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Abstract

Governments use procurement auctions for renewable energy support to stimulate investment in renewable energy. The main challenge in auction design is the balance between cost-efficient procurement and high post-auction realization, i.e., effective procurement. I empirically assess the effect of prevalent auction design elements on effectiveness, using a unique dataset with results of auctions for renewable energy support from 1990 to 2017. I find that pre-qualifications and penalties drive realization rates, while technological banding or the pricing rule do not affect effectiveness. The former is in line with existing theory, while the latter sheds new lights on auction models and case studies discussing auction outcomes, as literature has thus far broadly agreed on a major influence of all design elements. According to my results, policy makers which focus on high realization rates should include pre-qualification measures and penalties into their design. Importantly, they gain more degrees of freedom regarding other design features to tailor renewable energy auctions to their country. This freedom is advantageous in view of a large variety of countries adapting renewable energy auctions.

Keywords: Renewable Energy Support, Auction Design, Climate Change

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1. Introduction

The climate crisis urges policy makers to accelerate decarbonization. A first step in climate strategies is to decarbonize power markets, as two-thirds of global greenhouse gas emissions originate from the energy sector (OECD/IEA & IRENA, 2017). Emission reduction typically requires to shift production from fossil fuels towards nuclear and renewable generation (Williams et al., 2012). Although the cost of renewable energy production has dropped drastically in the last decades, new capacities still depend on subsidies—worldwide transfer payments for renewables amounted to $US 140 billion in 2016 (IEA, 2017).

Governments have used different support schemes, such as feed-in-tariffs, feed-in premiums, and tax reductions, to foster investment in renewable technologies. For many years, regulators have mainly determined subsidy rates based on cost estimates. Recently, governments started to allocate subsidies with auctions for renewable energy capacity (*renewable auctions*). In renewable auctions, governments auction off contracts that guarantee subsidized remuneration for producers of renewable energies (del Río and Linares, 2014; Buckman et al., 2014; Mayr et al., 2014). Regulators try thereby to exploit competition in order to discover relevant needs for subsidies.

Price discovery and competition have dropped auction prices far below expectations (del Río and Linares, 2014). But amid enthusiasm about cost efficiency in renewable auctions, authorities started to realize that winning bidders might have bid below cost, consequently not realizing their projects. In view of the climate crisis and the state of renewable generation in many countries, effectiveness (i.e., how much capacity is deployed) is just as important as efficiency (i.e., at what subsidy rate it is deployed). Obviously, the choice of the policy instrument is as important as its design (del Río, 2012; del Río et al., 2015). In a recent strand of literature, researchers have discussed auction design and its impact on the trade-off between efficiency and effectiveness (e.g., del Río and Linares, 2014; Kreiss et al., 2017b; Matthäus et al., 2019).

In this paper, I empirically analyze the effect of prevalent auction design elements on the effectiveness of renewable auctions. I use a unique hand-collected dataset comprising auction results from 1990 until 2017. I find that particularly pre-qualifications and penalties can act as powerful enforcement mechanisms to drive effectiveness. This confirms results from recent literature (Kreiss et al., 2017b; Gephart et al., 2017; Matthäus et al., 2019). However, I do not find evidence for effects of technological banding or pricing rule on effectiveness. This sheds new light on findings from auction models and case studies, which argue in favor of specific configurations of technological banding or pricing rule to steer effectiveness (e.g., Haas et al., 2004; Anatolitis and Welisch, 2017; Kreiss et al., 2017c,b; Mora et al., 2017; Haufe and Ehrhart, 2018; Kreiss, 2018). To the best of my knowledge, the study is the first to present a dataset of renewable auction results worldwide over a multi-year period. Thereby, it is also the first to test prevailing theoretical findings and anecdotal evidence on the design of renewable auctions.

The work closest to my approach is (Shrimali et al., 2016) and (Winkler et al., 2018). The former assess the impact of risk on efficiency and effectiveness on a sample of up to 20 auctions, mainly from India, UK, and South Africa. The latter employ a panel design for case studies on auctions from Brazil, Netherlands, France, Italy, and South Africa. They compare efficiency and effectiveness of renewable auctions to efficiency and effectiveness of previous subsidy schemes, such as feed-in-tariffs. Yet, they do not explore the effects of the particular auction design.

My study provides policy makers with two major implications on the design for renewable auctions. First, regulators should include pre-qualifications or penalties if they aim to boost realization rates. Both reduce the real-option value inherent in non-realization drastically (Kreiss et al., 2017b; Matthäus et al., 2019) and might impede highly aggressive market entry strategies (Gephart et al., 2017), attracting more serious bids through both channels. Second, policy makers can use other design criteria to adapt the auction design to the regulatory scheme, social norms, or non-monetary goals without deteriorating effectiveness. Regulators can, for example, unconcernedly choose between technological banding or technology-neutral auctions. The former can help to ensure a reliable mix of generation technologies and foster small scale, immature technologies (del Río and Linares, 2014). The latter has the potential to maximize efficiency (Kreiss et al., 2017c).

The remainder of this paper is organized as follows. In Section 2, I discuss the setting of renewable auctions, related literature, and the results to be tested. In Section 3, I present the research design and variable measurement. In Section 4, I provide background regarding data. I present my empirical findings Section 5. Section 6 concludes and provides policy implications.

2. Background: Designing Auctions for Renewable Energy Capacity

In a typical renewable auction, an auctioneer procures a previously fixed amount of renewable generation capacity. Bidders may develop several projects of different capacity size. Bidders submit a bid for each project, specifying the size (in MW) and the required subsidy per MWh of electricity generated from that project. The auctioneer gathers bids and chooses winning bidders. As renewable auctions are reverse auctions, the lowest bids are accepted until procured capacity is reached. Winning bidders receive subsidy rates according to a previously specified pricing rule, such as discriminatory or uniform pricing. Winning bidders have a grace period—typically between 2 and 5 years (del Río and Linares, 2014)—to develop their project. Variants of these multi-unit auctions find application across the globe and have consequently received an increased interest in research (e.g., Buckman et al., 2014; del Río and Linares, 2014; Mayr et al., 2014; Eberhard and Kåberger, 2016; Kruger and Eberhard, 2018) and status reports (REN21, 2010; Lucas et al., 2013; IRENA, 2015; REN21, 2016; IRENA, 2019). According to REN21 (2016), 64 countries used auction schemes to allocate renewable energy subsidies by 2016, compared to 21 in 2009 (REN21, 2010)

With an increasing popularity in political practice, researchers and regulators discuss cost-efficiency and effectiveness of renewable energy auctions. While cost-efficiency refers to cost of generation and support, effectiveness refers to the actual increase in renewable energy capacity (del Río and Linares, 2014). In terms of cost-efficiency, renewable auctions have exceeded expectations and support levels dropped considerably (del Río and Linares, 2014; Gephart et al., 2017). However, experience with past auctions reveals concerns about effectiveness (Mitchell, 2000; Mitchell and Connor, 2004; del Río and Linares, 2014). Literature has identified a variety of factors impeding effectiveness, such as low bids due to an inherit real-option value in auctioned subsidy contracts (Kreiss et al., 2017b; Matthäus et al., 2019), winner's curse (Gephart et al., 2017; Kreiss et al., 2017a), or aggressive market entry strategies (Gephart et al., 2017). Other factors include unreliable technical and financial background of project developers and undersubscribed auctions (del Río and Linares, 2014). Consequently, researchers and politicians have proposed and tested auction design elements to avoid bids below cost and ensure serious and reliable bids.

When designing renewable auctions, regulators have discretion about a wide variety of design elements with influence on admission for bidders, approved technologies, admitted bid range, winner selection, and post-auction project framework, among others. del Río and Linares (2014) provide a comprehensive review of design elements in renewable auctions worldwide. They differentiate between physical pre-qualification, financial pre-qualification, penalties, technology-specific banding, pricing rule, among others. Based on these categories, researchers have investigated the impact of auction design on effectiveness in renewable auctions. In the following paragraphs, I discuss the most prevalent design options in detail: physical pre-qualification, financial pre-qualification and penalties, technological banding, and the pricing rule. I also explain how these design options can influence effectiveness and use them in my study to test impact of auction design on post-auction realization.

Physical pre-qualification comprises non-financial criteria which bidders have to fulfill in order to participate in the auction. Common examples of physical pre-qualification measures are the attainment of building permits or completion of conduction studies previous to the auction (del Río and Linares, 2014). This may increase effectiveness of renewable auctions through two channels: First, physical pre-qualification can be considered a participation cost that ensures the capability of bidders. Only bidders with serious intent to deliver their project will bear the (otherwise sunk) cost. Second, bidders may have an information gain from completing requirements set by the auctioneer and adapt their bids accordingly. Based on the first channel, Kreiss et al. (2017b) establish a positive relationship between physical pre-qualification and effectiveness of renewable auctions in a simple single unit auction model.

Financial pre-qualification and penalties require payments from the bidder to the auctioneer. Financial pre-qualifications demand up-front payments of the bidders in order to participate in the auction. The pre-qualification payment is typically implemented as non interest-bearing deposit, a so called bid bond. In case of non-realization of the contract within the grace period, the deposit is not refunded. Pre-qualification payments are thereby easier to collect than penalties, as penalties are only claimed if a winning bidder does not complete its contract upon end of the grace period. Penalties and financial pre-qualification are comparable in their incentive structure and they are equivalent under the assumptions of no credit risk and without stochastic interest rates. Different researchers establish a positive relationship between financial pre-qualification or penalties and effectiveness of auctions through three channels: First, it makes a non-realization option less attractive, resulting in a lower real-option value of the project (Kreiss et al., 2017b; Matthäus et al., 2019). Second, it increases average bids and thereby average subsidies for all participants, making realization economically more viable (Matthäus et al., 2019). Third, it makes aggressive market entry strategies with strategic low bids less effective (Gephart et al., 2017).

Technology-specific banding, compared to technology-neutral auctions, refers to an auction design where different technologies do not compete directly in the same auction. For each technology—such as wind-offshore, wind-onshore, or solar—there is a separate tender. Scholars argue that technology-specific financial support is critical for the success of support systems (Haas et al., 2004).

Technology-specific designs help to address actual market conditions as well as the status of the technological life cycle. Furthermore, they avoid crowding out of less mature technologies (e.g., Haas et al., 2004; del Río and Bleda, 2012; Polzin et al., 2015). Investors face thereby less uncertainty, reducing system cost and capital cost, respectively (Kreiss et al., 2017c; Kreiss, 2018). Technology-neutral auctions might have additional negative effects on effectiveness: Few mature technologies outperform other technologies in the auction and receive the lion's share of capacity. Since the capacity was originally planned to be shared among different technologies, suitable construction space for the prevailing technology is more scarce than expected. The resulting post-auction competition for sites can severely harm effectiveness (Buckman et al., 2014).

The pricing rule of an auction determines the subsidy which is paid to winning bidders. I differentiate two main pricing rules for renewable auctions: uniform pricing and discriminatory pricing. With uniform pricing, all winning projects receive the clearing price, i.e., the last accepted bid. With discriminatory pricing (also called pay-as-bid pricing), each winning project obtains payments according the corresponding bid. The evidence in literature regarding the impact of pricing rules on effectiveness is divided. Anatolitis and Welisch (2017) and Matthäus et al. (2019) find that bid curves in uniform and pay-as bid pricing do not deviate much and are asymptotically identical. Accordingly, governments need to pay more subsidies and average profits for developers are higher when using uniform pricing. This comes at the benefit of higher effectiveness as more projects become economically viable. On the other hand, the model of Kreiss et al. (2017b) predicts higher expected award prices and thereby higher effectiveness in the discriminatory setting. Mora et al. (2017) and Haufe and Ehrhart (2018) support the latter view and advise for pay-as-bid pricing for higher effectiveness.

The influence of these four design elements (physical pre-qualification, financial pre-qualification and penalties, technological banding, pricing rule) on effectiveness and efficiency have been studied based on game-theoretic auction studies (Kreiss et al., 2017a,b; Ehrhart et al., 2018; Haufe and Ehrhart, 2018), simulations (Anatolitis and Welisch, 2017), or single country case studies (Mitchell, 2000; Mitchell and Connor, 2004; Buckman et al., 2014; Eberhard and Kåberger, 2016; Cassetta et al., 2017; Gephart et al., 2017; Bayer, 2018; Kruger and Eberhard, 2018, among others). In the present paper, I test predictions regarding effectiveness from game-theoretic models, simulations, and from case studies and assess them in an empirical framework.

3. Methodology

3.1. Research Design

I employ a two-tier research design to study the effect of auctions design on effectiveness of renewable auctions. First, I test the effect of auction design elements on mean effectiveness of renewable auctions individually. Second, I use a multivariable approach to test the effect of integrated auction design on effectiveness.

I establish base effects of auction design elements on effectiveness by splitting the sample in two groups, separating auctions with and without the respective design element. I compare average effectiveness of the groups with t-tests for each design element in question, thereby testing predictions of literature outlined in Section 2.

In renewable auctions, design elements do not occur individually, but are combined in a more elaborate design. To study the integrated effect of auction design, I estimate the multivariable model

$$\textit{Effectiveness}_i = \alpha_0 + \alpha_1 \cdot \textit{Auction Design}_i + \alpha_2 \cdot \textit{Controls}_i + \varepsilon_i. \qquad (1)$$

In this model, *Effectiveness* measures the actual increase in renewable energy capacity, *Auction Design* includes the specific design of the auction deconstructed into single elements, and *Controls* is a vector of control variables.[1]

[1] One could argue that auction design influences auction effectiveness via the mediator price. Here, I focus on the gross effect of auction design. Disentangling the paths to allow for

3.2. Variable Measurement

I measure *Effectiveness* of renewable auction as the share of contracted capacity actually being commissioned. This so called realization rate of auctions has been used as proxy to study effectiveness in previous studies (e.g., Huber et al., 2004; del Río and Linares, 2014; Shrimali et al., 2016). Prior literature defined realization rate either as the ratio of commissioned capacity to *auctioned* capacity, or as the ratio of commissioned capacity to *contracted* capacity. I opt for the latter definition and use the share of contracted capacity as this treats over- and undersubscribed auctions more evenly. The realization rate takes values between 0 and 1, where 1 is a highly effective auction with the entire contracted capacity being commissioned. I expect the realization rate and thereby *Effectiveness* to depend strongly on *Auction Design*.

The measurement of *Auction Design* is straightforward. I view the auction design as a set of dummy variables indicating the auction design elements employed. I consider physical pre-qualification, financial pre-qualification and penalties, technology-specific banding, and pricing rule, as discussed in Section 2. This selection includes the most important components of the auction designs which are likely to influence *Effectiveness*. Yet, some factors beyond auction design might affect realization rates as well.

In the vector of *Controls*, I include 5-year periods to capture effects of economic cycles, technological development, and the learning curve of renewable energies and auction design. The results are robust to changes in the length of the periods.

3.3. Implementation

My dependent variable ranges from 0 to 1. Hence, I use a Tobit regression (Tobin, 1958). This estimator offers a better fit compared to a standard ordinary least squares (OLS). Yet, I also include an OLS estimator with robust standard

more causal evidence would be interesting. Unfortunately, the current data availability does not allow for such an analysis.

errors for small sample sizes as best linear approximation in the regression tables. I conduct all computations in R version 3.6.1 (R Core Team, 2019) and rely for my analysis on packages VGAM, lmtest, and mltools (Yee, 2015; Zeileis and Hothorn, 2002; Gorman, 2018). I use packages texreg, stargazer, and ggplot2 for creating tables and plots (Leifeld, 2013; Hlavac, 2018; Wickham, 2016).

4. Data

4.1. Sample Description

I use hand-collected data from scientific journals, government reports, policy reports, and government websites to construct my sample. Each observation contains information about auction year, country, governmental program name, auctioned capacity, contracted capacity, commissioned capacity, grace period, and the employed auction design.

The dependent variable *Effectiveness* is compiled from realization rates of the auctions. For past auctions with expired grace period, I use completed capacity.[2] For auctions with still active grace period, I use project level data of more than 1,500 capacity investments to project realization rates. A project is regarded as realized if its construction has made significant progress and is expected to be completed on schedule. I use projected realization rates for roughly 10 percent of the observations.

Auction design is my independent variable of interest. It is stored in the dummy variables *Physical*, *Financial*, *Tech Band*, and *Pay-as-bid*. *Physical* takes value one if participation in the auction requires any building permits, environmental permits, or prior experience with renewable energy projects in the respective country. The variable *Financial* equals one if the auction requires either up-front financial payments or deposits, or if bidders need to pay a penalty for non-compliance. I treat financial pre-qualification and penalties

[2] The data abstracts from any delay in the process as exact start of commercial operation cannot be determined for many past projects.This means, the realization rate includes every completed project until now, regardless of its start of operation.

equivalently. The variables *Tech Band* and *Pay-as-bid* take value one if the auction is technology specific, or follows a pay-as-bid-pricing rule, respectively.

The control variable *Auction Year Bins* contains the year of the auction. To adjust variable number to sample size, I do not use dummies for every year. I split the interval from 1990 to 2017 into five equal bins. Results are stable for bins of longer and shorter period.

4.2. Descriptive Statistics

I start by collecting information on 189 observations of renewable auctions from 42 countries held between 1990 and 2017. In line with the increasing popularity of renewable auctions, 138 observations took place after 2010, while 39 took place between 2000 and 2010, and only 13 auctions took place between 1990 and 2000. About half the sample (102 observations) is from OECD countries, while the other half is from emerging markets and developing countries in Central and South America (41), Asia (28), Africa (11), Eastern Europe (5), and the Middle East (4). 36 auctions were single-unit auctions. Figure 1 provides an overview of 132 auctions where realization rates are available. The data is balanced regarding economic background and exhibits a significant variation in the dependent variable.

For my analysis, I restrict the sample in three steps. First, I drop observations where I can not compute realization rates due to missing data, reducing the sample size from 189 to 131. Second, I exclude 11 observations with realization rate equal to zero, corresponding to auctions such as VRET (Australia 2017), Large Scale CSP 2 (France 2013), or Al Jouf and Rafha (Saudi Arabia 2017). In these auctions, authorities have revoked the call for tender prior to awarding any contracts, or problems in the bureaucratic process forestalled construction. Third, I exclude all 36 single unit auctions from my sample, arriving at a final sample size of 94 observations. Final contracts in single unit auctions are often based on bilateral negotiation. Hence, realization is less dependent on actual action design, but on the contractual post-auction process.

Table 1 summarizes descriptive statistics of my sample. Panel A presents

Table 1
Descriptive Statistics

The sample consists of 94 observations of auctions. My dependent variable is *Effectiveness*, measured as realization rate of the auction. *Physical* is a dummy variable with value one if participation in the auction requires any building permits, environmental permits, or prior experience with renewable energy projects in the respective country. *Financial* is a dummy variable with value one if the auction requires either up-front financial payments or deposits, or includes a penalty for non-compliance. *Tech Band* is a dummy variable with value one if the auction is technology specific. *Pay-as-bid* is a dummy variable with value one if the auction follows a pay-as-bid pricing rule. *Auction Year Bins* are dummy variables with value one if the auction took place in the respective period.

Panel A: Summary Statistics

	Num. obs.	Mean	St. Dev.	Min	Median	Max
Effectiveness	94	0.743	0.280	0.100	0.885	1
Physical	93	0.839	0.370	0	1	1
Financial	93	0.860	0.349	0	1	1
Tech Band	94	0.436	0.499	0	0	1
Pay-as-bid	94	0.915	0.281	0	1	1
Auction Year Bins						
1990 - 1995	94	0.064	0.246	0	0	1
1995 - 2000	94	0.064	0.246	0	0	1
2000 - 2006	94	0.032	0.177	0	0	1
2006 - 2011	94	0.181	0.387	0	0	1
2011 - 2017	94	0.660	0.476	0	1	1

Panel B: Correlation Matrix

	Effectiveness	*Physical*	*Financial*	*Tech Band*
Physical	0.482			
Financial	0.510	0.835		
Tech Band	0.165	0.213	0.233	
Pay-as-bid	0.065	0.387	0.208	0.041

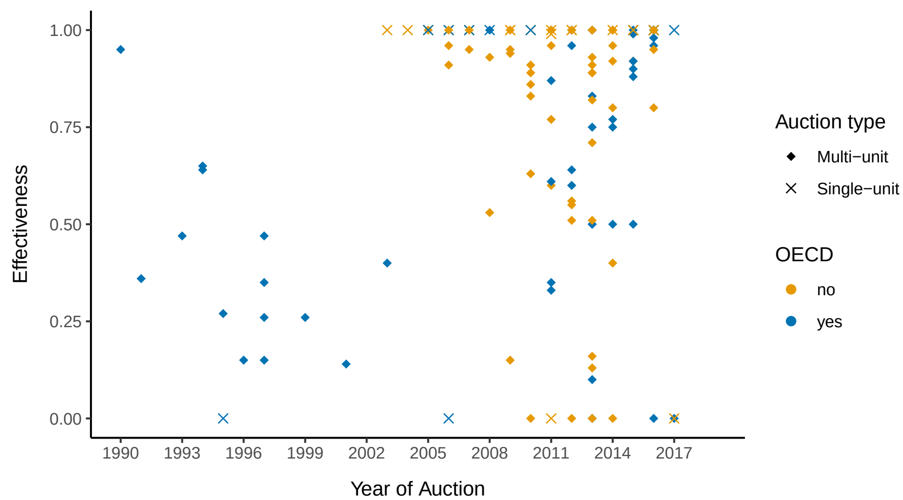

Figure 1: Overview of the dataset where a realization rate is known. Effectiveness is measured as the share of contracted capacity actually being commissioned. Early auctions took mostly place in OECD countries, while in recent years the sample is balanced between OECD and non-OECD countries. Single unit auctions typically have realization rates close to zero and close to one.

number of observations, means, standard deviations, minima, medians, and maxima for each variable. My main dependent variable *Effectiveness* has a mean of 0.743, a median of 0.885 and exhibits considerable variation. At first glance, mean and median seems surprisingly high, but having in mind that all project developers are bound by a contract to deliver their capacity sets the numbers into perspective. The median auction features all design elements except for technological banding. Most notably, a considerable amount of auctions (91.5 %) feature pay-as-bid pricing. Panel B depicts the correlation table of my sample. *Effectiveness* is positively correlated with all design elements. Most correlations of design elements among one another are positive and between 0.2 and 0.4. Notable exceptions are the correlation of *Physical* and *Financial*, which is high at 0.835, and the correlation of *Tech Band* and *Pay-as-bid*, which is low at 0.041. This means, physical pre-qualification and financial pre-qualification or penalties are particularly often employed together. Furthermore, technology-neutral auctions are more often designed with uniform pricing rule.

5. Results and Discussion

I test predictions from Section 2 on the influence of physical pre-qualification, financial pre-qualification or penalties, technological banding, and pricing rule on *Effectiveness*. Literature predicts a positive effect on *Effectiveness* for all design options under consideration. Regarding the pricing rule, model predictions are mixed. I establish base effects of auction design elements in t-tests on split samples, followed by a multivariable approach.

Results of t-tests are reported in Table 2. The mean *Effectiveness* of auctions with physical pre-qualification, financial pre-qualification or penalties, and technological banding respectively, is higher compared to auctions without the respective design feature. This is in line with predictions of literature. The difference in the sample split is more pronounced for pre-qualifications. Average realization rates in the sample with pre-qualification measures are approximately 40 percentage points higher and statistically significant at the 1 %-level. Technological banding increases average realization rates by about 10 percentage points. This result is statistically significant at the 5 %-level. Mean realization rates for pay-as-bid auctions are about 6 percentage points higher than mean realization rates for uniform auctions, which is in favor of the theory developed in (Kreiss et al., 2017b; Mora et al., 2017; Haufe and Ehrhart, 2018). Yet, this difference is not statistically significant at usual levels. Apparently, the choice of pricing rule does not play a major role in designing effective renewable energy auctions. This is surprising as theory predicts (either way) a relevant impact on effectiveness. Yet, results regarding pricing rule have to be taken with a grain of salt as a vast majority of auctions in my sample employs discriminatory pricing, limiting the variance in the data.

My approach provides a clear picture of the individual effects and serves as a first basis. Yet, it is prone to an omitted variable bias and might not be able to capture the complex auction environment. To this end, I use a multivariable approach and regress *Effectiveness* on a vector of design elements and a vector of control variables, as specified in Equation (1). Table 3 presents regression

Table 2
t-Tests Mean Effectiveness

This table presents effects of *Auction Design* on *Effectiveness* in t-tests. For each t-test, I split the sample into two subsamples with respect to the auction design element under consideration. I report mean and standard deviation of the subsamples with (yes) and without (no) the design element under consideration. Reported t-values are based on t-tests for samples with the same variance. For unambiguous predictions (*Physical*, *Financial*, and *Tech Band*), I use one-sided t-tests. For ambiguous predictions (*Pay-as-bid*), I use a two-sided t-test. *Physical*, *Financial*, and *Tech Band* have a positive impact on *Effectiveness* on a 0.01, 0.01, and 0.05 percent level, respectively. I cannot reject the null hypothesis for *Pay-as-bid*, i.e., I can not infer a significant difference in average effectiveness for a change in pricing rule.

	Means and STD of *Effectiveness* for subsamples					
	Mean (yes)	St. Dev. (yes)	Mean (no)	Std. Dev. (no)	t-value	Num. obs.
Physical	0.8041	0.2444	0.4380	0.2628	5.2498***	93
Financial	0.8025	0.2423	0.3915	0.2401	5.6599***	93
Tech Band	0.7968	0.2917	0.7006	0.2664	1.6667**	94
Pay-as-bid	0.7478	0.2787	0.6863	0.3109	0.5918	94

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

results. The dependent variable in all columns is *Effectiveness*. The auction design variables *Physical*, *Financial*, *Tech Band*, and *Pay-as-bid* are my primary variables of interest. I present results of the Tobit estimator in columns (1) and (3), complemented by results of the OLS estimator with robust standard errors for small sample sizes in columns (2) and (4).

The coefficient of *Financial* is positive and insignificant in my baseline Tobit estimator, but significantly positive in the baseline OLS estimator. The economic effect is meaningful and estimated at an increase of 25 percentage points in realization rates. Surprisingly, all other variables have coefficients that are not significantly different from zero. My estimators are able to explain a fair portion of the variation with an R^2 of 0.14 for the Tobit estimator and an adjusted R^2 of 0.25 for the OLS estimator.

Yet, the findings in the first columns may result from an insufficiently specified regression model. Realization rates might also be driven by technological advancement, economic cycles, or learning curves, among others. I control for these macroeconomic effects by including five dummy variables that are equal to one in the periods 1990 - 1995, 1995 - 2000, 2000 - 2006, 2006 - 2011, 2011 -

Table 3
Effectiveness

This table shows regression estimates of *Auction Design* on *Effectiveness*, specified by the model

$$Effectiveness_i = \alpha_0 + \alpha_1 \cdot Auction\ Design_i + \alpha_2 \cdot Controls_i + \varepsilon_i.$$

Effectiveness is the realization rate of the auction, and auction design elements are as specified in Sections 2 to 4. The two right columns include the vector of control variables. Standard errors are depicted in parentheses. For the OLS estimators, I use robust standard errors for small sample sizes.

	Effectiveness			
	Tobit	OLS	Tobit	OLS
Physical	0.21	0.19	0.29	0.28*
	(0.17)	(0.13)	(0.23)	(0.16)
Financial	0.26	0.25*	0.36**	0.35***
	(0.17)	(0.14)	(0.18)	(0.11)
Tech Band	0.07	0.02	0.08	0.03
	(0.07)	(0.05)	(0.06)	(0.05)
Pay-as-bid	−0.06	−0.10	−0.04	−0.08
	(0.13)	(0.09)	(0.14)	(0.08)
Tobit Constant 1	0.41***		0.25*	
	(0.12)		(0.14)	
Tobit Constant 2	−1.22***		−1.29***	
	(0.10)		(0.10)	
OLS Constant		0.45***		0.28***
		(0.12)		(0.10)
Control Variables	No	No	Yes	Yes
Num. obs.	93	93	93	93
R^2	0.14		0.19	
Adj. R^2		0.25		0.31

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

2017, respectively and zero otherwise.[3] The results are robust to changes in the period length of these dummies. The coefficient of *Financial* continues to be significantly positive. Bidders in auctions with financial pre-qualification or penalties realize significantly more projects, increasing the realization rate by about 35 percentage points. This effect is economically meaningful and in the same order of magnitude as my results of the t-tests. The coefficients of *Pay-as-bid* and particularly *Tech Band* remain insignificant. This suggests that only pre-qualification measures are necessary to push realization rates. Yet, the interpretation of the combined effect of *Physical* and *Financial* remains difficult.

[3] Note that the period length is equally spaced on a monthly basis.

Based on column (4) of Table 3, one might conclude that introducing physical pre-qualification on top of financial pre-qualification leads to a further increase in realization rate by 28 percentage points. I analyze this inference in more detail by assessing the interaction of *Financial* and *Physical*. I present results of this analysis in Table 4. To allow for a apparent inference, I change the base levels of *Financial* and *Physical* when moving from the models shown in columns (1) and (2) to the models shown in columns (3) and (4).

All columns confirm that adding physical pre-qualification or financial pre-qualification has a positive effect on effectiveness. This is in line with theory and with results in Table 3. Also, the coefficients of *Tech Band* and *Pay-as-bid* continue to be insignificant. The effect of financial pre-qualification is significant in columns (2)-(4) and the effect of physical pre-qualification is significant in column (2). Column (2) suggests that adding physical pre-qualification to a design with financial pre-qualification can increase realization rates by 30 %. Columns (3) and (4) reveal an effect of about 46 % when adding financial pre-qualification to a design with physical pre-qualification. This indicates that financial pre-qualification carries a slightly larger effect, but a combination of both design features helps to design effective auctions.

Apart from auction design, there are likely other sources influencing effectiveness. Literature finds an effect of country characteristics, such as OECD versus non-OECD or developing versus developed country, on investment in renewable energies (Painuly, 2001; Schmidt, 2014; Polzin et al., 2015; Eberhard et al., 2017). Based on a larger dataset, it would be possible to assess how these findings transfer to the effectiveness of renewable energy auctions. Future research could disassemble country categories into single factors—such as regulatory quality, political stability, and amount of foreign direct investment—and study interactions with auction design. This could yield interesting insights for policy makers. After understanding the underlying mechanisms of renewable energy auctions, it is essential to tailor auction design to the specific circumstances in each country. So far, my sample size does not admit for analyses with multiple interactions, but with a multitude of auctions in 2018 and 2019,

Table 4

Additional Analysis: Effect of Financial and Physical Pre-Qualification

This table shows regression estimates of *Auction Design* on *Effectiveness*, specified by the model

$$\textit{Effectiveness}_i = \alpha_0 + \alpha_1 \textit{Financial} \times \textit{Physical} + \alpha_2 \cdot \textit{Auction Design}_i + \alpha_3 \cdot \textit{Controls}_i + \varepsilon_i.$$

Effectiveness is the realization rate of the auction. *Financial* and *Physical* are the indicator variables for financial and physical prequalification and *Auction Design* contains the remaining design elements as specified in Sections 2 to 4. I include the same control variables as in Table 3 in all columns. Analyses without control variables yield the same results. Standard errors are depicted in parentheses. For the OLS estimators, I use robust standard errors for small sample sizes.

	Effectiveness			
	Tobit	OLS	Tobit	OLS
Physical	0.32	0.31^{*}		
	(0.23)	(0.17)		
No Financial	-0.28	-0.28^{*}		
	(0.23)	(0.16)		
No Financial × *Physical*	-0.21	-0.18		
	(0.36)	(0.16)		
Financial			0.49^{*}	0.46^{***}
			(0.28)	(0.03)
No Physical			-0.11	-0.13
			(0.38)	(0.17)
Financial × *No Physical*			-0.21	-0.18
			(0.36)	(0.16)
Pay-as-bid	-0.04	-0.08	-0.04	-0.08
	(0.14)	(0.08)	(0.14)	(0.08)
Tech Band	0.07	0.02	0.07	0.02
	(0.06)	(0.05)	(0.06)	(0.05)
Tobit Constant 1	0.57^{***}		0.39	
	(0.18)		(0.35)	
Tobit Constant 2	-1.29^{***}		-1.29^{***}	
	(0.10)		(0.10)	
Constant		0.60^{***}		0.44^{***}
		(0.14)		(0.15)
Control Variables	Yes	Yes	Yes	Yes
Num. obs.	93	93	93	93
R^2	0.18		0.18	
Adj. R^2		0.31		0.31

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

a larger dataset is realistically obtainable in the near future.

6. Conclusion and Policy Implications

This paper analyzes outcomes of auctions for renewable energy capacity. It uses a unique dataset containing auction design and realization rates for auctions between 1990 and 2017. On this data, I test predictions from literature regarding the effects of auction design on realization rates. My analysis confirms strong effects of pre-qualification and penalties, which is in line with literature and robust in several tests. I find no association of technological banding or the pricing rule with the realization rate of auctions in a multivariable setting. This is surprising as existing literature suggests a strong effect. Collectively, my findings suggest that proper auction design does have a positive influence on realization rates. Yet, less design options than expected have substantial impact on effectiveness.

Some constraints might limit my analysis. My result are based on an empirical analysis which is inherently descriptive. This means I cannot expect a causal relation between my independent and dependent variables. Yet, my setup is less exposed to issues of reverse causality. Post-auction realization rates are very unlikely—if not incapable—to affect the pre-auction design choice. Still, missing country-characteristics and economic cycles might explain parts of the effect. Unfortunately, my sample size does not allow for large a vector of control variables. Still, effects are stable when controlling for year effects, which cover economic trends, learning curves, and technological advancement.

This paper has important implications for policy makers and researchers who work on the design of renewable energy auctions. Regulators should include financial pre-qualification in form of bid bonds if the auction design aims for high realization rates. This reduces the value of non-realization and thereby decreases the value of the underlying real option. This mechanic increases realization probability and leads to more substantial bids. Also, aggressive market entry strategies to push competitors out of the market become more expensive and less likely. Both financial pre-qualifications and penalties have the same effect from a theoretical point of view, but the former are easier to collect for the auctioneer and might set stronger incentives in practice. Physical pre-qualification should be implemented in an auction design aiming for high realization rates as well. However, investors face often time consuming and costly bureaucratic procedures to pre-qualify. Governments should not impose bureaucratic barriers, insurmountable particularly for smaller investors[4].

Rather, regulators should use the degrees of freedom they have in the other design elements (i.e., technological banding and pricing rule of the auction) to aim for a lean and easy process. They should also use their options to tailor the auction to the regulatory scheme, social norms, or non-monetary goals. For example if a high technology diversity is desired, technology banding should be implemented. This allows to steer the generation system to a reliable mix of production capacities and helps to foster small scale, immature technologies (del Río and Linares, 2014). On the other hand, if technological diversity is a lesser concern than price, a technology-neutral set up shifts procured capacities towards cost-efficient technologies. Also, to counter implicit collusion, governments might consider to alternate pricing rules between uniform and pay-as-bid pricing as this makes consistent price-rigging more difficult.

When aiming for high effectiveness, regulators need to keep in mind that there is a substantial trade-off with efficiency. Pushing bidders towards realization of the projects comes at the cost of a risk premium for projects. Participants in the auction require compensation for excluding strategies from their decision space. The exact balance between effectiveness and efficiency is an important part of the respective country's decarbonization strategy.

Adapting a policy framework that suits the specific needs and financial capabilities of the country is essential for its success and the design of the instrument is as important as its choice (del Río, 2012). With policy makers worldwide choosing renewable auctions for the dissemination of renewable energies, my study advocates for pre-qualifications and penalties to push realization rates in-

[4]If bidder diversity matters to the auctioneer, also employing very high financial pre-qualifications can be detrimental. Smaller bidders are less likely and typically less capable of paying high bid bonds.

dependent of the specific country context. Yet, the individual traits of a country might interact with the particular design element. Future studies could investigate the interaction of country characteristics and auction design elements on a larger dataset based on country attribute such as regulatory quality, political stability, or investment climate.

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8. Data Availability

Data is hand-collected from scientific journals, government reports, policy reports, and government websites. Please contact the corresponding author for details. A list of sources, the full dataset, and the regression input are available as .csv files upon reasonable request.

9. Declaration of Interest

None

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