1, while turning 0 if the auction was undersubscribed[10].

4. Methodology

4.1. Model selection

In our study, we employ a panel data regression model to study the impact of various design elements on the auctions' efficiency. As already stated, we consider the support cost efficiency, i.e., the achievement of low awarded prices (Ehrhart et al., 2019). In our model setting, we can assume that the unobserved individual-specific effects, such as the overall energy policy framework, to be correlated with our predictors, i.e., the implemented auction design elements. Thus, we decided to estimate a fixed instead of a random effects model, specifically on the country level to control for those unobserved effects. We use the country fixed effects to control for time-invariant differences between countries, e.g., weather conditions. Additionally, the result of the pFtest (Croissant and Millo, 2008) supports our decision to use a country fixed effects compared to a pooled OLS model with a 1% significance level.

To quantify the effect of the design elements on the auctions' efficiency and thus, the auction prices, we estimate the following multivariate model:

$$p_{ict} = \beta X_{ict} + \gamma C_{ict} + \alpha_c + \epsilon_{ict} \tag{1}$$

Here, p_{ict} represents the average awarded price in an observation i in country c in the year t, which is our dependent variable. We apply a logarithmic transformation to our dependent variable to allow the interpretation of our results as a percentage change of prices. Furthermore, the transformation helps normalising the residuals of the model, which would alternatively show a positive skew. X_{ict} represents a vector of independent variables consisting of the investigated auction design elements, while β is the vector of their coefficients. The vector C_{ict} includes country and year-specific control variables, while γ captures their effects on the awarded prices. The variable α_c is the intercept that captures the time-invariant fixed effects on country level. Variable ϵ_{ict} is the error term of our model.

RES technology costs decreased over the years and for all countries alike (IRENA, 2021). In addition, there are other factors common in all countries that can have an effect on awarded prices, e.g., financial shocks. Thus, to account for those unobserved time-varying variables, we include time fixed effects in our model (Wooldridge, 2010).[11] Accordingly, our baseline model (1) is extended as follows:

$$p_{ict} = \beta X_{ict} + \gamma C_{ict} + \alpha_c + \tau t + \epsilon_{ict} \tag{2}$$

To account for the time fixed effects, we thus include the variable t which represents the respective auction's year, while τ captures the time's effect on the prices.

Table 2
Results of regression models.

	Dependent variable:		
	ln_price		
	(1)	(2)	(3)
Year		−0.104***	−0.089***
		(0.038)	(0.032)
RES_share	−3.109***	1.588	1.152
	(0.845)	(1.650)	(1.504)
Competition	−0.045	−0.085**	−0.115***
	(0.038)	(0.040)	(0.034)
Multi-technology	−0.005	−0.023	−0.118*
	(0.053)	(0.064)	(0.065)
Technology_PV	−0.006	0.012	0.116**
	(0.094)	(0.099)	(0.050)
Project_small	0.025	0.176**	0.442***
	(0.160)	(0.080)	(0.066)
Ceiling	−0.328***	−0.137**	−0.195***
	(0.039)	(0.063)	(0.056)
Fin_prequalification	−0.049	−0.037**	−0.305***
	(0.042)	(0.017)	(0.083)
Multi-criteria	0.139	0.128	0.046
	(0.151)	(0.105)	(0.059)
Quota	0.084	0.041	0.079*
	(0.079)	(0.084)	(0.041)
Remuneration_FIP	0.108	−0.236	−0.140
	(0.211)	(0.220)	(0.156)
Remuneration_FIT	0.365***	0.130	0.219***
	(0.074)	(0.082)	(0.073)
Realisation	−0.005	−0.003	−0.008***
	(0.005)	(0.004)	(0.003)
Flexibility	−0.097***	−0.055	−0.053
	(0.021)	(0.061)	(0.069)
Multi-technology:Project_small			0.264***
			(0.084)
Technology_PV:Project_small			−0.388***
			(0.059)
Fin_prequalification:Realisation			0.012***
			(0.004)
Country FE	*Yes*	*Yes*	*Yes*
Time Fe	*No*	*Yes*	*Yes*
Observations	250	250	250
Adjusted R^2	0.531	0.620	0.677

Note:
*p<0.1; **p<0.05; ***p<0.01.

We conducted several tests with both models to check for multicollinearity, heteroskedasticity and correlation that might bias the inference of our results.

First, we used the variance inflation factor (VIF) which indicated the absence of multicollinearity in our models.[12]

Next, we used the Breusch-Pagan (Breusch and Pagan, 1979) test to check for heteroskedasticity. As the test rejected the null hypothesis (p<0.01), we concluded that there is heteroskedasticity in our data. To test for serial correlation, we followed Wooldridge (2010). Again, the null hypothesis was rejected (p<0.01), which indicated that there is serial correlation in our data. Consequently, we employ standard errors clustered at country level, which are robust to the presence of heteroskedasticity and serial correlation using Arellano's method (White, 1980; Arellano, 1987).

[10] In case the submitted and auctioned capacity were not published, the researchers used submitted and auctioned electricity or budget to calculate the level of competition.

[11] Our choice was supported by the pFtest (Croissant and Millo, 2008) at a 1% significance level. The pFtest compares our country fixed effects model with a model including both country and time fixed effects.

[12] Please note that due to some explanatory variables having more than one degree of freedom, we apply the generalised VIF approach (Fox and Monette, 1992; Fox and Weisberg, 2019). As none of the squares of $GVIF^{1/(2df)}$ surpasses the VIF rule of thumb threshold of 10 (better 5), the GVIF approach indicates that multicollinearity is not an issue in our models (O'brien, 2007).

4.2. Technical model implementation

We estimate the models in equations (1) and (2) using a linear panel model. All computations were done in R version 4.0.3 (R Core Team, 2020), while we used the following packages for our calculations and tests: “plm” for the panel data regression, the test for serial correlation in panel models, the test for individual and/or time effects in our model (Croissant and Millo, 2008) and the robust standard error estimation (Millo, 2017), “lmtest” for the Breush-Pagan test for heteroskedasticity (Zeileis and Hothorn, 2002), and “car” to test for multicollinearity (Fox and Weisberg, 2019). For visualisation purposes, we used the packages “stargazer” (Hlavac, 2018), “ggplot2” (Wickham et al., 2016), as well as Excel 2016.

5. Results and discussion

5.1. General results

In this section, we test whether the predictions from the literature (Section 2) hold for our empirical data. Our baseline model (Model 1) concentrates on the variables we have identified in Section 2 and mentioned in Section 4.1 excluding those with data constraints. Furthermore, we expand our baseline model by including time fixed effects (Model 2) on a yearly basis. Lastly, since we expect the effects of some of the variables to be dependent on each other, we decided to include several (multiplicative) interaction terms to account for this interdependence (Model 3). The results of our models are summarised in Table 2.

In terms of model quality, the baseline model can already explain a fair amount of variation with an adjusted R^2 of 0.531. Introducing the time fixed effects increases the adjusted R^2 to 0.620, while our interaction model achieves the highest adjusted R^2 of 0.677.

A first observation is that *Year*, our proxy for the time fixed effects, shows a negative and significant effect in Model 2 and 3. This shows that time-varying effects lead to decreasing awarded prices across countries in our model.[13]

5.1.1. Control variables

Our control variable *RES_share* has a negative effect on the prices, although the effect is only significant in the first model. By including time fixed effects, the effect becomes insignificant.

Competition, which theory predicts to be the main driver of the awarded prices, indeed shows a negative effect in all three models, yet only significant when time fixed effects are introduced, i.e., in Model 2 and 3. Thus, an oversubscribed auction leads to lower prices compared to the case where not enough bidders participate.

5.1.2. Explanatory variables

The main objective of our analysis is to identify the effects of auction design elements on the support cost efficiency of RES auctions. We first present the results of the stand-alone variables and then we continue with the variables included in interaction terms.

Implementing a ceiling price decreases the awarded prices, as *Ceiling* has a significant negative effect in all three models. In contrast, introducing award criteria in the auction procedure besides the bid price (*Multi-criteria*) has no significant effect in any model. Although *Quota* has an increasing effect on prices in all three models (as expected), the effect is only significant in Model 3. Regarding the *Remuneration scheme*, a FIP seems to have no significant effect compared to a CfD. The FIT tends to increase the awarded prices compared to a CfD significantly (except in Model 2). Giving bidders the *Flexibility* to deviate from their awarded bids in terms of their projects’ capacity, leads to lower prices in auctions, although only significantly in Model 1. Since no significance can be shown after the introduction of time fixed effects, those time fixed effects might already capture the effect of *Flexibility*.

Our first variable that is included in an interaction term is *Multi-technology*. Without including the interaction term in the model, implementing multi-technology auctions has a negative, yet insignificant effect. Nevertheless, as we expect that multi-technology auctions are usually only applied to large-scale projects, whose project developers are typically professionals and can deal with this increased inter-technology competition, we include the interaction term of *Multi-technology* and *Project_small* in Model 3. Here, the coefficient of *Multi-technology* remains negative and becomes significant, with the interaction term having a significant and positive effect. Thus, we can conclude that the introduction of multi-technology auctions for small-scale projects has a price-increasing effect (0.146), while their introduction in auctions not limited to small-scale projects has a significant price-decreasing effect (−0.118).

Limiting auctions to small-scale projects has a price-increasing effect in all constellations, which is in line with our prediction. *Project_small* shows a positive effect in Model 1 and 2, yet being only significant in Model 2. In Model 3, taking into account the two significant interaction terms in which *Project_small* is included as well as the significant variable itself, we arrive at the following conclusions: in a multi-technology auction setting, *Project_small* leads to higher prices, regardless whether we look at PV (0.318) or onshore wind (0.706). The same price-increasing effect of *Project_small*, although weaker, can be seen in technology-specific auctions, regardless of the technology (0.054 and 0.442 for PV and onshore wind, respectively). Thus, we can state that limiting auctions to small-scale projects leads to higher prices in both auction formats, but the effect is stronger in the multi-technology setting.

From a technological perspective, we can conclude the following: limiting auctions to small-scale projects leads to higher prices, while the effect is higher for onshore wind compared to PV, regardless of whether multi-technology or technology-specific auctions are in place.

The significant effect of the interaction term *Technology_PV:Project_small* provides insights into the impact of the technology choice as well. In terms of *Technology_PV*, in Model 1 and 2, the awarded prices do not differ significantly between the technologies. In Model 3, *Technology_PV* has a positive and significant effect on the prices. The interaction term which takes into account the size of projects admitted to the auction is also positive and significant. Thus, in an auction for small-scale projects, PV tends to perform better in terms of prices compared to onshore wind (−0.272), while in auctions for large-scale projects, PV seems to increase the prices compared to onshore wind (0.116).

Fin_prequalification has a significant negative effect on the awarded prices in all models. Nevertheless, in Model 3, taking into account the interaction term *Fin_prequalification:Realisation*, the effect of financial prequalifications depends on how many months bidders have to build their project. With a realisation period between 0 and 25.4 months, introducing financial prequalifications has a price-decreasing effect compared to the same realisation period without financial prequalifications. For a given realisation period higher than 25.4 months, introducing financial prequalifications leads to higher prices. Based on our sample, i.e., with an average realisation period of 26.1 months, the effect of *Fin_prequalification* on prices thus becomes positive, while it should be noted that the effect remains negative when considering the median of 24 months. Moreover, for almost a third of our observations

[13] It should be noted that we can only state that awarded prices are decreasing (significantly) over the years, but we cannot state which of the potential reasons, e.g., the globally decreasing technology costs (IRENA, 2021), is the main driver.

and especially for onshore wind (almost 60%), the realisation period exceeds the 25.4 months. The interaction term *Fin_prequalification: Realisation* impacts the effect of *Realisation* in Model 3 as well. In the absence of any financial prequalifications, increasing *Realisation* has a negative and significant effect on the awarded prices (−0.008), which is in line with our prediction. In case financial prequalifications are in place, the effect changes and a higher realisation period leads to slightly higher prices (0.004). In Model 1 and 2, *Realisation* has a negative, yet insignificant, effect on the prices.

5.2. Robustness checks

In order to verify our results, we performed a number of robustness checks. First, we estimated all three models, but used only countries with more than 10 observations, so that the number of observations decreased to 221. The results are presented in Table A.4. We also estimated the three models excluding observations before 2014 (see Table A.5) to eliminate the bias of early auctions. Lastly, we perform the estimation of the three models using only the significant independent variables (see Table A.6). As we only observe minor deviations in terms of significance and the effects' signs remain mostly unchanged over the various models, we conclude that our estimations are robust.

In addition, we perform an estimation of a pooled model (Table A.7), i.e., without country fixed effects, to gain insights whether the time-invariant design elements described in Section 3.2 have an effect on the awarded prices. As shown in Table A.7, we do not find evidence (besides for a support duration of 12 years) that these design elements have a significant effect on the awarded prices.

5.3. Discussion

The results presented in this study are robust, reliable and are mostly in line with the existing literature. As we used auctions exclusively from Europe, auction results from other regions could change our findings. Furthermore, we exclusively analysed the objective of efficiency in this paper. We used the definition of (static) support cost efficiency, i.e., the achievement of low awarded prices in the auctions. It should be kept in mind that auction design elements have effects on other objectives as well, such as e.g., effectiveness and actor diversity. For instance, on the one hand, implementing auctions exclusively for small-scale projects (*Project_small*) typically has a negative effect on support cost efficiency. On the other hand, small-scale projects are given a higher chance to be awarded, which supports the objective of actor diversity in the sense of size diversity (Álvarez and del Río, 2022). Hence, design elements should be chosen carefully when designing auctions.

Although our dataset is highly unbalanced and does not necessarily correspond to standard panel data, we suspect several unobserved country-specific and time-invariant circumstances to have an important effect on awarded prices. Hence, to account for these heterogeneous differences between countries, we opted for using a panel data regression model.

Several potential sources for bias remain in our analysis, as our model does not capture country-specific shocks and changes that are not time-invariant. For instance, a change in the country-specific financing conditions, i.e., the weighted cost of capital (WACC), or changes in the regulatory framework of a country, can have an impact on the awarded prices and thus, if correlated with our explanatory variables, can bias the estimated effects. Nonetheless, we tried to limit the potential bias 1) by including time fixed effects, which capture at least the shocks and changes occurring in all countries in our sample, and 2) by omitting auctions before 2014, limiting the possibility of potential changes. Although auctions are by now the major RES support scheme in Europe, there are still instruments with administratively-set support levels in place, especially for small-scale projects. In addition, an increasing number of merchant projects are built not requiring any government support. Since those projects do not participate in the auctions, this might lead to lower competition, potentially leading to higher awarded prices. Another source for bias could be the omission of auction volume. In theory, the higher the auction volume, the higher the prices, as more expensive projects are awarded. Another potential bias stems from our definition of *Project_small*. The variable takes into account all the auction rounds in which no projects above 1 MW could participate. Nevertheless, this does not rule out that small-scale projects under 1 MW participated in auctions where large-scale projects were allowed, as e.g., in Germany, all projects larger than 750 kW had to participate in the auctions to gain support. Theoretically, it could be the case that only small-scale projects participated in these auctions (e.g., due to a lack of suitable sites for large-scale projects) and were awarded comparably higher prices, which can lead to an underestimation of *Project_small*.

Another limitation of the study is the lack of variability of five auction design elements, which we expected to have an impact on the awarded prices: *auction type, material prequalification, penalties, multi-unit auctions, and* support *duration*. Since these variables are time invariant on country-level, i.e., all countries in our model stick to one specific design, our model is not able to estimate their effects (see Section 3.2). Nevertheless, we can exclude a bias in our estimation, since their effects are captured by the applied country fixed effects (Wooldridge, 2010). However, to gain an indication of their effects, we conducted a robustness check using a pooled regression model (see Table A.7), which does not control for country fixed effects. The results do not indicate that these design elements have a significant effect on the awarded prices.

Our proxy for the time fixed effects, *Year*, shows a negative and significant effect, meaning that awarded auction prices showed a significant downward trend over the years for all countries alike. Although we are not able to rule out any other factors, decreasing technology costs seem like a promising factor to have contributed to this effect. This is in line with the findings of Batz Liñeiro and Müsgens (2021), who have shown that decreasing PV technology costs have had a significant negative effect on bid prices in the German PV auctions. Our first control variable, *RES_share*, shows no convincing effect on the awarded prices, except in Model 1, as the effect becomes insignificant when we introduce time fixed effects (Model 2 and 3). One further issue we face is the question whether *Competition* can be treated as an exogenous variable or whether it depends on the design elements. Some authors argue that design elements, such as financial prequalification criteria, can prevent certain bidders from participating in the auction and thus decrease the overall level of competition (e.g., del Río, 2017; IRENA, 2017). Still, we include it as a control variable, to reduce the potential bias induced by omitting it, since we expect low awarded prices to be highly dependent on sufficient competition. Indeed, our results indicate that sufficient competition is a driving factor for low prices. This is in line with the findings of Cassetta et al. (2017), who found a significant negative effect of higher competition (defined as the total number of project developers in an auction round) on the awarded prices in Italy, as well as Batz Liñeiro and Müsgens (2021) who show that a higher level of competition decreases the prices significantly in the German PV auctions.

Table 3
General overview of results.

	Effect of variable on awarded price						
	Prediction	Model 1		Model 2		Model 3[a]	
Year	–			–	***	–	***
RES_share	–	–	***	+		+	
Competition	–	–		–	**	–	***
Multi-technology	–	–		–		– /+	*/***
Technology_PV	±	–		+		+ /–	**/***
Project_small	+	+		+	**	+ /+ /+	***/***/***
Ceiling	–	–	***	–	***	–	***
Fin_prequalification	±	–		–	**	– /±	***/***
Multi-criteria	+	+		+		+	
Quota	±	+		+		+	*
Remuneration_FIP	–	+		–		–	
Remuneration_FIT	–	+	***	+		+	***
Realisation	–	–		–		– /+	***/***
Flexibility	–	–	***	–		–	

Notes: *p<0.1; **p<0.05; ***p<0.01.

± indicates that both positive and negative effects can be expected regarding the predictions and that both effects are possible in Model 3, depending on the interaction term(s) and thus on the value of the interrelated variable.

[a] In the column of Model 3, the first sign indicates the effect of the variable without taking into account the interaction term, while the second and potentially third sign show the effect together with the interaction term. Similarly, the first stars indicate the level of significance of the effect on its own, while the remaining stars indicate the level of significance of the interaction term(s).

The design variables that showed a contrary effect to what the literature predicted (see Section 2) are discussed in the following. Additionally, we discuss the relevance of including interaction terms in our model.

Multi-technology shows a positive, yet insignificant effect in Models 1 and 2. Only when the interaction term *Multi-technology:Project_small* is introduced, the effect becomes negative and significant. This indicates that the effect of introducing multi-technology auctions depends strongly on the size of the projects. For large-scale projects, multi-technology auctions tend to decrease prices, while in auctions for small-scale projects, the effect becomes positive. Overall, the evidence is not entirely convincing, that multi-technology auctions decrease the prices, as literature predicts (del Río, 2017; Gephart et al., 2017).

Multi-criteria auctions seem to have no significant effect, although it should be noted that in the robustness check excluding observations before 2014 in Table A.5, the positive effect becomes significant. This could be explained by the fact that before 2014, only one country conducted very few multi-criteria auctions, which resulted in similar prices as price-only auctions in the same country, having an impact on our statistical inference. Thus, we would not entirely exclude the possibility of *multi-criteria* auctions increasing the prices, which would be in line with the literature.

Regarding the *remuneration scheme*, we expected to see lower prices under the FIT-scheme compared to the CfD, while no clear prediction could be made for the FIP. Indeed, for the latter we do not find any significant difference compared to a CfD. With further decreasing technology costs and increasing electricity market prices, this effect might change, as bidders have the incentive to factor in additional revenues from the electricity market (see explanation in Section 2). The robustness check in Table A.5 might give a first indication of this effect: considering only auctions from 2014 on, FIP decreases the awarded prices significantly compared to a CfD (in Model 3). The FIT seems to increase the prices compared to the CfD. At least in Model 1, this can be explained by the fact that in contrast to the CfD, a large proportion of observations with FIT stem from the years before 2016, in which rather high awarded prices were achieved (likely due to high technology costs).[14]

We expected *Realisation* to have a negative effect on prices. Nevertheless, in our analysis, this is only the case if financial prequalifications are not in place. We expect that bidders might use a longer realisation period to bet on decreasing technology costs and thus take them into account when calculating their bid prices. Similarly, we expected *Fin_prequalification* to increase the risk of participants and thus their prices. Nevertheless, we observed a negative effect in all three models. Only in Model 3, the effect becomes positive for realisation periods longer than 25.4 months. One potential explanation could be that professional project developers do not enter an auction if financial prequalifications are absent, due to the fear of unexperienced bidders submitting unsustainably low bids. Nevertheless, for long realisation periods, the aforementioned effect of betting on falling technology costs in the absence of financial prequalifications seems to prevail, and thus the introduction of prequalifications leads to higher prices. Furthermore, it should be kept in mind that in almost all of our observations, material prequalifications were in place, which already support the achievement of effectiveness.

Finally, we only observed differences in awarded prices between PV and onshore wind when controlling for time and project size. Thereby, our results indicate that in auctions restricted to small-scale projects below 1 MW, PV performs better in terms of prices, which might be attributable to lower LCOE of PV in this segment. In contrast, onshore wind yields lower awarded prices in auctions not restricted to small-scale projects, again most probably resulting from different LCOE through potentially higher economies of scale or higher market values than PV. Nevertheless, it remains to be seen whether increasing site restrictions, permitting/acceptance issues, and changes in the expected market values per technology might reverse this finding in the future.

6. Conclusions and policy implications

In our study, we use a dataset of 250 observations from 220 auction rounds from 16 European countries to assess the effects of various auction design elements on the awarded prices. We use a fixed effects panel data model to estimate these effects (refer to Table 3 for an overview) and derive conclusions for policymakers.

Our analysis shows that over the years, the awarded auction prices

[14] From 2016, support for RES projects above 500 kW needs to be paid out as a premium, thus practically abolishing the FIT for large-scale projects (European Commission, 2014a).

experienced a significant downward trend. In contrast, our first control variable, the countries' RES shares, does not seem to have an effect. Sufficient competition, on the other hand, seems to play an important role in driving down prices in the auctions.

If low awarded prices, i.e., support cost efficiency, are the only objective of concern regarding the auction outcome, policymakers should take into account the following results:

- Restricting auctions to small-scale projects under 1 MW should be avoided.
- A ceiling price should be implemented.

Since some of the effects are interdependent and ambiguous, the following design elements should be implemented carefully:

- Multi-technology auctions should not be implemented for small-scale projects. In contrast, in auctions open to large-scale projects, they could decrease the awarded prices.
- If auctions are restricted to small-scale projects, PV should be the favoured technology. In auctions open to large-scale projects, onshore wind seems to perform better than PV.
- Quotas seem to increase the awarded prices.
- The choice of the realisation period needs to be carefully coordinated with the introduction of financial prequalification requirements: policymakers should either strive for short realisation periods with financial prequalifications or for long realisation periods with no financial prequalifications in place.

Based on our data and analysis, we find no convincing evidence for flexibility for bidders and multi-criteria auctions to have a significant impact on the prices. Furthermore, while our results suggest that the effect on awarded prices is not significantly different between a FIP and a CfD, we need to acknowledge that this finding is subject to change if longer periods with market values above the respective LCOE are expected in the future (compare Section 3.2), as indicated in the robustness checks.

Nevertheless, it should be noted that auction design elements have effects on several objectives, and in some cases even contrary ones. Most notably, striving for low prices in the auctions can harm the effectiveness, e.g., due to undersubscription of the auction or through a low realisation rate of the awarded projects, and thus endanger the achievement of the respective RES expansion targets. Therefore, policymakers need to carefully balance these trade-offs when designing their auctions. Nevertheless, in the case of financial prequalification, we found evidence that this design element can decrease the awarded prices and could thus be favourable both in terms of efficiency, as well as effectiveness, as Matthäus (2020) has shown.

For further research, we suggest to include countries from other world regions that have long experience with RES auctions, e.g., Brazil or South Africa. Moreover, more country-specific and time-varying framework conditions could be included in future analyses as control variables, such as regulatory changes, to control for and analyse their specific effects on the awarded prices. Lastly, the effect of certain design elements on different dependent variables could be examined, e.g., on the level of competition or on the winning probability of certain technologies in multi-technology auctions.

CRediT authorship contribution statement

Vasilios Anatolitis: Conceptualization, Methodology, Validation, Software, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Visualization. **Alina Azanbayev:** Methodology, Software, Investigation, Data curation, Writing – review & editing, Visualization. **Ann-Katrin Fleck:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We would like to thank Barbara Breitschopf and Jenny Winkler (Fraunhofer ISI), as well as our fellow AURES II project partners, for their valuable feedback and comments that greatly improved this paper. Vasilios Anatolitis would like to thank Mario Ragwitz (Fraunhofer IEG), Barbara Koch (Chair of Remote Sensing and Landscape Information Systems (FeLis) at the University of Freiburg), and Anne Held (Fraunhofer ISI) for their support and guidance. Alina Azanbayev thanks Matthias Blonski and Steffen Eibelshäuser (Goethe University Frankfurt) and Ann-Katrin Fleck thanks Karl-Martin Ehrhart (Karlsruhe Institute of Technology) for their support and guidance.

This research was conducted as part of the project AURES II (Auctions for Renewable Energy Support II). This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 817619.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enpol.2022.112982.

Appendix B. Robustness checks

Table A4
Results for countries with more than 10 observations

	Dependent variable:		
	ln_price		
	(1)	(2)	(3)
Year		−0.102***	−0.089***
		(0.039)	(0.033)
RES_share	−3.104***	1.418	1.039
	(0.725)	(1.694)	(1.509)
Competition	−0.059	−0.109***	−0.144***
	(0.039)	(0.035)	(0.029)
Multi-technology	−0.010	−0.018	−0.125*
	(0.059)	(0.070)	(0.073)
Technology_PV	−0.009	0.023	0.135***
	(0.105)	(0.108)	(0.049)
Project_small	−0.055	0.150	0.461***
	(0.176)	(0.108)	(0.085)
Ceiling	−0.371***	−0.162**	−0.209***
	(0.032)	(0.075)	(0.061)
Fin_prequalification	−0.069	−0.039**	−0.275***
	(0.042)	(0.019)	(0.077)
Multi-criteria	0.163	0.136	0.029
	(0.173)	(0.115)	(0.054)
Quota	0.078	0.039	0.080**
	(0.083)	(0.089)	(0.040)
Remuneration_FIP	0.080	−0.224	−0.121
	(0.239)	(0.225)	(0.153)
Remuneration_FIT	0.393***	0.139	0.224**
	(0.088)	(0.099)	(0.087)
Realisation	−0.006	−0.002	−0.006***
	(0.005)	(0.005)	(0.002)
Flexibility	−0.101***	−0.061	−0.054
	(0.025)	(0.058)	(0.064)
Multi-technology:Project_small			0.317***
			(0.085)
Technology_PV:Project_small			−0.425***
			(0.041)
Fin_prequalification:Realisation			0.010**
			(0.004)
Country FE	*Yes*	*Yes*	*Yes*
Year FE	*No*	*Yes*	*Yes*
Observations	221	221	221
Adjusted R^2	0.569	0.648	0.708

Note:
*p<0.1; **p<0.05; ***p<0.01.

Table A5
Results excluding observations before 2014

	Dependent variable:		
	ln_price		
	(1)	(2)	(3)
Year		−0.065***	−0.062***
		(0.022)	(0.019)
RES_share	−2.338***	0.201	0.253
	(0.382)	(0.983)	(1.013)
Competition	−0.070*	−0.088**	−0.110***
	(0.039)	(0.043)	(0.039)
Multi-technology	0.016	0.003	−0.075**
	(0.048)	(0.057)	(0.035)
Technology_PV	−0.015	−0.004	0.086
	(0.093)	(0.099)	(0.055)
Project_small	0.123**	0.190***	0.473***
	(0.062)	(0.053)	(0.106)
Ceiling	−0.308***	−0.208***	−0.251***
	(0.031)	(0.037)	(0.029)
Fin_prequalification	−0.045**	−0.048***	−0.499***
	(0.019)	(0.013)	(0.090)
Multi-criteria	0.241**	0.197*	0.119***
	(0.106)	(0.105)	(0.033)
Quota	0.035	0.026	0.054

(*continued on next page*)

Table A5 (*continued*)

	Dependent variable:		
	ln_price		
	(1)	(2)	(3)
	(0.092)	(0.091)	(0.042)
Remuneration_FIP	0.141	−0.095	−0.062*
	(0.105)	(0.104)	(0.037)
Remuneration_FIT	0.136***	0.048	0.096*
	(0.047)	(0.052)	(0.049)
Realisation	−0.003	−0.003	−0.015***
	(0.004)	(0.004)	(0.002)
Flexibility	−0.082*	−0.063	−0.061
	(0.046)	(0.061)	(0.065)
Multi-technology:Project_small			0.171***
			(0.066)
Technology_PV:Project_small			−0.348***
			(0.068)
Fin_prequalification:Realisation			0.020***
			(0.004)
Country FE	*Yes*	*Yes*	*Yes*
Year FE	*No*	*Yes*	*Yes*
Observations	226	226	226
Adjusted R^2	0.458	0.486	0.565

Note:
*p<0.1; **p<0.05; ***p<0.01.

Table A6
Results for only significant explanatory variables

	Dependent variable:		
	ln_price		
	(1)	(2)	(3)
Year		−0.086***	−0.070***
		(0.021)	(0.013)
RES_share	−2.871***		
	(0.953)		
Competition		−0.105**	−0.114***
		(0.047)	(0.034)
Multi-technology			−0.127**
			(0.064)
Technology_PV			0.128***
			(0.043)
Project_small		0.294***	0.435***
		(0.087)	(0.090)
Ceiling	−0.308***	−0.133**	−0.213***
	(0.016)	(0.065)	(0.045)
Fin_prequalification		−0.016	−0.259***
		(0.029)	(0.058)
Remuneration_FIP	−0.005		−0.094
	(0.040)		(0.119)
Remuneration_FIT	0.427***		0.261***
	(0.019)		(0.042)
Realisation			−0.007***
			(0.002)
Flexibility	−0.080*		
	(0.045)		
Multi-technology:Project_small			0.301***
			(0.070)
Technology_PV:Project_small			−0.408***
			(0.056)
Fin_prequalification:Realisation			0.010**
			(0.004)
Quota			0.094***
			(0.030)
Country FE	*Yes*	*Yes*	*Yes*
Year FE	*No*	*Yes*	*Yes*
Observations	250	250	250
Adjusted R^2	0.506	0.582	0.676

Note:
*p<0.1; **p<0.05; ***p<0.01.

Table A7
Results for pooling OLS models

	Dependent variable:		
	ln_price		
	(1)	(2)	(3)
Year		−0.063***	−0.059***
		(0.020)	(0.018)
RES_share	−1.674***	−0.967*	−0.981
	(0.555)	(0.588)	(0.675)
Competition	−0.100*	−0.174***	−0.198***
	(0.051)	(0.037)	(0.038)
Multi-technology	0.059	0.094	0.015
	(0.057)	(0.059)	(0.095)
Technology_PV	−0.115	−0.086	0.004
	(0.104)	(0.098)	(0.082)
Project_small	0.064	0.178*	0.444***
	(0.171)	(0.092)	(0.106)
Ceiling	−0.303***	−0.191***	−0.237***
	(0.057)	(0.050)	(0.037)
Fin_prequalification	−0.036	−0.012	−0.051
	(0.053)	(0.045)	(0.203)
Multi-criteria	0.077	0.128	0.063
	(0.118)	(0.094)	(0.100)
Quota	−0.081	−0.106	−0.080
	(0.120)	(0.094)	(0.095)
Remuneration_FIP	0.063	0.031	0.024
	(0.109)	(0.078)	(0.084)
Remuneration_FIT	0.329***	0.131**	0.192**
	(0.094)	(0.058)	(0.077)
Realisation	−0.014*	−0.012**	−0.008
	(0.008)	(0.006)	(0.007)
Flexibility	−0.141	−0.049	−0.042
	(0.109)	(0.061)	(0.063)
Mat_prequalification	0.205	0.235	0.228
	(0.235)	(0.282)	(0.349)
Type	0.033	0.004	0.003
	(0.114)	(0.070)	(0.084)
Duration_12	−0.670***	−0.645***	−0.658***
	(0.193)	(0.206)	(0.240)
Duration_20	−0.005	−0.118	−0.099
	(0.124)	(0.150)	(0.188)
Penalty	−0.084	−0.005	0.002
	(0.221)	(0.116)	(0.133)
Multi-technology:Project_small			0.171
			(0.176)
Technology_PV:Project_small			−0.372***
			(0.100)
Fin_prequalification:Realisation			0.0002
			(0.009)
Constant	5.471***	132.726***	124.352***
	(0.478)	(40.806)	(35.686)
Country FE	*No*	*No*	*No*
Year FE	*No*	*Yes*	*Yes*
Observations	250	250	250
Adjusted R^2	0.664	0.721	0.740

Note:
*p<0.1; **p<0.05; ***p<0.01.

References

Akella, A., Saini, R., Sharma, M.P., 2009. Social, economical and environmental impacts of renewable energy systems. Renew. Energy 34, 390–396. https://doi.org/10.1016/j.renene.2008.05.002. https://www.sciencedirect.com/science/article/abs/pii/S0960148108002073.

Álvarez, F., del Río, P., 2022. Is small always beautiful? Analyzing the efficiency effects of size heterogeneity in renewable electricity auctions. Energy Econ. 106, 105698 https://doi.org/10.1016/j.eneco.2021.105698. URL: https://www.sciencedirect.com/science/article/pii/S0140988321005508.

Anatolitis, V., 2020. Auctions for the support of renewable energy in Greece. Report of the EU-funded AURES II project D2.1-EL URL: http://aures2project.eu/wp-content/uploads/2020/03/AURES_II_case_study_Greece.pdf.

Anatolitis, V., Klobasa, M., 2019. Impact of a yearly reference period on the sliding feed-in premium for onshore wind in Germany. In: 2019 16th International Conference on the European Energy Market (EEM). IEEE, pp. 1–7. https://doi.org/10.1109/EEM.2019.8916394. https://ieeexplore.ieee.org/abstract/document/8916394.

Anatolitis, V., Welisch, M., 2017. Putting renewable energy auctions into action–an agent-based model of onshore wind power auctions in Germany. Energy Pol. 110, 394–402. https://doi.org/10.1016/j.enpol.2017.08.024. https://www.sciencedirect.com/science/article/abs/pii/S0301421517305189.

Arellano, M., 1987. Computing robust standard errors for within group estimators. Oxf. Bull. Econ. Stat. 49, 431–434. https://doi.org/10.1111/j.1468-0084.1987.mp49004006.x. https://onlinelibrary.wiley.com/doi/10.1111/j.1468-0084.1987.mp49004006.x.

AURES II, 2020. Auction Database. Deliverable of the EU-funded AURES II project. http://aures2project.eu/auction-database/. (Accessed 20 March 2021).

Batz Liñeiro, T., Müsgens, F., 2021. Evaluating the German PV auction program: the secrets of individual bids revealed. Energy Pol. 159, 112618 https://doi.org/10.1016/j.enpol.2021.112618. URL: https://www.sciencedirect.com/science/article/pii/S0301421521004845.

Bayer, B., 2018. Experience with auctions for wind power in Brazil. Renew. Sustain. Energy Rev. 81, 2644–2658. https://doi.org/10.1016/j.rser.2017.06.070. https://www.sciencedirect.com/science/article/abs/pii/S1364032117310092.

Bayer, B., Schäuble, D., Ferrari, M., 2018. International experiences with tender procedures for renewable energy – a comparison of current developments in Brazil, France, Italy and South Africa. Renew. Sustain. Energy Rev. 95, 305–327. https://doi.org/10.1016/j.rser.2018.06.066. URL: https://www.sciencedirect.com/science/article/pii/S1364032118304994.

Bersalli, G., Menanteau, P., El-Methni, J., 2020. Renewable energy policy effectiveness: a panel data analysis across Europe and Latin America. Renew. Sustain. Energy Rev. 133, 110351 https://doi.org/10.1016/j.rser.2020.110351. URL: https://www.sciencedirect.com/science/article/pii/S1364032120306390.

Breusch, T.S., Pagan, A.R., 1979. A simple test for heteroscedasticity and random coefficient variation. Econometrica 47, 1287–1294. URL: http://www.jstor.org/stable/1911963.

Cassetta, E., Monarca, U., Nava, C.R., Meleo, L., 2017. Is the answer blowin' in the wind (auctions)? An assessment of the Italian support scheme. Energy Pol. 110, 662–674. https://doi.org/10.1016/j.enpol.2017.08.055. URL: https://www.sciencedirect.com/science/article/pii/S0301421517305591.

Croissant, Y., Millo, G., 2008. Panel data econometrics in R: the plm package. J. Stat. Software 27, 1–43. https://doi.org/10.18637/jss.v027.i02.

del Río, P., 2016. Auctions for Renewable Energy Support in Portugal: Instruments and Lessons Learnt. AURES. AURES Report D4.1-PT. http://aures2project.eu/wp-content/uploads/2021/07/pdf_portugal.pdf.

del Río, P., 2017. Designing Auctions for Renewable Electricity Support. Best Practices from Around the World, vol. 41. Energy for Sustainable Development, pp. 1–13. https://doi.org/10.1016/j.esd.2017.05.006. URL: https://www.sciencedirect.com/science/article/pii/S0973082617300029.

del Río, P., Haufe, M.C., Wigand, F., Steinhilber, S., 2015a. Overview of Design Elements for RES-E Auctions. http://aures2project.eu/2021/07/06/overview-of-design-elements-for-res-e-auctions/. (Accessed 10 March 2021).

del Río, P., Linares, P., 2014. Back to the future? Rethinking auctions for renewable electricity support. Renew. Sustain. Energy Rev. 35, 42–56. https://doi.org/10.1016/j.rser.2014.03.039. https://www.sciencedirect.com/science/article/abs/pii/S1364032114002007.

del Río, P., Steinhilber, S., Wigand, F., 2015b. Assessment Criteria for RES-E Auctions. http://aures2project.eu/2021/07/06/assessment-criteria-for-res-e-auctions/?utm_source=rss&utm_medium=rss&utm_campaign=assessment-criteria-for-res-e-auctions. (Accessed 10 March 2021).

Dobrotkova, Z., Surana, K., Audinet, P., 2018. The price of solar energy: comparing competitive auctions for utility-scale solar PV in developing countries. Energy Pol. 118, 133–148. https://doi.org/10.1016/j.enpol.2018.03.036. https://www.sciencedirect.com/science/article/abs/pii/S0301421518301708.

Egli, F., Steffen, B., Schmidt, T.S., 2018. A dynamic analysis of financing conditions for renewable energy technologies. Nat. Energy 3, 1084–1092. https://doi.org/10.1038/s41560-018-0277-y. https://www.nature.com/articles/s41560-018-0277-y.

Ehrhart, K.M., Hanke, A.K., Anatolitis, V., Winkler, J., 2019. Auction-theoretic Aspects of Cross-Border Auctions. AURES II Report D6.2. http://aures2project.eu/wp-content/uploads/2020/02/MultiAuctions_final_anv.pdf. (Accessed 3 March 2022).

European Commission, 2014a. Communication from the Commission - Guidelines on State Aid for Environmental Protection and Energy 2014–2020. Official Journal of the European Union (2014/C 200/01). https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52014XC0628(01)&from=EN.

European Commission, 2014b. Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions - a Policy Framework for Climate and Energy in the Period from 2020 to 2030. https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52014DC0015&from=EN. (Accessed 25 March 2021).

European Commission, 2019. Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions - the European Green Deal. https://eur-lex.europa.eu/resource.html?uri=cellar:b828d165-1c22-11ea-8c1f-01aa75ed71a1.0002.02/DOC_1&format=PDF. (Accessed 25 March 2021).

European Commission, 2022. Communication from the Commission – Guidelines on State Aid for Climate. environmental protection and energy, 2022. https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=OJ:C:2022:080:FULL&from=EN. (Accessed 10 March 2022).

European Parliament and European Council, 2018. Directive (EU) 2018/2001 of the European Parliament and of the Council of 11 December 2018 on the promotion of the use of energy from renewable sources (recast). https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32018L2001&from=EN. (Accessed 10 April 2021).

Eurostat, 2020. Shares 2019 Summary Results. https://ec.europa.eu/eurostat/de/web/energy/data/shares. (Accessed 11 January 2021).

Fitch-Roy, O., Woodman, B., 2016. Auctions for Renewable Energy Support in the United Kingdom: Instruments and Lessons Learnt. Report of the EU-funded AURES project D4.1-UK. http://aures2project.eu/wp-content/uploads/2021/07/pdf_uk_rev1.pdf.

Fox, J., Monette, G., 1992. Generalized collinearity diagnostics. J. Am. Stat. Assoc. 87, 178–183. https://doi.org/10.1080/01621459.1992.10475190. https://www.tandfonline.com/doi/abs/10.1080/01621459.1992.10475190.

Fox, J., Weisberg, S., 2019. An R Companion to Applied Regression, third ed. Sage, Thousand Oaks CA https://socialsciences.mcmaster.ca/jfox/Books/Companion/.

Gawel, E., Purkus, A., 2013. Promoting the market and system integration of renewable energies through premium schemes—a case study of the German market premium. Energy Pol. 61, 599–609. https://doi.org/10.1016/j.enpol.2013.06.117. URL: https://www.sciencedirect.com/science/article/pii/S0301421513006241.

Gephart, M., Klessmann, C., Wigand, F., 2017. Renewable energy auctions–when are they (cost-) effective? Energy Environ. 28, 145–165. https://doi.org/10.1177/0958305X16688811. https://journals.sagepub.com/doi/10.1177/0958305X16688811.

GIZ, 2015. Renewable Energy Auctions. Goal-Oriented Policy Design. GIZ. https://mia.giz.de/cgi-bin/getfile/53616c7465645f5f7d660cf1c3fcc2623d767e74092157fd9e557c348fca1997ccd41674d16fd460f6e4070992b439e264c45edd77068d39db9089460a78e87b3c53a0c2aefaf215/giz2015-0191en-renewable-energy-auctions.pdf.

González, M.G., Kitzing, L., 2019. Renewable Energy Auctions in Denmark: A Case Study on Results and Lessons Learnt. Report of the EU-funded AURES II project D2.1-DK. http://aures2project.eu/wp-content/uploads/2019/12/AURES_II_case_study_Denmark.pdf.

Grashof, K., Berkhout, V., Cernusko, R., Pfennig, M., 2020. Long on promises, short on delivery? Insights from the first two years of onshore wind auctions in Germany. Energy Pol. 140, 111240 https://doi.org/10.1016/j.enpol.2020.111240. https://www.sciencedirect.com/science/article/abs/pii/S0301421520300033.

Haelg, L., 2020. Promoting technological diversity: how renewable energy auction designs influence policy outcomes. Energy Res. Social Sci. 69, 101636 https://doi.org/10.1016/j.erss.2020.101636. URL: https://www.sciencedirect.com/science/article/pii/S2214629620302115.

Haufe, M.C., Ehrhart, K.M., 2016. Report D3.1, Assessment of Auction Types Suitable for RES-E. http://aures2project.eu/2021/07/06/assessment-of-auction-types-suitable-for-res-e/. (Accessed 3 October 2021).

Haufe, M.C., Ehrhart, K.M., 2018. Auctions for renewable energy support – suitability, design, and first lessons learned. Energy Pol. 121, 217–224. https://doi.org/10.1016/j.enpol.2018.06.027. URL: https://www.sciencedirect.com/science/article/pii/S0301421518304166.

Held, A., Ragwitz, M., Gephart, M., de Visser, E., Kleßmann, C., 2014. Design Features of Support Schemes for Renewable Electricity. https://ec.europa.eu/energy/sites/ener/files/documents/2014_design_features_of_support_schemes.pdf. (Accessed 16 January 2021).

Held, A., Ragwitz, M., del Río, P., Resch, G., Klessmann, C., Hassel, A., Elkerbout, M., Rawlins, J., 2019. Do almost mature renewable energy technologies still need dedicated support towards 2030? Economics of Energy & Environmental Policy 8. URL: http://www.iaee.org/en/publications/eeeparticle.aspx?id=280.

Hlavac, M., 2018. Stargazer: Well-Formatted Regression and Summary Statistics Tables. Social Policy Institute, Bratislava, Slovakia. R package version 5.2.2. https://CRAN.R-project.org/package=stargazer.

Hochberg, M., Poudineh, R., 2018. Renewable Auction Design in Theory and Practice: Lessons from the Experience of Brazil and Mexico. Oxford Institute for Energy Studies. https://www.oxfordenergy.org/wpcms/wp-content/uploads/2018/04/Renewable-Auction-Design-in-Theory-and-Practice-Lessons-from-the-Experiences-of-Brazil-and-Mexico-EL-28.pdf. (Accessed 16 January 2021).

IRENA, 2013. Renewable energy auctions in developing countries. https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2013/IRENA_Renewable_energy_auctions_in_developing_countries.pdf. (Accessed 25 March 2021).

IRENA, 2017. Renewable Energy Auctions: Analysing 2016. https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2017/Jun/IRENA_Renewable_Energy_Auctions_2017.pdf. (Accessed 25 March 2021).

IRENA, 2021. Renewable Power Generation Costs in 2020. Technical Report. International Renewable Energy Agency. Abu Dhabi. URL: https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2021/Jun/IRENA_Power_Generation_Costs_2020.pdf.

IRENA and CEM, 2015. Renewable energy auctions – a guide to design. https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2015/Jun/IRENA_Renewable_Energy_Auctions_A_Guide_to_Design_2015.pdf. (Accessed 25 March 2021).

Jakob, M., Noothout, P., von Bluecher, F., Klessmann, C., 2019. Auctions for the Support of Renewable Energy in the Netherlands: Results and Lessons Learnt. Report of the EU-funded AURES II project D2.1-NL. http://aures2project.eu/wp-content/uploads/2019/12/AURES_II_case_study_Netherlands.pdf.

Kagel, J.H., 1990. Auctions: a Survey of Experimental Research'. University of Pittsburgh. https://www.asc.ohio-state.edu/kagel.4/HEE-Vol2/Auction survey_all_1_31_15.pdf.

Kilinc-Ata, N., 2016. The Evaluation of Renewable Energy Policies across EU Countries and US States: an Econometric Approach, vol. 31. Energy for Sustainable Development, pp. 83–90. https://doi.org/10.1016/j.esd.2015.12.006. URL: https://www.sciencedirect.com/science/article/pii/S097308261500143X.

Kitzing, L., Wendring, P., 2015. Auctions for Renewable Support in Denmark: Instruments and Lessons Learnt. Report of the EU-funded AURES project D4.1-DK. http://aures2project.eu/wp-content/uploads/2021/07/pdf_denmark.pdf.

Kreiss, J., Ehrhart, K.M., Hanke, A.K., 2017a. Auction-theoretic analyses of the first offshore wind energy auction in Germany. J. Phys. Conf. 926, 012015 https://doi.org/10.1088/1742-6596/926/1/012015. URL: https://doi.org/10.1088/1742-6596/926/1/012015.

Kreiss, J., Ehrhart, K.M., Haufe, M.C., 2017b. Appropriate design of auctions for renewable energy support–prequalifications and penalties. Energy Pol. 101, 512–520. https://doi.org/10.1016/j.enpol.2016.11.007. https://www.sciencedirect.com/science/article/abs/pii/S0301421516306012.

Kreiss, J., Ehrhart, K.M., Haufe, M.C., Soysal, E.R., 2021. Different cost perspectives for renewable energy support: assessment of technology-neutral and discriminatory auctions. Economics of Energy & Environmental Policy 10. https://doi.org/10.5547/2160-5890.10.1.jkre. https://www.iaee.org/eeep/article/360.

Krishna, V., 2009. Auction Theory. Academic press.

Kruger, W., Eberhard, A., 2018. Renewable Energy Auctions in Sub-saharan Africa: Comparing the South African, Ugandan, and Zambian Programs, vol. 7. Wiley Interdisciplinary Reviews: Energy and Environment, p. e295. https://wires.onlinelibrary.wiley.com/doi/abs/10.1002/wene.295.

Lazard, 2021. Lazard's Levelized Cost of Energy Analysis - Version 15.0. Technical Report. Lazard. URL: https://www.lazard.com/media/451905/lazards-levelized-cost-of-energy-version-150-vf.pdf.
Lundberg, L., 2019. Auctions for all? Reviewing the German wind power auctions in 2017. Energy Pol. 128, 449–458. https://doi.org/10.1016/j.enpol.2019.01.0. URL: https://ideas.repec.org/a/eee/enepol/v128y2019icp449-458.html.
Mankiw, N.G., 2020. Principles of Economics. Cengage Learning.
Maskin, E., et al., 2001. Auctions and Efficiency. School of Social Science, Institute for Advanced Study.
Matthäus, D., 2020. Designing effective auctions for renewable energy support. Energy Pol. 142, 111462 https://doi.org/10.1016/j.enpol.2020.111462. URL: https://www.sciencedirect.com/science/article/pii/S0301421520302135.
Menezes, F.M., Monteiro, P.K., 2000. Auctions with endogenous participation. Rev. Econ. Des. 5, 71–89. https://doi.org/10.1007/s100580050048. https://link.springer.com/article/10.1007/s100580050048.
Menzies, C., Marquardt, M., 2019. Auctions for the Support of Renewable Energy in Alberta, Canada: Main Results and Lessons Learnt. Report of the EU-funded AURES II project D2.1-CA. http://aures2project.eu/wp-content/uploads/2020/02/AURES_II_case_study_Canada.pdf.
Menzies, C., Marquardt, M., Spieler, N., 2019. Auctions for the Support of Renewable Energy in Argentina: Main Results and Lessons Learnt. Report of the EU-funded AURES II project D2.1-AR. http://aures2project.eu/wp-content/uploads/2020/02/AURES_II_case_study_Argentina.pdf.
Millo, G., 2017. Robust standard error estimators for panel models: a unifying approach. J. Stat. Software 82, 1–27. https://doi.org/10.18637/jss.v082.i03.
Mora, D., Islam, M., Soysal, E.R., Kitzing, L., Blanco, A.L.A., Förster, S., Tiedemann, S., Wigand, F., 2017a. Experiences with auctions for renewable energy support. In: 2017 14th International Conference on the European Energy Market (EEM), pp. 1–6. https://doi.org/10.1109/EEM.2017.7981922. IEEE. https://ieeexplore.ieee.org/document/7981922.
Mora, D., Kitzing, L., Soysal, E.R., Steinhilber, S., del Río, P., Wigand, F., Klessmann, C., Tiedemann, S., Blanco, A.L.A., Welisch, M., et al., 2017b. Auctions for renewable energy support-taming the beast of competitive bidding. AURES Report D9. 2.
Neuhoff, K., May, N., Richstein, J.C., 2018. Renewable energy policy in the age of falling technology costs. DIW Berlin Discussion Paper URL: https://www.diw.de/documents/publikationen/73/diw_01.c.594384.de/dp1746.pdf.
Noothout, P., Winkel, T., 2016. Auctions for Renewable Energy Support in the Netherlands: Instruments and Lessons Learnt. Report of the EU-funded AURES project D4.1-NL. http://aures2project.eu/wp-content/uploads/2021/07/pdf_netherlands.pdf.
O'brien, R.M., 2007. A caution regarding rules of thumb for variance inflation factors. Qual. Quantity 42, 673–690. https://doi.org/10.1007/s11135-006-9018-6. URL: https://link.springer.com/article/10.1007/s11135-006-9018-6.
Probst, B., Anatolitis, V., Kontoleon, A., Anadón, L.D., 2020. The short-term costs of local content requirements in the indian solar auctions. Nat. Energy 5, 842–850. https://doi.org/10.1038/s41560-020-0677-7.
Quintana-Rojo, C., Callejas-Albiñana, F.E., Tarancón, M.Á., Martínez-Rodríguez, I., 2020. Econometric studies on the development of renewable energy sources to support the European Union 2020–2030 climate and energy framework: a critical appraisal. Sustainability 12, 4828. https://doi.org/10.3390/su12124828. https://www.mdpi.com/2071-1050/12/12/4828.
R Core Team, 2020. R: a Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/.
Sach, T., Lotz, B., von Bluecher, F., 2019. Auctions for the Support of Renewable Energy in Germany: Main Results and Lessons Learnt. Report of the EU-funded AURES II project D2.1-DE. http://aures2project.eu/wp-content/uploads/2020/04/AURES_II_case_study_Germany_v3.pdf.
Shrimali, G., Konda, C., Farooquee, A.A., 2016. Designing renewable energy auctions for India: managing risks to maximize deployment and cost-effectiveness. Renew. Energy 97, 656–670. https://doi.org/10.1016/j.renene.2016.05.079. https://www.sciencedirect.com/science/article/abs/pii/S096014811630489X.
Tiedemann, S., 2015. Auctions for Renewable Energy Systems in Germany: Pilot Scheme for Ground-Mounted PV. Report of the EU-funded AURES II project D4.1-DE. http://aures2project.eu/wp-content/uploads/2021/07/pdf_germany.pdf.
Timilsina, G.R., 2021. Are renewable energy technologies cost competitive for electricity generation? Renew. Energy 180, 658–672. https://doi.org/10.1016/j.renene.2021.08.088. URL. https://www.sciencedirect.com/science/article/pii/S0960148121012568.
USAID, 2020. Renewable energy auctions toolkit - setting financial guarantees and penalties. https://www.usaid.gov/sites/default/files/documents/1865/USAID_SURE_Renewable-Energy-Auctions_Financial-Guarantees-Penalties.pdf. (Accessed 1 July 2021).
Weber, R.J., 1983. Multiple-object auctions. In: Shubik, M., Stark, R.M., Engelbrecht-Wiggans, R. (Eds.), Auctions, Bidding, and Contracting: Uses and Theory. New York University Press, pp. 165–191 chapter Issues in Theory of Auctions.
Welisch, M., 2018. The importance of penalties and pre-qualifications: a model-based assessment of the UK renewables auction scheme. Economics of Energy & Environmental Policy 7, 15–31. https://doi.org/10.5547/2160-5890.7.2.mwel. https://www.iaee.org/eeep/article/226.
Welisch, M., 2019. Multi-unit renewables auctions for small markets-designing the Danish multi-technology auction scheme. Renew. Energy 131, 372–380. https://doi.org/10.1016/j.renene.2018.07.044. https://www.sciencedirect.com/science/article/abs/pii/S0960148118308413.
Welisch, M., Kreiss, J., 2019. Uncovering bidder behaviour in the German PV auction pilot: insights from agent-based modeling. Energy J. 40 https://doi.org/10.5547/01956574.40.6.mwel. http://www.iaee.org/en/publications/ejarticle.aspx?id=3426.
White, H., 1980. A heteroskedasticity-consistent covariance matrix and a direct test for heteroskedasticity. Econometrica 48, 817–838. https://doi.org/10.2307/1912934.
Wickham, H., Navarro, D., Pedersen, T., 2016. ggplot2: Elegant Graphics for Data Analysis. Springer-Verlag, New York. https://ggplot2.tidyverse.org.
Wigand, F., Förster, S., Amazo, A., Tiedemann, S., 2016. Auctions for Renewable Energy Support: Lessons Learnt from International Experiences. Report of the EU-funded AURES project D4.2. http://aures2project.eu/wp-content/uploads/2021/07/aures_wp4_synthesis_report.pdf.
Winkler, J., Magosch, M., Ragwitz, M., 2018. Effectiveness and efficiency of auctions for supporting renewable electricity–what can we learn from recent experiences? Renew. Energy 119, 473–489. https://doi.org/10.1016/j.renene.2017.09.071. https://www.sciencedirect.com/science/article/abs/pii/S0960148117309357.
Woodman, B., Fitch-Roy, O., 2019. Auctions for the Support of Renewable Energy in the UK: Updated Results and Lessons Learnt. Report of the EU-funded AURES II project D2.1-UK. http://aures2project.eu/wp-content/uploads/2019/10/AURES_II_UK_case_study.pdf.
Wooldridge, J.M., 2010. Econometric Analysis of Cross Section and Panel Data. MIT press.
Zeileis, A., Hothorn, T., 2002. Diagnostic checking in regression relationships. R. News 2, 7–10. URL: https://CRAN.R-project.org/package=lmtest.