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Empirical evidence on discrimination in multi-technology renewable energy auctions in Europe

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ABSTRACT

Auctions are a widely used policy instrument to support the deployment of renewable energies (RE). Yet, their complex design raises concerns about explicitly or implicitly discriminatory effects against particular technologies. Such discriminatory effects would distort fair competition, reduce economic efficiency, and potentially violate European Union law.

Several studies analysed discriminatory auction design from a theoretical and simulation perspective but actual empirical evidence is limited. Here, we demonstrate the existence of technology discrimination in European RE auctions empirically. We apply a fractional logit model to empirically measure the impact of various auction design elements on the success of two technologies, solar PV and onshore wind, based on 57 European multi-technology RE auctions from 2011–2021.

Our results confirm the existence of discriminatory effects of several auction design elements in RE auctions, such as installation size restriction, support duration, realisation period, ceiling price, and financial prequalification. The results are stable against various robustness checks such as varying the countries included, the time frame, and the composition of the regions controlled for.

Our findings advance the understanding of explicitly and implicitly discriminatory effects against particular technologies in multi-technology auctions and we propose steps to reduce technology discrimination in future multi-technology RE auctions.

1. Introduction

Auctions have helped to reduce renewable energy (RE) installation costs effectively and contributed to a rapid decrease in RE generation costs of up to 85% since 2010 (IRENA, 2021). After being well established as a RE support instrument, the political and academic debate on RE auctions now focuses on the optimal design of such. With its 2014–2020 Environmental and Energy State Aid Guidelines (EEAG) (European Commission, 2014), the Renewable Energy Directive (RED II) (European Parliament and European Council, 2018), and the newly adopted Guidelines on State Aid for Climate, Environmental Protection and Energy 2022 (CEEAG) (European Commission, 2022), the European Commission has taken a clear stand for the principles of non-discrimination and openness in auction schemes. This requires multiple suitable technologies to compete against each other in the same auction on a non-discriminatory basis. Such multi-technology auctions have been conducted in the EU since 2011 (and to a certain extent, even before) and include any scheme that is not exclusively designed for one technology and range from technology-basket auctions to integrated auctions with combined storage or other Greenhouse Gases-reducing technologies, according to the definition of Winkler (2021). They were developed by a few Member States in parallel to technology-specific auctions and experienced substantial growth in numbers, yet not at the same rate as their technology-specific counterparts, which make up the majority of RE auctions today in the EU as well as globally (Del Río and Kiefer, 2021; Winkler, 2021).

The advantages of a multi-technology setup in auctions compared to technology-specific support are a matter of debate. Economic arguments are typically brought forward in favour of multi-technology schemes, such as a higher static efficiency of the RE capacity procurement as well as higher participation and a lower risk of undercontracting the auctions (Kreiss, 2018; IRENA, 2015; Jerrentrup et al., 2019; Fleck and Anatolitis, 2023). Anatolitis et al. (2022) showed empirically that multi-technology RE auctions lead to lower awarded prices compared to their technology-specific counterparts, at least if the auctions are not limited to small-scale projects. Critical positions of multi-technology setups acknowledge secondary policy objectives, such

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as controlling the security of supply and total system costs, dynamic efficiency and complex practical realisation (del Río, 2017; Jerrentrup et al., 2019; Fleck and Anatolitis, 2023), and under specific circumstances, even negative effects of multi-technology auctions on static efficiency (Anatolitis and Winkler, 2023). Fabra and Montero (2020) came to a more nuanced conclusion in their micro-economic study: whether technology-specific or multi-technology RE auction are superiour "depends on the costs of the available technologies, their degree of substitutability, the extent of information asymmetry, and the costs of public funds". Some scholars have furthermore suggested that the implementation of a level playing field for all participating technologies is difficult to realise and that the required non-discrimination is not achieved in today's multi-technology schemes (Kreiss, 2018; Haelg, 2020; Diallo and Kitzing, 2020). These schemes may explicitly or implicitly discriminate against certain technologies due to their asymmetric techno-economical characteristics. For setting up a truly non-discriminatory support scheme, often also called technology-neutral schemes, a better understanding of the auction design impact on the chances of each technology to be awarded is required. In particular the implicit discriminatory effects, that certain design configurations may unfold on technology outcome, are not well researched so far and literature lacks empirical insight.

The aim of this work is an empirical investigation of potentially discriminatory design elements in multi-technology RE auctions already identified in the existing literature, especially in the works of Diallo and Kitzing (2020) and Haelg (2020). Diallo and Kitzing (2020) investigated discriminatory effects of various auction design elements in multi-technology auctions using a model-based approach. Haelg (2020) evaluated the influence of certain auction design elements on the outcomes of multi-technology auctions. Our work goes beyond the existing studies in several aspects. First, we provide the first empirical econometric investigation of auction design elements on the success rate of RE technologies in such auctions. Second, we cover more design elements than previous studies for their potentially discriminatory effects.

The remainder of our work is structured as follows: Section 2 provides background information and presents the literature concerned with discriminatory effects in the context of multi-technology RE auctions. Section 3 goes on to introduce data and methodology, presenting an overview of the variables as well as the fractional logit approach. Section 4 reports the results, while Section 5 provides a discussion. Finally, Section 6 concludes and derives policy implications.

2. Background and literature review

2.1. Techno-economical asymmetries of PV and onshore wind

With multi-technology auctions on the rise, scholars are becoming increasingly interested in the optimal design of such schemes. As Ehrhart et al. (2018) note, by opening a RE auction up to multiple technologies, its design becomes increasingly complex. For our analysis, we focus on PV and onshore wind, which are by far the most represented types in multi-technology auctions (AURES II Database, 2021). This section illustrates the main techno-economical asymmetries between the two focal technologies. Diallo and Kitzing (2020) build on the short conference paper from Kreiss (2018) to provide a first overview of such asymmetries as a possible source for discriminatory effects. This section will be guided by their collection, yet extends on it through own research. It serves as a basis to detect design elements possibly associated with these asymmetries.

Both generation technologies exhibit significant differences in their *upfront investment (CAPEX)*, financing conditions, and their operating and *maintenance expenditures (OPEX)*. For CAPEX, solar PV shows significantly lower investment cost per kW installed than onshore wind, only about half of the cost (Diallo and Kitzing, 2020; Kost et al., 2021). Additionally, these capital expenditures are subject to different financing conditions. Steffen (2020) finds the pattern that solar PV projects face a smaller weighted-average cost of capital (WACC) than onshore wind projects. For OPEX, differences are also substantial. Typically, a utility-scale PV installation faces about a third lower generation-dependent as well as about half lower fixed maintenance costs than onshore wind projects (Diallo and Kitzing, 2020; Kost et al., 2021). Thus for the same capacity installed, the two technologies exhibit a clear difference in CAPEX and OPEX with onshore wind carrying the higher financial burden.

Onshore wind projects typically exhibit a higher capacity factor and a flatter generation profile that is (seasonally) more correlated with energy demand compared to the one of solar PV (Eising et al., 2020). Thus, in the Levelised Cost of Electricity (LCOE) metric, the high overall expenditures of wind are compensated over a project's lifetime and both technologies currently generate power at similar costs of around 40–50 EUR/MWh (Kost et al., 2021). Furthermore, onshore wind projects recover their upfront costs at a faster rate due to a higher *market value* of generation. The market value is viewed as a function of the capacity factor, generation volatility and the infeed-price correlation (Klie and Madlener, 2020).

A further difference can be seen in the *planning and preparation efforts* of a project. The physical or permit prequalification step in the project development involving site assessment and technical studies contributes to the upfront investment and represents sunk costs, thus increasing bidder risk (Haelg, 2020). For a solar PV project, these costs tend to be smaller than for the development of a onshore wind farm (Kreiss, 2018).

The average utility-scale PV *project size* installed in Germany was 10 MW (IRENA, 2021). It is known that PV can be efficiently deployed at small scales, such as in rooftop installations, yet the technology may also profit immensely from economies of scale, as recent examples of extremely large (2 GW) single-unit auctions in the Middle East showed (IRENA, 2021). These projects are able to bid for electricity at around 10 USD/MWh. Thus, PV can be used very flexible in terms of installation size. Good data on average onshore wind farm size is hard to find, although they tend to be larger than utility-scale PV. Enevoldsen and Valentine (2016) analyse a sample of 33 mostly European onshore wind farms, for which the median size is around 40 MW.

Haelg (2020) assumes a higher *learning rate* for PV (15%) than for onshore wind (5%) technology, thus relatively faster cost decreases in CAPEX and OPEX. IRENA (2021) find a similar tendency with smaller differences. It is uncertain if these historical trends will continue, however for projects in the short-term future they will likely uphold.

Similarly to the difference in planning efforts, the two technologies also exhibit different *efforts in eventually constructing the site*. Kreiss (2018) hints at this asymmetry in his paper. It also is expressed in the significantly higher upfront investment for installation material and labour related to onshore wind projects. The difference also shows in the required *lead time to build* of European auctions, which mostly exhibit shorter deadlines for PV compared to the onshore wind auctions (AURES II Database, 2021).

2.2. Literature on discriminatory effects of multi-technology auction design

Discrimination against particular bidder groups in public procurement has been a topic of interest for quite a while now. Already in the early 1990s, under the concept of favouritism, economists investigated particular favourable conditions and possible collusion between auction designers and bidders (Laffont and Tirole, 1991; Vagstad, 1995). Such phenomena have been illuminated in the context of defence and electricity procurement as well as in the case of EU Member States public procurement in the late 1980s, which were awarding government contracts to an abnormally large share (above 95%) to domestic actors.

Now in the context of RE multi-technology auctions, the issue of fair conditions rearises. In many auctions, design parameters are being actively differentiated between technologies, in which case the design exhibits explicitly discriminatory design features (Jerrentrup et al., 2019). Of course, these design features can then manifest in *explicitly discriminatory effects* for a technology, i.e., a technology actually having a lower chance of success. It is further important to notice that given the individual technology characteristics, multiple technologies may be affected differently even if there are no apparent explicitly discriminatory design features (Kreiss, 2018). For a design configuration with all equal design elements that still unfolds discriminatory effects on success, this paper uses the term *implicitly discriminatory effects*.

Kreiss (2018) highlights implicit discriminatory effects as one of the main challenges in designing multi-technology auctions. He notes that the technological differences are a possible source for a distorted competitive bidding process and therefore challenges the actual neutrality (i.e., non-discrimination) of these auction schemes. Conceptually, he highlights the ambiguity of the term technology-neutrality in this context, asking whether it refers to the same factual conditions of participation or whether it implies the creation of a level playing field. The auction design elements he brings into play are *prequalification requirements*, *realisation period* and *price ceiling*. *Physical and permit prequalification requirements* affect bidder groups via different sunk costs of qualification. The *realisation period* affects the bidder groups via different construction times. Price ceiling differences are used as an example for possible explicitly discriminatory effects. Unfortunately, no formulation of the expected direction of the discriminatory effects is derived here.

Haelg (2020) provides a comprehensive framework for auction design and further investigates the effect on technology outcome in detail. She uses an LCOE model to show how generation (i.e., bid) prices are affected by changes in the parameters of three design elements, thus quantifying the expected direction of the resulting implicit discriminatory effects. According to her model, as the realisation period increases, the costs for PV fall substantially stronger than for onshore wind. This is due to the distinct assumed learning rate potential, which can be utilised through later construction. Altering the remuneration scheme from a tariff to a sliding or a fixed premium, increases the cost for onshore wind more than for PV. A fixed premium or even more so a sliding premium exposes the projects to market price risks, which increases cost of capital, according to her model. This effect translates differently to the technologies due to their cost structures with onshore wind having the higher CAPEX. Finally, according to Haelg (2020), as bid bonds, which act as a security for potential penalties and are deposited/submitted during the auction procedure, increase, PV is more affected by a small rise in cost. Here, the moderate increase in CAPEX from the bid bonds carries more weight in the calculation for PV costs.

Diallo and Kitzing (2020) also investigate implicitly discriminatory effects in multi-technology auctions by constructing an LCOE model to approximate bidding behaviour of various technology projects. They investigate the design elements *support period*, *realisation period*, and *remuneration* scheme in scenarios with and without considering externalities. Our paper focuses on the latter case, since externalities are rarely included in the auctions in practice. They find that a very short (10 years) to short (15 years) support period is favourable for wind. The longer the support is granted, the better the chances for PV become. In the long scenario (25 years), PV is the favoured technology, being able to offer bids at lower cost. The reason for this development is to find in the authors' assumptions of cannibalisation effects, which are seen to be stronger for PV, thus these projects have difficulties recovering investment expenditures from electricity market revenues after the support period has expired. In contrast to Haelg (2020), Diallo and Kitzing (2020) find that increasing the realisation period leads to higher costs for both technologies, yet more so for PV. Different realisation periods thus lead to a disadvantage for the technology with the longer realisation period. This is due to the authors' assumption that a longer realisation period causes a later project realisation, for which the technologies face differently falling market prices over time. Lastly, switching the remuneration scheme from a fixed premium to a one-sided sliding premium increases the costs significantly in the model. This effect is stronger for onshore wind. On top, a two-sided sliding premium is slightly increasing the discrimination against onshore wind further.

Consequently, to the best of our knowledge, most of the existing literature has analysed discriminatory effects of auction design elements in multi-technology RE auctions only theoretically, based on modelling or auction theory. Empirical insights and evidence on the discriminatory effects are still scarce. This follows the general finding of Quintana-Rojo et al. (2020) that there is a lack of econometric analyses dealing with RE auctions. One noteable exception is the recently published paper by Melliger (2023), who empirically investigated the effects of auction design elements and country-specific factors in multi-technology auctions using statistical methods, mostly ANOVA. While he was able to show that 80% of all multi-technology auction rounds from 2011 to 2020 in Europe were skewed, the investigated design elements and general context factors could not explain this finding.

Nevertheless, our study goes beyond the existing literature by conducting an econometric analysis to control for the effects of the various design elements and context factors in a holistic manner. Moreover, in our analysis, we cover more design elements than previous studies. Thus, on the basis of these key contributions, particularly interesting design elements for the analysis of discriminatory effects can be abstracted. We present those in Fig. 1. Both explicitly discriminatory design and implicitly discriminatory effects are addressed in these works, yet knowledge about the implicit effects is especially interesting for the analysis due to their covered nature.

3. Data and method

3.1. Data

The data used for this analysis stems from the open-source auction database of the AURES II research project (AURES II Database, 2021). In the latest version dating April 2021, the database contains 417 auction rounds from 20 EU Member States in the years 2011–2021. 307 rounds were conducted targeting one specific technology, while 107 rounds are multi-technology auctions according to the definition of Winkler (2021). When examining the variety of technologies eligible in the multi-technology rounds, it shows that onshore wind (64 rounds) and PV (63 rounds) are by far the most represented of all technologies. Also, these two technologies are awarded most of the volume. The two focal technologies are also best comparable to each other in terms of LCOE, variability of generation, maturity and system penetration. The final dataset consists of 57 multi-technology auctions rounds from 12 EU Member States (Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Italy, Netherlands, Poland, Slovenia, and Spain) and can be found on an online repository (Buschle et al., 2023).

3.1.1. Dependent variable

Our dependent variable is set as the success rate of the focal technologies PV and onshore wind. *Technology success rate* is calculated as the capacity awarded to the respective technology divided by the total capacity being awarded support in that auction round.

Over time, there is a positive trend for the success rate of PV and a slightly negative trend for the one of onshore wind in the considered European multi-technology auctions. Yet, there is large variance throughout all the years. The general trend in favour of PV is in line with the literature on price development of RE technologies, portraying a substantial price fall in the last decade and a faster capacity expansion compared to onshore wind (IRENA, 2021; Kost et al., 2021).

AUTHOR		Kreiss (2018)		Haelg (2020)		Diallo & Kitzing (2020)		Own expectations
FOCUS		Designing multi-technology auctions		Effect of auction design on technology diversity		Effect of auction design on technology bias		
METHODOLOGY		Conceptual		LCOE model		LCOE model		Based on review of technological asymmetries
Framework elements by Haelg (2020)		Elements considered	Discriminatory impact on technologies	Elements considered	Discriminatory impact on technologies	Elements considered	Discriminatory impact on technologies	Discriminatory impact on technologies
Auction scope	Installation size specificity	Project size	not specified					(Higher) minimum size may affect flexible PV projects more (Lower) maximum size may restrict typically large wind installations more
Qualification requirements	Financial prequalification	Prequalification criteria	not specified					
	Equipment prequalification	Prequalification criteria	not specified					(Higher) material PQ may lead less of a burden for PV
	Connection prequalification	Prequalification criteria	not specified					
	Permit prequalification	Prequalification criteria	not specified					(Higher) material PQ may lead less of a burden for PV
	Physical prequalification	Prequalification criteria	not specified					(Higher) material PQ may lead less of a burden for PV
	Financial securities/bid bonds			Bid bonds	Higher bonds lead to increase in costs of both, yet less for wind			
	Performance/Completion bond							Similar in effect to bid bonds, (higher) bonds may lead to less impact on wind
Allocation process	Ceiling prices	Maximum bid prices	not specified					Lower price ceiling may affect wind more due to higher CAPEX and need for recovery
Contract design	Remuneration type			Remuneration type	Switching from fixed to sliding premium leads to higher cost of both, yet less for PV	Remuneration scheme	Switching from fixed to (1s or 2s) sliding premium lead to higher costs for both, yet less for PV	
	Contract duration					Support period	Longer period leads to lower cost of both, yet more so for PV	
	Lead time to build	Planning and construction time	not specified	Lead time to build	Longer periods lead to lower costs of both, yet more so for PV	Granted realisation period	Longer period leads to higher costs of both, yet less for wind	

Fig. 1. Summary of design elements potentially contributing to implicit discriminatory effects based on the literature and analysis of technology asymmetries with assumed direction of effect, based on own analysis and Kreiss (2018), Haelg (2020), and Diallo and Kitzing (2020).

3.1.2. Explanatory variables

Based on the elaborations in Section 2, a relationship between auction design and the success of individual technologies is hypothesised. The independent variables for the analysis are thus the auction design elements of interest derived before, which are presented in Fig. 1 and whose parameter specifications are observed in the data set.

Particular attention is paid to the selection and encoding of the explanatory variables, i.e., the auction design elements. The combination of the small sample size of 60 observations (57 after outlier removal, see Section 3.2) and the large number of potentially influential design elements presents a key challenge for our quantitative analysis. The issue is aggravated by the fact that six design elements of interest are designed explicitly discriminatory, which means they exhibit distinct parameters per technology. Thus, their technology-specific values additionally need to be incorporated in the analysis. The factor variables reduce the model's degrees of freedom (df) further for each factor level. In general, for the encoding of the variables we focused on reducing the appropriation of df's while keeping as much information about the auction design in the model as possible. A further issue is multicollinearity among the large set of explanatory variables, which we addressed by keeping an eye on the Variance Inflation Factor (VIF) of the variables. *Bid bonds* and *performance bonds* were summarised into one new variable *financial prequalification*, containing all payable financial securities. Both types of bonds are securities to safeguard potential penalties for non-realisation or delays and are submitted by the bidders during and after the (successful) participation in the auction, respectively. While timing and risk profile of these payments are not identical, both are contributing to higher upfront expenditures and their effects should be in a similar range.

Both *minimum size restriction* and *maximum size restriction* are often explicitly discriminatory elements, while in some instances even the existence of the requirement differs for the technologies. This makes it challenging to correctly encode and cover all the cases, i.e., it would absorb a high number of df's. Simply including two technology-specific continuous variables each is also problematic since these variables correlate strongly with each other. A solution was found by reducing informational content, yet still accommodating the explicitly discriminatory aspect. Consequently, for both design elements a new categorical variable was introduced with their factor levels set to *none restricted*, *only PV restricted* and *both restricted*, covering all present cases in the data. In a similar way, informational density was reduced for *financial prequalification* to further manoeuvre the multicollinearity issue in the model. In its original continuous form, the element contributed to the issue with a VIF greater than 10. Encoded as a categorical variable with the four levels *none, of similar magnitude, higher for PV*, and *higher for wind*, now explicitly as well as implicitly discriminatory effects can be captured, while collinearity is mitigated.

The two continuous variables *realisation period* and *price ceiling* enter as ratio variables, whereby the continuous design element parameters for PV are divided by the values for onshore wind. This allows us to accommodate explicitly discriminatory design in one variable. *Support duration* is included with its original continuous value from the database, as it is not designed explicitly discriminatory in the observed auctions. This way, potential implicit discriminatory effects can be captured.

We decided not to consider *material prequalification* in the model due to the low variance of the binary variable in the data. The overwhelming majority (49 observations) of auctions impose material prequalifications on both technologies, therefore the variable's individual effect cannot be well determined empirically.

In addition, *remuneration* exhibits a high VIF, in particular due to a high association with *financial prequalification*. With its four categories, the variable reduces model df unproportionally. Above threshold levels of multicollinearity as well as a loss of statistical power in the model led to a choice of either including *financial prequalification*, *remuneration* or both combined in a single variable. The last option lacks theoretical

Table 1
Summary statistics of auction design elements as they are encoded in the econometric model.

Statistic	N	Mean	St. dev.	Min	Max	$GVIF^{1/2Df}$
Success PV [%]	57	0.56	0.381	0	1	
Success onshore wind [%]	57	0.3	0.352	0	1	
Support duration [years]	57	16.72	2.889	12	25	2.06
Price ceiling ratio [PV to wind]	57	1.09	0.217	0.68	1.55	1.84
Realisation ratio [PV to wind]	57	0.84	0.145	0.5	1	2.68
Success other technologies [%P]	57	14.8	26.343	0	99	1.49
Year	57	2018.28	2.085	2011	2021	1.90
Minimum size restriction	57					2.43
None	16 (28%)					
PV only	18 (32%)					
Both	23 (40%)					
Maximum size restriction	57					2.21
None	27 (47%)					
PV only	6 (11%)					
Both	24 (42%)					
Financial prequalification	57					2.85
None	21 (37%)					
PV higher	7 (12%)					
PV lower	15 (26%)					
Similar	14 (25%)					
Region Europe	57					2.27
Central Western	22 (39%)					
Eastern	18 (32%)					
North Eastern	5 (8%)					
Southern	12 (21%)					

Note: $GVIF^{1/2Df}$ should be squared to apply common rules of thumb.

motivation and a combined interpretation is not meaningful in an economic sense. In order to capture the explicit discriminatory effects from *financial prequalification*, which are of high interest given that the ratio ranges from a 0.34 to a 1.67-fold value for PV relative to onshore wind, we decided to keep *financial prequalification* and drop *remuneration* from the model.

Table 1 presents summary statistics for the design elements as they enter the econometric model as well as the corresponding Generalised Variance Inflation Factors (GVIF), adjusted for Df of categorical variables.

3.1.3. Control variables

Any empirical analysis that aims to draw conclusions on the effects of auction design on certain outcomes has to be conducted very carefully. As noted by Mora et al. (2017), auction designs are highly context-specific and the exact outcome of an auction may differ from market to market. Thus, it is essential to control for factors that might have influenced the technology success. Therefore, several factors were considered in the model, which are presented in this section.

The model needs to control for the success of other participating technologies to measure the true relative effect of ratio variables. In many multi-technology auctions, renewable technologies other than PV and onshore wind are eligible to participate and secured a considerable share of the volume.

Further, the data set at hand exhibits characteristics of two-level data (Gelman and Hill, 2006). The first level contains the individual auctions, which are nested in the second data level, the countries. For such data, Gelman and Hill (2006) advise to consider the variance between higher-level structures, which can considerably influence the technology success. Thus, to account for unobserved regional heterogeneity, the model controls for four regional clusters *Central Western Europe* (France, Germany, and the Netherlands), *Eastern Europe* (Hungary, Poland, and Slovenia), *North Eastern Europe* (Denmark, Estonia, and Finland), and *Southern Europe* (Greece, Italy, and Spain).

Finally, general changes over time are controlled for by including the year of the auction (subtracted by 2000 to obtain a similar range to the other variables).

3.2. Regression model

This paper deploys a fractional logit regression approach to empirically analyse the relationship between auction design elements and the impact on the individual success of PV and onshore wind in multi-technology auctions. *Technology success rates* are a share in the interval [0,1]. This type of dependent variable is very common in econometric research, yet it requires special handling compared to linear OLS regression (Papke and Wooldridge, 1996).

We use a fractional logit regression (Papke and Wooldridge, 1996) with varying intercepts (Gelman and Hill, 2006). This is a well established approach in the econometric literature for dependent variables that are percentages as in our case here with success rates (Gelman and Hill, 2006). Separate models are applied to individually investigate the effects on the success rates of the most prominent RE technologies in the multi-technology auctions, PV and onshore wind.

To isolate the effects of the design elements from other influences and to avoid omitted variable bias, we control for several factors. First, the success rate of other technologies besides PV and onshore wind are considered. Second, expected regional unobserved heterogeneity is accounted for by varying intercepts depending on four granular geographic country clusters α_i. Third, a trend variable γ_i is included to control for different technology learning rates and cost reductions. The mathematical model formulation is given by

$$\begin{aligned}
&E(technology\ success\ rate_i|x_i) = \\
&G(\beta_0 + \beta_1 minimum\ size\ restriction_i + \beta_2 maximum\ size\ restriction_i \\
&+\beta_3 financial\ prequalification_i \\
&+\beta_4 realisation\ ratio_i + \beta_5 price\ ceiling\ ratio_i + \beta_6 support\ duration_i \\
&+\beta_7 success\ rate\ other\ technologies_i + \beta_8 \alpha_i + \beta_9 (year - 2000)_i) \qquad (1)
\end{aligned}$$

The country clusters α_i are employed through indicator variables. The cluster *Central Western Europe* is set as the reference due to its central location and importance in the EU. The effect of the remaining regions is then measured in relative terms to the reference cluster, i.e., whether they are offering better or worse conditions for technology success.

The trend variable γ_i is employed as the year (subtracted by 2000) of the observed auction i. To make sure that the model is well fitted, several tests and regression diagnostics are applied. Following Zhang (2016) with a focus on logistic regression, visual investigation of the residual plot and Cook's distance revealed two outliers and one highly influential observation. Consequently, these three observations were removed from the data set. Further, Pearson residual plots for each predictor show a linear horizontal trend, indicating that no single predictor exhibits issues being fitted by the model. Visual inspection as well as the Breusch–Pagan test suggest that heteroscedasticity is present. As Wooldridge (2010) suggests for fractional logit, robust variance estimators are used for the results. To accommodate the nested data structure, the robust standard errors are clustered at the regional level.

Additionally, a goodness-of-fit test for the logistic link function is applied in line with Stata's command *linktest*, based on Pregribon (1980). This test addresses any possible specification error regarding the link function or the relationship between dependent and independent variables. The result of this test does not indicate such specification error in the model. The issue of multicollinearity, i.e., a high correlation in the set of explanatory variables, is taken care of very attentively. For its indication, Generalised Variance Inflation Factors (GVIF) (Fox and Monette, 1992) are used, which account for degrees of freedom of categorical variables. In the model, the squared $GVIF^{1/2Df}$ metric lies well below the threshold of 10 (Vittinghoff et al., 2012) for all predictors. This suggests that multicollinearity in the data lies within an acceptable range and estimations are reliable in this matter. Furthermore, the choice of control variables has been separately confirmed by Lasso regression which indicates that the choice of control variables used here is adequate from a statistical point of view. In addition, beta regression has been tested as alternative to the fractional logit specification made here and led to similar results (see robustness checks in section 4.3 for beta regression and 5.2 for Lasso).

The quantitative part of this paper is conducted with the statistical software R (RStudio Team, 2020). The fractional logit regression was implemented with the embedded R function *glm* and the quasi-binomial family. This approach is similar to the implementation that the authors from Papke and Wooldridge (1996) suggest themselves for Stata, which was later replicated by Oberhofer and Pfaffermayr (2012). Robust standard errors are obtained from the function *vcovHC* of the *sandwich* package (Zeileis et al., 2020). Average Marginal Effects (AME) are calculated with the function *margins* (Leeper, 2021).

4. Results

Table 2 presents the Average Marginal Effects (AME) of the explanatory variables on the success rate of both PV and onshore wind in European multi-technology auctions. The AME should be interpreted as a change in the success rate of the respective technology in terms of percentage points (pp). In other words, the effects describe how the share of the technology in the awarded auction volume is affected on average by a change of the respective variable. Robust standard errors reported in parentheses and p-values indicate statistical significance. Both models are highly significant and most independent variables are significantly different from zero. Further, the model shows high explanatory power in terms of the McFadden Pseudo R^2 in line with the overall high significance of the predictors. These results indicate that the empirical data of technology success in RE auctions can be well explained by the design elements selected for this analysis as well as by the control variables assumed to be influential.

Since the data is preselected to auctions with both focal technologies participating, it comes at no surprise that what is beneficial for the one technology, is usually similarly detrimental for the other. This tendency holds true for all explanatory variables except for *success of other technologies* which, as it grows, is naturally detrimental for both technologies.

4.1. Analysing the effects of the individual design elements

4.1.1. Minimum size restriction

The reference level for *minimum size restriction* is 'no restriction' for both. Thus, the AME for the two other levels need to be interpreted in contrast to having no restriction.

The first level represents the case where the restriction applies to both technologies, thus a setting with no explicit discrimination apparent[1]. The results indicate that PV projects now have a 17.5 percentage points (pp) lower success rate compared to their success rate in case of 'no restriction' for both technologies. The AME now capture implicit discrimination in the auction design, as they indicate a considerable negative effect on PV success and a positive effect on onshore wind (an 18.3pp higher success rate) compared to no restriction. The second level represents the case where only PV projects are subject to a minimum installation size requirement. The results indicate that under this circumstances, PV projects have on average a 55.4pp lower chance of being awarded compared to the case of 'no restriction' for both technologies. This setting depicts clearly a large negative effect with regard to explicit technology discrimination in auction design.

This is in line with our expectations, although *minimum size restriction* is not mentioned explicitly in the literature concerned with discriminatory auction design. However, from the study of technology-specific characteristics, we know that PV can be deployed more flexibly compared to wind, which are mostly larger projects. A minimum requirement would therefore rather impede the chances of PV projects.

4.1.2. Maximum size restriction

Maximum size restriction is structured the same way as minimum restriction. Similarly, no definite expectation of implicit discriminatory effects can be extracted from the literature. When recapitulating the technology-specific asymmetries, a maximum restriction would rather be expected to disadvantage wind projects compared to PV projects. Onshore wind installations are typically larger than PV projects, a technology that operates efficiently at a wide range of installation sizes.

The first level of the variable again represents a restriction for both technologies. The results indicate that when restricting both technologies increasing the chances of PV being awarded significantly by 47.9pp compared to the 'no restriction' reference level. Thus, the model seems to capture implicit discrimination again by revealing a significantly positive effect on PV. On the other hand, wind projects show a significantly 35.7pp lower success rate in case both technologies are restricted. Consequently, the result is in line with expectations. The second level of the variable again represents a restriction for PV only, and here the result is not as expected. Basic model AMEs suggest that this configuration is highly beneficial for PV projects, which show a significant 64.6pp higher success rate compared to the case of no restrictions. The success rate of onshore wind decreases again significantly, namely by 29.1pp. A possible economic or practical reasoning for this finding could not be elaborated and would lead into speculation.

4.1.3. Financial prequalification

In our analysis, the variable *financial prequalification* is composed of both bid bonds as well as performance bonds. In terms of implicit discrimination, expectations are that as bonds grow in size, wind projects are less affected in terms of their LCOE due to their cost structure. The upfront cost increases are carried with less weight into the LCOE calculation since CAPEX is high anyway. The reference level for *financial prequalification* is again set to no prequalification requirements at all. Only two Member States design auctions without

[1] In the data, there are technology-specific differences in the magnitude of requirements in three observations, however such quantitative information unfortunately is lost after encoding.

Table 2
Complete data base model, Average Marginal Effects for both technologies.

	Effects on PV		Effects on onshore wind	
	Dependent variable:		*Dependent variable:*	
	Success PV	P-value	Success onshore wind	P-value
Minimum size restriction: Both	−0.175 (0.016)	<10e−4	0.183 (0.021)	<10e−4
Minimum size restriction: PV only	−0.554 (0.013)	<10e−4	0.497 (0.017)	<10e−4
Maximum size restriction: Both	0.479 (0.024)	<10e−4	−0.357 (0.023)	<10e−4
Maximum size restriction: PV only	0.646 (0.018)	<10e−4	−0.291 (0.036)	<10e−4
Financial prequalification: PV higher	−0.192 (0.012)	<10e−4	0.108 (0.208)	0.6026
Financial prequalification: PV lower	0.585 (0.017)	<10e−4	−0.455 (0.017)	<10e−4
Financial prequalification: similar	0.356 (0.018)	<10e−4	−0.238 (0.015)	<10e−4
Price ceiling ratio	−0.926 (0.121)	<10e−4	0.770 (0.107)	<10e−4
Realisation period ratio	−1.109 (0.212)	<10e−4	0.765 (0.182)	<10e−4
Support duration [years]	0.038 (0.010)	0.0003	−0.028 (0.009)	0.0014
Success other technologies [%P]	−0.003 (0.001)	0.0001	−0.004 (0.000)	<10e−4
Region: Eastern Europe	−0.389 (0.019)	<10e−4	0.422 (0.018)	<10e−4
Region: North Eastern Europe	−0.728 (0.022)	<10e−4	0.828 (0.022)	<10e−4
Region: Southern Europe	−0.552 (0.015)	<10e−4	0.626 (0.025)	<10e−4
Year	0.145 (0.019)	<10e−4	−0.118 (0.017)	<10e−4
Num.Obs.	57		57	
Pseudo R2 (McFadden)	0.92		0.89	

Note: Clustered Robust SE in ().

any financial prequalification, however for the considerable number of multi-technology auction rounds conducted in the Netherlands and Slovenia, this level is represented at a similar frequency to the others.

The level *PV higher* of the categorical variable represents a case of explicit discrimination, in which PV projects face higher total financial prequalification. Model results suggest unsurprisingly that such a configuration of the design variable has a negative impact on PV success, i.e., PV projects are expected to have a 19.2pp lower success rate compared to the case without prequalification requirements. On the other hand, a higher financial prequalification for PV projects has a positive, yet insignificant, effect on the success rate of onshore wind projects. Conversely, the level *PV lower* captures cases with a lower burden for PV, for which the model conclusively estimates a considerable and significant positive impact on PV projects (of a 58.5pp higher success rate) and a significant, negative effect of −45.5pp on wind compared to the no prequalification case. The final level *similar* with both technologies facing similar financial prequalification captures implicit discrimination. AME generally indicate a positive and significant effect on PV success of 35.6pp. The missing interaction with the absolute bond size complicates the interpretation of this case and the comparison to the expectation. Since expectations in the literature are formulated in relative terms (any increase is favourable for x) and not in absolute terms (this level is favourable for x), a direct comparison of the results is not possible.

It can be concluded that at the levels determined in practice, the average effect of setting the financial prequalification similarly for both technologies has shown beneficial for PV compared to the case of no prequalification. By increasing the prequalification requirements above these levels, it can be expected to reduce the advantage for PV.

4.1.4. *Price ceiling ratio*

The first continuous variable that is considered in more detail is the ratio of the PV-specific and the wind-specific *price ceiling. Price ceiling* is mentioned in the literature on technology-specific discrimination, yet unfortunately without further specification of the workings and the relationship of this design element and discrimination.

Analysing the data, it can be seen that price ceilings are often set technology-specific, thus explicitly discriminatory, with 38 auctions exhibiting such configuration. These asymmetric prices do not exhibit a systematic discrimination of one technology. Instead, the ratio of technology-specific ceilings ranges from 0.68 to 1.55 with the mean at 1.09, implying that explicit discrimination is actually rather balanced across observations and policymakers do not seem to follow any particular pattern here, indicating a lack of established guidelines.

The analysis of technology asymmetries showed that both technologies generate electricity at a similar cost level, thus it seems one would not expect substantial implicit discriminatory effects from setting equal parameters. Consequently, this cost parity suggests that it would not require corrections via explicit discrimination in price ceilings.

The empirical (and significant) results are not intuitive at first glance. They suggest that the higher the relative price ceiling for PV projects is set, i.e., the more relative freedom in submitting bid prices they have, the lower the success of PV projects. However, the results also mean that the higher the *price ceiling* is set for wind relative to PV, the larger the success of solar projects. From this perspective, the result seems more plausible. The literature offers a possible explanation with the phenomenon of price anchoring triggered by the disclosure of price ceilings (IRENA, 2015). It is found that often bidding behaviour is oriented towards the ceiling price as a reference point, thus a higher ceiling for one technology may actually be detrimental. Yet, whether price anchoring also applies to multi-technology auctions with individual price ceilings remains ambiguous.

4.1.5. Realisation period

Likewise included as a continuous ratio variable, the empirical effect of *realisation period* is discussed next. *Realisation period* is one of the typical design elements, for which implicit discrimination is expected in the literature and is suited well as an example to illustrate the concept. Yet, the two main papers concerned with technology favouritism obtain different results for both the general effect direction as well as the discriminatory effect of expanding realisation periods. While Haelg (2020) argues that a longer realisation period allows PV projects to benefit from the faster technology cost improvements and thus being favoured, Diallo and Kitzing (2020) see in a longer realisation period mainly a later remuneration in a cannibalising market environment. They expect projects to face falling market prices over time, with PV being more affected than onshore wind.

In practice, more than half (34/57) of the auctions exhibit an explicitly discriminatory setup. For these setups and in contrast to *price ceilings*, policymakers coherently seem to follow the guideline that PV projects need to face shorter realisation periods, assumingly in order to compensate for their lower preparation and development efforts. The ratio ranges between half the period for PV and equal realisation times.

The model results suggest that this explicit discrimination is actually beneficial for PV. The larger the realisation period for PV and the closer the parameter is set to parity, the lower the success of PV[2]. More specifically, if the ratio of the realisation periods of PV and onshore wind increases by 0.1, the success rate of PV decreases by 11.0pp. Conversely, the longer the realisation period of PV becomes relative to the one of onshore wind, the success rate of onshore wind projects increases. This seems surprising at first glance, since PV projects are granted more flexibility in their development, possibly capturing technology improvements in line with Haelg (2020). If we follow the argumentation from Diallo and Kitzing (2020), however, a longer period may also have negative effects for a project, especially if it implies a delay of the support payments. The empirical perspective seems to be confirming the view that for a longer (possibly longer than needed for PV) realisation period, negative effects prevail.

4.1.6. Support duration

As the final design element, the effects of *support duration* are explored. The literature clearly mentions this design feature in the context of implicit technology discrimination. Diallo and Kitzing (2020) expect very short to short contract duration of 10–15 years to be advantageous for wind projects. As the contract duration is expanded, this favouring effect melts away and turns into an advantage of PV projects for long periods of 25 years.

In all observations, *support duration* has consistently been applied equally to both technologies, which allows us to include the design element as a continuous variable. Thus, any favouring effect associated with the element can be interpreted as an implicit discriminatory effect.

Indeed, the model reveals a statistically significant relationship between the support duration and technology success. The direction of the effect seems to be in line with the expectations by Diallo and Kitzing (2020), confirming a moderate and significant beneficial effect of 3.8pp on PV projects' success rate per year the period extends. In this case, the Average Marginal Effects can be interpreted very intuitively. With every extra year that support is granted, PV projects capture on average an additional share of 3.8pp of the total auction volume. At the same time, onshore wind projects lose a share of around 3pp for each year the support is extended.

[2] A note on the confusing magnitude of the AME below −1 in the base model, which seems wrong given the effect is expressed on the probability scale: The reason lies in the small range of the ratio variable, for which observations spans only from 0.5 to 1. A full step of 1 on the variable scale is not sensible, thus neither is the full AME on the probability scale.

4.2. Influence of region and time

The regional environment and timing of an auction are expected to influence the technology outcome in multi-technology auctions besides the design elements themselves. There are many potentially influencing factors in play, which are absorbed across the geographic and the time dimension in the model. This section now investigates the model results concerning these two control variables.

4.2.1. Influence of regional heterogeneity

As outlined in Section 3.1, auctions function distinctively depending on the regional market and the potential influences span from the cultural and behavioural dimension to the political and regulatory dimension. Not to forget is the geographic dimension itself, which includes the differences in the technologies' generation capacity.

In terms of expectations, overall regional effects are hard to predict, as the country variables include and control several different (and potentially opposite) effects. Kaspar et al. (2019) find that the further south a region is located in Europe, the higher the solar irradiance and the capacity factor for PV will be. Conversely, Northern coastal areas are offering better conditions for wind generation. Yet, the relative weight of these resource endowment effects amongst other non-observable effects, such as political and cultural conditions, is not determined.

The model results indeed reveal a significant impact for all considered regions. Interestingly, all regions show on average negative effects on PV success and positive impact on wind projects compared to Central Western Europe, which is set as the reference level. Their effects vary in magnitude, but all are of considerable to even major influence. The largest effect is calculated for *North Eastern Europe*, where the success rate of PV projects is on average reduced by 0.73pp compared to PV success in *Central Western Europe*. For *Southern Europe*, the model suggests a reduction of 0.55pp for a ceteris paribus switch from the reference region. Finally, the most moderate decrease for PV success is empirically found in *Eastern Europe* with 0.39pp. A potential explanation for this observation can be the fact that in both France and Germany multi-technology auctions were conducted in parallel to technology-specific ones (Winkler, 2021). And in both countries, the respective auctions for onshore wind were undersubscribed, thus guaranteeing bidders an award (at the ceiling price). Thus, project developers with onshore wind projects did not have any incentive to compete against PV projects in the multi-technology auctions. This led to only PV projects being awarded in the multi-technology auctions in both France and Germany. While no technology-specific auctions ran in parallel in the Netherlands, solar PV projects were still more successful than onshore wind projects, thus further strengthening the effect. In all other regions of our sample, the technology-specific auctions were only open to specific sizes of onshore wind projects or no technology-specific auctions were conducted in parallel, thus onshore wind projects had to participate in the multi-technology auctions to receive support.

To confirm the joint significance of regional effects, a Likelihood Ratio Test is applied (McCullagh and Nelder, 2017), comparing the full model to a specification without regional effects. The test is highly significant, thus we can reject the null hypothesis and conclude that the full model offers a significantly better fit of the data.

4.2.2. Influence of time

As explored in Section 3.1, one can expect EU-wide time effects related to the focal technologies, which may have altered the conditions for technologies over time.

The same Likelihood Ratio Test conducted for the model specification with regions is not needed to confirm the significance of accounting for time effects. The trend variable enters the model as a single continuous variable, therefore the Wald test of significance calculating the known p-values is sufficient.

For the time effect, the model indeed reports a highly significant relationship with technology outcome during the observed time period. The direction of the effect is as expected, thus over time PV projects are able to capture more total auction volume. Consequently, the success rate of onshore wind projects declined. With every year passing, the average improvement of PV success rate is estimated to be around 0.15pp.

4.3. Robustness checks

To ensure robustness of the model results, several robustness checks are performed. The aim of these checks is to exclude certain observations from the data that are assumed to be influenced by further exogenous factors or exhibit idiosyncratic characteristics compared to the other auctions. The regression results of the individual robustness checks are given in the appendix for completeness and transparency.

First, we perform a check excluding observations from the Netherlands, as their auctions are budget-based and, further, do not require any financial securities in Table 3. Second, German observations are excluded since parallel to the multi-technology auctions, technology-specific ones were in place, constituting potential outside options for the bidders in Table 4. Third, early multi-technology rounds as well as inexperienced countries are excluded in Table 6 to validate the results against any adaptation effects and, fourth, the composition of the country clusters is altered to test their influence in Table 8. Fifth, to validate against possible methodological issues with the fractional logit model and Maximum Likelihood estimates, a beta regression model is estimated in comparison in Table 10, which showed almost the same significance levels as the base model.

The results of these additional models are reported in the appendix and show no qualitative deviation from the base model results, indicating that the model is relatively robust against the identified potential influences.

5. Discussion

Our results come with some uncertainty that will be discussed in the present section. Generally, the present analysis does not aim to derive quantitatively exact recommendations on design element configuration in order to level out the playing field and to design non-discriminatory auctions. Rather, the results shall reveal empiric relationships of auction design elements influencing the technology outcome in a certain direction, thereby exhibiting smaller or larger systematic effects.

5.1. Multicollinearity

The fact that design elements are not always chosen independently from each other, i.e., multicollinearity can be present in the set of auction design elements, is a challenge for the analysis of the question at hand. In Section 3 we describe how we carefully encode our variables to reduce multicollinearity in the data. The Variance Inflation Factors of our final variables are found within, yet at the upper range of rule-of-thumb values typically advised in the literature. When specifying the model factors, we are faced with a trade-off in statistical biases, namely multicollinearity and omitted variable bias. Due to the large number of theoretically motivated and influential design elements, we are very cautious of dropping variables from the model due to a narrow focus on rules of thumb for VIF values. As O'Brien (2007) warns, such focus can introduce more sources of bias to the model than it cures.

5.2. Limited sample size and overfitting

We want to address potential technical concerns regarding the high number of highly significant variables and the very good fit of the data. A concern might be related to the issue of overfitting, a phenomenon in which the model capitalises on the idiosyncrasies of the sample and thus may not be able to fit new data well (Babyak, 2004). This issue should be investigated especially when many variables are fit to the data (Zhang, 2014). We address this in three points.

First, we use cross-validation to test the predictive abilities of several models increasing in the number of predictors, starting from only one to the full base model. We added new variables in the order we have displayed for the base model, as there are no obvious key variables in our case. For each model, we split the data randomly in 2/3 training and 1/3 test data 50 times and determine the mean MSE for both training and test data. As expected, we find the training MSE to decrease significantly with increasing predictors. More importantly however, we also find the MSE on the test data to decrease to its minimum at the full base model . This indicates that our base model shows good predictive ability compared to less potent models and the test does not show indication of overfitting, given the uncertainty from the limited sample size. Second, we applied the LASSO technique (Tibshirani, 1996) to our model predictors to validate the variable selection. Indeed, we find that 14 of the 15 factors remain in the model after applying LASSO, indicating their explanatory power from a purely statistical point of view. This result complements nicely our theoretically based selection. Third, while most regression analyses rely on a small sample of the population, we have almost has the entire to-date population of multi-technology auctions available. Thus it is not possible to obtain a better quantitative picture of the important issue at hand.

5.3. General considerations

Auction design and the relationship with its outcome is a complex matter, as the outcome depends on more factors than could have been considered in our analysis. Among these factors, interactions between design elements have to be mentioned. For example, when most other elements are arranged favourable for one technology, the individual favouring effect of one particular element will tend to be less pronounced compared to a scenario where the other elements are conversely set discriminatory in effect. These interactive influences are not accounted for in the model and the results refer to average effects at observed values.

Due to the limitations in availability of design elements observed in the database as well as in statistical degrees of freedom, the present analysis only considers the main subset of elements. Other design elements such as the quotas of all kinds are not observed. When more data is available on multi-technology auctions, these elements should additionally be considered to understand their influence.

Likewise, there are numerous factors outside the auction design that can have an influence on the outcome. Accounting for these influences with regional effects may not be enough. For example, Pakalkaite and Jones (2019) hint in their profound blog post at the possibility of intentionally manufactured outcomes in seemingly technology-neutral auctions. In such cases, additional unobserved regulatory framework conditions may be influencing the technology outcome. Another example of particular external factors are outside support options for technologies, such as in the case of the German multi-technology auctions. Further, there is a stream in the RE auctions literature that views the right to build a project resulting from an auction as obtaining a real option, closely related to a financial product (Matthäus et al., 2021). The value of this option and thus the bidding behaviour depends on expectations on the future development of LCOEs, amongst others, which are likely to differ for the technologies as we have shown in Section 2. It might be worthwile to investigate external factors associated to future LCOE development. Thus, further research could expand the set of control variables and focus on revealing systematic influence of outside factors, which is also what Matthäus (2020) suggests in his empirical analysis on RE auction effectiveness.

6. Conclusion and policy implications

This paper applies an econometric approach to complement the literature on technology discrimination in multi-technology auctions with empirical insights. Our findings reveal discriminatory effects of individual auction design elements as they are applied in practice for two focal technologies, PV and onshore wind. We include a set of selected design elements, for which either literature or technological asymmetries suggest discriminatory effects. For the data, 57 observations from the comprehensive AURES II auction database tracking EU RE auctions exhaustively for the years 2011–2021 was used. Several robustness checks were conducted in order to test model sensitivities against varying the countries in the data, the time frame, and the composition of the regions controlled for. These robustness checks do not suggest any particular sensitivity.

Our empirical findings suggest an influence for all design elements considered, confirming the existence of discriminatory effects in practice. Thus, the following results and recommendations should be taken into account by policymakers when designing multi-technology RE auctions:

- When applying equal *installation size restrictions* to both technologies, a *minimum size restriction* favours onshore wind projects, whereas a *maximum size restriction* is favourable to PV compared to the scenario without such restrictions. This relationship confirms the existence of implicitly discriminatory effects in practice, which may have been hidden to the auctioneer so far. According to the results, it also should be avoided to apply size restrictions exclusively to a single technology. If size restrictions are to be applied to both technologies, explicit discrimination in the design may be a way to reduce the inherent implicitly discriminatory effects of the design element.
- A longer *support duration*, which is always set equally for both technologies in the observations, is beneficial for PV. Thus, explicit design discrimination by lowering the *support duration* for PV can be expected to work towards more equal conditions.
- The *realisation period* for PV is set either shorter or equal to wind in the observations. A longer *realisation period* for PV, i.e. approaching the one of wind, is actually detrimental for PV projects.
- *Price ceilings* are set lower, equally or higher for PV in current auctions, with no clear tendency. Empirically, the higher the *price ceilings* relative to the other technology, the lower the success in auctions. Thus, for both technologies it is important to note that relatively higher ceiling prices are not beneficial, according to the analysis.
- Discriminatory effects of *financial prequalification*, i.e., combined bid bonds and performance bonds, are conclusive for explicit discrimination, i.e., higher bonds for one technology are detrimental. If they are they set at a similar range for both technologies, PV projects benefit compared to the case of no prequalifications. Thus, to compensate for the implicit effect, PV projects could be burdened moderately higher than onshore wind projects.

These insights advance understanding of explicit and, in particular, implicit discriminatory effects in multi-technology RE auctions. A generalisation of the results to future auctions should be made with care. More observations, possibly including more technologies, and a more pronounced control dimension could further improve model quality and lead to more refined results. A focus on factors outside the auction design itself can offer interesting insights given the high contextual sensitivity of RE auctions, which could be fed back into the multi-technology auction design.

CRediT authorship contribution statement

Julius Buschle: Conceptualization of this study, Methodology, Software, Writing – original draft. **Vasilios Anatolitis:** Conceptualization of this study, Methodology, Writing – review & editing. **Patrick Plötz:** Conceptualization of this study, Methodology, Writing – review & editing.

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.

Data availability

Data is shared on Mendeley Data http://dx.doi.org/10.17632/b5n4jphtmr.1.

Appendix

A.1. Excluding the Netherlands

Multi-technology auctions from the Netherlands represent the largest portion in the data of a single Member State. This does not come as a surprise as the Dutch auction scheme SDE was pioneering multi-technology schemes in the EU in 2011. Its successor programmes SDE+ and SDE++ are still at the forefront of RES auction design, offering support schemes open to all CO2-reducing technologies including Carbon Capture and Storage or low carbon heat. This role makes the 14 Dutch observations stand out, together with the fact that the Netherlands are one of two countries using a budget-based scheme and not requiring any financial securities from the participants. To check the base model against sensitivities for such influences, the model is fitted with data excluding observations from the Netherlands.

Table 3 shows the AMEs for the specification without the Dutch auctions. When comparing these results with the complete base model results, it firstly shows that the direction as well as the significance of most design element effects holds. For two elements, the relationship cannot be determined with significance, which are the influence on wind projects of *price ceiling* and the factor level indicating higher PV *financial prequalification*. Overall, the effects remain very similar in magnitude compared to the base model, suggesting robust estimations against unobserved influences from the unique characteristics and context of Dutch auctions.

A.2. Excluding Germany

While Germany is conducting technology-specific auctions in considerable numbers since 2015, multi-technology schemes started only in 2018 and were then conducted seven times in the observed time period. For these auctions, there are two basic configurations in Germany. Six auctions were conducted as *technology basket* auctions with the only two eligible technologies being PV and onshore wind. The other programme is more flexible in the form of a *mixed auction*, allowing for the inclusion of storage capacity with RES-E generation. Highly noteworthy about the German multi-technology auctions is the technology outcome. Of the six *technology basket* auctions, the entire auction volume was captured by PV projects. Experts attribute this to a large extent to the attractive simultaneous outside options for wind projects. The technology-specific wind auctions had a relatively low competition level and project developers expected to realise higher support prices (Winkler, 2021). Outside options are neither invariant with respect to region nor time and are therefore not controlled for

Table 3
Specification without the Netherlands, Average Marginal Effects for both technologies.

	Effects on PV	Effects on onshore wind
	Dependent variable:	
	Success PV	Success onshore wind
Min restriction: Both	−0.215***	0.191***
	(0.024)	(0.024)
Min restriction: PV only	−0.552***	0.589***
	(0.014)	(0.029)
Max restriction: Both	0.470***	−0.396***
	(0.037)	(0.038)
Max restriction: PV only	0.690***	−0.515***
	(0.032)	(0.041)
Fin prequalification: PV higher	−0.142***	0.075
	(0.037)	(0.132)
Fin prequalification: PV lower	0.566***	−0.489***
	(0.037)	(0.034)
Fin prequalification: similar	0.226*	−0.160*
	(0.092)	(0.064)
Price ceiling ratio	−0.548***	0.001
	(0.141)	(0.239)
Realisation period ratio	−1.198**	0.617*
	(0.377)	(0.284)
Support duration	0.037***	−0.030***
	(0.009)	(0.008)
Success other technologies	−0.002*	−0.009***
	(0.001)	(0.001)
Region: Eastern Europe	−0.292	0.277
	(0.594)	
Region: North Eastern Europe	−0.797***	0.727
	(0.145)	
Region: Southern Europe	−0.548	0.434
	(0.610)	
Year	0.143***	−0.127***
	(0.022)	(0.025)
Num.Obs.	43	43
Pseudo R2 (McFadden)	0.93	0.93

Note: Clustered Robust SE in ()
*p < 0.1; **p < 0.05; ***p < 0.01.

Table 4
Specification without Germany, Average Marginal Effects for both technologies.

	Effects on PV	Effects on onshore wind
	Dependent variable:	
	Success PV	Success onshore wind
Min restriction: Both	−0.189***	0.209***
	(0.017)	(0.025)
Min restriction: PV only	−0.612***	0.566***
	(0.014)	(0.021)
Max restriction: both	0.469***	−0.407***
	(0.024)	(0.019)
Fin prequalification: PV lower	0.666***	−0.518***
	(0.019)	(0.022)
Fin prequalification: similar	0.405***	−0.271***
	(0.021)	(0.021)
Price ceiling ratio	−1.016***	0.877***
	(0.132)	(0.234)
Realisation period ratio	−1.216***	0.873**
	(0.232)	(0.265)
Support duration	0.041***	−0.032**
	(0.011)	(0.011)
Success other technologies	−0.003***	−0.005***
	(0.001)	(0.001)
Region: Eastern Europe	−0.316***	0.343***
	(0.022)	(0.022)
Region: North Eastern Europe	−0.701***	0.804***
	(0.025)	(0.026)
Region: Southern Europe	−0.501***	0.574***
	(0.017)	(0.030)
Year	0.159***	−0.134***
	(0.021)	(0.020)
Num.Obs.	50	50
Pseudo R2 (McFadden)	0.9	0.88

Note: Clustered Robust SE in ()
*p < 0.1; **p < 0.05; ***p < 0.01.

in the model. A robustness check is conducted excluding the German observations.

The results presented in Table 4 are consistently in line with the base model results concerning direction and significance of the effects. Also for the magnitude, a considerable deviation cannot be observed. Our model is therefore robust against the idiosyncrasies of the German auctions. Yet, since unobserved outside options may influence outcomes in other countries as well, endogeneity issues from this factor cannot be ruled out for the entire model.

A.3. Excluding inexperienced countries

In this data set variation, all countries having conducted only two or less multi-technology auction rounds are excluded. These inexperienced countries include France, Finland, Denmark, Greece and Estonia. This way, it can be tested if adaptation effects of stakeholders within a market play a distorting role (see Table 5).

The model results of this data specification exhibit minor deviations to the full data model. First, since all countries making up the *North Eastern* geographic cluster are removed, this introduces some changes to the effect sizes of the remaining regions, with the AME of *Eastern Europe* being considerable smaller (from −0.73 to −0.51 on PV success).

Also, the effect of *support duration* in this check is not significant anymore. Apart from these deviations, the indication of significance, direction, and magnitude of the majority of predictors remain robust against possible idiosyncratic influences from auctions in inexperienced environments.

A.4. Excluding early multi-technology auctions

In this data set variation, all of the very early multi-technology auction rounds before 2016 are excluded. Similarly to the test before, this specification aims at testing robustness against any disturbance present during the first-time global auctions when participants as well as auctioneers had no experience.

In this robustness check aiming at behaviour adjustments after early auctions, the model results are less deviant than in the test before concerning the regionally contextualised learning effects. Yet again, contrary to the base model *support duration* is found to be non-significant on PV as well as onshore wind success. *Eastern Europe* shows on average a considerably larger effect (from −0.39 to −0.54) in this specified data set. All other effects are very similar in significance, direction and magnitude to the base model specification.

A.5. Varying the regional clusters

Country clusters have been established as a second-best solution to directly including the countries, representing the second level of the nested structure of the data. In order to test the model sensitivity against the composition of these geographic country clusters, a last robustness check is applied. For this check, every cluster composition is varied as well as an additional cluster introduced to increase granularity. The new clusters are also based on geographic proximity and are presented in Table 7. To ensure a relatively equal distribution of observations, geographical proximity has to be stretched compared to the closer tied base cluster.

The AME results in Table 8 are consistent with the base model for the majority of factors in terms of effect directions and significance

Table 5
Specification without inexperienced countries, Average Marginal Effects for both technologies.

	Effects on PV	Effects on onshore wind
	Dependent variable:	
	Success PV	Success onshore wind
Min restriction: Both	−0.010	0.073*
	(0.030)	(0.036)
Min restriction: PV only	−0.434***	0.515***
	(0.024)	(0.045)
Max restriction: Both	0.610***	−0.379***
	(0.016)	(0.011)
Max restriction: PV only	0.769***	−0.246***
	(0.014)	(0.070)
Fin prequalification: PV higher	−0.246***	0.364***
	(0.026)	(0.022)
Fin prequalification: PV lower	0.427***	−0.446***
	(0.037)	(0.022)
Fin prequalification: similar	0.435***	−0.274***
	(0.035)	(0.021)
Price ceiling ratio	−0.809***	0.605**
	(0.093)	(0.186)
Realisation period ratio	−0.881***	0.503*
	(0.216)	(0.253)
Support duration	−0.009	−0.005
	(0.012)	(0.011)
Success other technologies	−0.003***	−0.004***
	(0.001)	(0.001)
Region: Eastern Europe	−0.510***	0.535***
	(0.063)	(0.036)
Region: Southern Europe	−0.563***	0.660***
	(0.041)	(0.030)
Year	0.126***	−0.095***
	(0.018)	(0.018)
Num.Obs.	49	49
Pseudo R2 (McFadden)	0.95	0.92

Note: Clustered Robust SE in ()
*p < 0.1; **p < 0.05; ***p < 0.01.

levels. Effect sizes deviate more than in previous robustness checks, indicating the relevance of the regional effects. As single exemption of a switched sign, higher PV burden in *financial prequalification* is significantly positive for PV success. Further, the AMEs of the regions naturally differ with the new composition. Explanatory power in terms of the McFadden indicator is similar to the base model. Overall, model results seem to be sensitive to the composition of country clusters, however effect direction and significance is stable. Given the arbitrary configuration of these clusters used to approximate country effects, the result of this check is important.

A.6. Including penalties

Penalties are not explicitly included in our base model due to the low variation of the binary variable in the data set. Implicitly, the volume of *penalties* are recognised in our model predictor *financial prequalification*, which is often set to be retained in the case of non-realisation. In this robustness check, we nevertheless test influence of the *penalties* variable of the data set.

We find including *penalties* to have astonishingly little effect on the estimations of the other predictors (see Table 9). The explanation here however seems to lie in the fact that the only observations not having *penalties* employed are from one country, the Netherlands, and also have otherwise identical characteristics in almost all variables, except for the *price ceiling* ratio. Thus, the new variable is almost fully linear dependent on the set of other predictors, making this robustness test add little information.

A.7. Beta regression model

As a final robustness check, we include a run of our model specification on a further regression class for fractional data, named beta

Table 6
Specification without early auction rounds before 2016, Average Marginal Effects for both technologies.

	Effects on PV	Effects on onshore wind
	Dependent variable:	
	Success PV	Success onshore wind
Min restriction: Both	−0.259***	0.128
	(0.021)	(0.102)
Min restriction: PV only	−0.563***	0.497***
	(0.010)	(0.060)
Max restriction: Both	0.337***	−0.351***
	(0.096)	(0.072)
Max restriction: PV only	0.596***	−0.378***
	(0.034)	(0.062)
Fin prequalification: PV higher	−0.213***	−0.029
	(0.012)	(0.213)
Fin prequalification: PV lower	0.548***	−0.405***
	(0.017)	(0.049)
Fin prequalification: similar	0.258***	−0.134+
	(0.026)	(0.069)
Price ceiling ratio	−0.767***	0.098
	(0.131)	(0.211)
Realisation ratio	−1.130***	0.754**
	(0.221)	(0.248)
Support duration	−0.038	−0.035
	(0.032)	(0.038)
Success other technologies	−0.002***	−0.006***
	(0.001)	(0.001)
Region: Eastern Europe	−0.539***	0.311***
	(0.054)	(0.064)
Region: North Eastern Europe	−0.801***	0.751***
	(0.032)	(0.092)
Region: Southern Europe	−0.511***	0.506***
	(0.062)	(0.134)
Year	0.156***	−0.125***
	(0.019)	(0.018)
Num.Obs.	51	51
Pseudo R2 (McFadden)	0.93	0.93

Note: Clustered Robust SE in ()
*p < 0.1; **p < 0.05; ***p < 0.01.

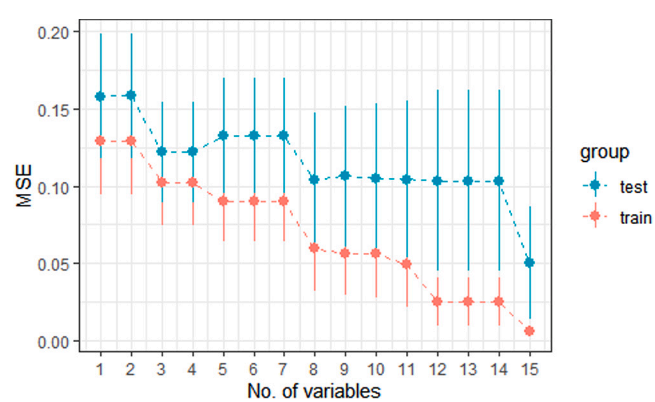

Fig. 2. Development of the MSE and standard deviation on training and test data with an increasing number of predictors, Predictors include categorical variables with multiple levels, thus steps are not always equal to one.

regressions (Cribari-Neto and Zeileis, 2010). Beta models rely on the assumption of a beta-distributed dependent variable compared to the (quasi-)binomial distribution of fractional logit models. One drawback of regular beta models is the lacking ability to produce values at the interval bound, i.e., 0 and 1, of which our data set has a significant amount. For this test, our observations reduce to 37.

We were actually surprised to find the beta model to show very similar results to our base model, even on the drastically reduced data

Table 7
Composition of new country clusters for robustness check.

New cluster	Countries contained	Observations
Central Western Europe	France, the Netherlands	15
Central Eastern Europe	Finland, Denmark, Poland, Germany, Estonia	19
Southern Europe	Spain, Italy	10
Eastern Europe	Slovenia, Hungary, Greece	13

Table 8
Model with varied regional country clusters, Average Marginal Effects for both technologies.

	Effects on PV	Effects on onshore wind
	Dependent variable:	
	Success PV	Success onshore wind
Min restriction: Both	−0.194***	0.192***
	(0.033)	(0.033)
Min restriction: PV only	−0.480***	0.399***
	(0.043)	(0.047)
Max restriction: Both	0.517***	−0.393***
	(0.034)	(0.029)
Max restriction: PV only	0.682***	−0.323***
	(0.030)	(0.082)
Fin prequalification: PV higher	0.542***	−0.699***
	(0.042)	(0.013)
Fin prequalification: PV lower	0.486***	−0.450***
	(0.020)	(0.035)
Fin prequalification: similar	0.546***	−0.552***
	(0.031)	(0.030)
Price ceiling ratio	−0.944***	0.777**
	(0.144)	(0.243)
Realisation period ratio	−1.110***	0.764**
	(0.252)	(0.276)
Support duration	0.038**	−0.028**
	(0.012)	(0.011)
Success other technologies	−0.003***	−0.004***
	(0.001)	(0.001)
Region: Eastern Europe	−0.229***	0.262***
	(0.018)	(0.015)
Region: Central Eastern Europe	−0.402***	0.444***
	(0.025)	(0.033)
Region: Southern Europe	−0.625***	0.700***
	(0.029)	(0.026)
Year	0.147***	−0.118***
	(0.023)	(0.021)
Num.Obs.	57	57
Pseudo R2 (McFadden)	0.92	0.89

Note: Clustered Robust SE in ()
*p < 0.1; **p < 0.05; ***p < 0.01.

Table 9
Model with penalties included, Average Marginal Effects for both technologies.

	Effects on PV	Effects on onshore wind
	Dependent variable:	
	Success PV	Success onshore wind
Min restriction: Both	−0.175***	0.183***
	(0.016)	(0.022)
Min restriction: PV only	−0.554***	0.497***
	(0.013)	(0.018)
Max restriction: Both	0.479***	−0.357***
	(0.024)	(0.017)
Max restriction: PV only	0.646***	−0.291***
	(0.018)	(0.067)
Fin prequalification: PV higher	−0.192***	−0.217
	(0.012)	
Fin prequalification: PV lower	0.585***	−0.455***
	(0.017)	(0.019)
Fin prequalification: similar	0.356***	−0.238***
	(0.018)	(0.018)
Price ceiling ratio	−0.926***	0.770***
	(0.121)	(0.205)
Realisation period ratio	−1.109***	0.765**
	(0.212)	(0.233)
Support duration	0.038***	−0.028**
	(0.010)	(0.009)
Penalty: yes	−0.427***	0.451
	(0.021)	
Success other technologies	−0.003***	−0.004***
	(0.001)	(0.001)
Region: Eastern Europe	−0.294	0.307***
		(0.053)
Region: North Eastern Europe	−0.725***	0.825***
	(0.011)	(0.036)
Region: Southern Europe	−0.511	0.576***
		(0.115)
Year	0.145***	−0.118***
	(0.019)	(0.018)
Num.Obs.	57	57
Pseudo R2 (McFadden)	0.88	0.86

Note: Clustered Robust SE in ()
*p < 0.1; **p < 0.05; ***p < 0.01.

set (see Table 10). This comes with a loss of a few observed levels for the categorical variables *financial prequalification* and *minimum size restriction*, however for the remaining predictors, effect directions and magnitudes are very alike to the base model. Statistical significance also still shows for all predictors, albeit at a less confident level, which we attribute to the smaller sample and computational differences. Overall, this final robustness test is suited well to confirm our main statistical approach in this work.

A.8. Checks for potential overfitting

In Section 5.3 we elaborate on potential concerns of an overfitted model due to large number of predictors. Here, we present two checks we applied in order to detect potential overfitting. First, we tested the predictive abilities of several models increasing in the number of predictors, starting from only one to the full base model. We added the variables in the order we have displayed for the base model, as there are no obvious key variables in our case. For each model, we split the data randomly in 2/3 training and 1/3 test data 50 times and determine the mean MSE for both training and test data. As expected, we find the training MSE to decrease significantly with increasing predictors (see Fig. 2). More importantly however, we also find the MSE on the test data to decrease to its minimum at the full base model. This indicates that our base model shows the best predictive ability of all and justifies the inclusion and explanatory relevance of all variables of our base model. Second, we apply the LASSO methodology to our base model to double check the relevance of our predictors from a pure statistical point of view (see Fig. 3). LASSO shrinks the influence of less relevant variables to zero according to a penalty function. As a result, only the categorical level *Financial prequalification: PV higher* is identified by LASSO to not be relevant, whereas the best model includes 14 of our 15 predictors. Both tests complement our theoretically motivated inclusion of predictors with a purely statistical argument.

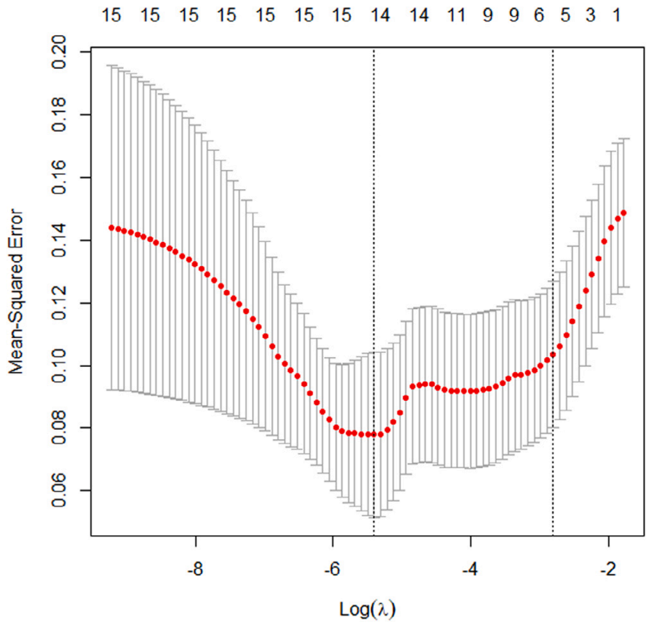

Fig. 3. LASSO results indicating the best model contains 14 of our 15 variables of the base model.

Table 10
Beta regression model, Average Marginal Effects for both technologies, only observations without success rates of 0 and 1 due to model restrictions.

	Effects on PV	Effects on onshore wind
	Dependent variable:	
	Success PV	Success onshore wind
Min restriction: Both	−0.173***	0.186***
	(0.020)	(0.026)
Min restriction: PV only	−0.571***	0.456***
	(0.018)	(0.021)
Max restriction:both	0.496***	−0.395***
	(0.037)	(0.034)
Financial prequalification: PV lower	0.678***	−0.522***
	(0.015)	(0.018)
Financial prequalification: similar	0.382***	−0.237***
	(0.016)	(0.016)
Price ceiling ratio	−1.150***	0.962***
	(0.172)	(0.199)
Realisation period ratio	−1.268***	0.852**
	(0.254)	(0.292)
Support duration [years]	0.031**	−0.026*
	(0.011)	(0.012)
Success other technologies [%P]	−0.005***	−0.005***
	(0.001)	(0.001)
Region: Eastern Europe	−0.327***	0.446***
	(0.024)	(0.029)
Region: North Eastern Europe	−0.740***	0.876***
	(0.013)	(0.015)
Region: Southern Europe	−0.561***	0.687***
	(0.018)	(0.024)
Year	0.165***	−0.141***
	(0.017)	(0.018)

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