Firms' Bidding Behavior in a New Market: Evidence from Renewable Energy Auctions*

Stefan Lamp† Mario Samano‡ Silvana Tiedemann§

August 19, 2024

Abstract

Auctions are increasingly used by governments to select suppliers and determine levels of policy support. In the context of renewable energy (RE) investment, they have become dominant in the ongoing energy transition. Using unique bid-level data from German RE auctions (2015-2019), this paper documents bidding behavior and recovers bidders' costs under uniform and pay-as-bid pricing rules by estimating a structural model of multi-unit auctions that accounts for future cash flows from subsidies. By conducting counterfactual analyses on the impact of switching to a non-discriminatory auction, we find that such a change may have reduced subsidy expenditures and mitigated market power.

JEL codes: D44, L51, Q42, Q48

Keywords: electricity markets, renewable energy, pay-as-bid auctions, non-discriminatory auctions, government support policies.

---

*We thank Nicolas Astier, Riccardo Camboni, Alan Crawford, Natalia Fabra, Daniel Herrera-Araujo, Par Holmberg, Harim Kim, Mario Liebensteiner, Mathias Reynaert, Stan Reynolds, Eric Richert, Morten Saethre, Francois Salanie, Philipp Schmidt-Dengler, Matthias Wrede, and participants at the Bergen Competition Policy Conference, EAERE, IFN Stockholm Conference, Mannheim Energy Conference, Southern Economic Association Conference, Toulouse Energy and Climate Conference, Friedrich-Alexander-Universität, TSE, UC3M, University of Padova, and the members of the Center for Sustainability at the Hertie School for their insightful comments and discussion. A previous version of this paper was titled "Bidders' Experience and Prices in Renewable Energy Auctions". S. Lamp acknowledges support from ANR under grant ANR-17-EURE-0010 (Investissements d'Avenir program). S. Tiedemann gratefully acknowledges financial support from the German Federal Ministry of Education and Research through the ARIADNE Project (FKZ 03SFK5K0). M. Samano acknowledges financial support from the Social Sciences and Humanities Research Council of Canada grant 435-2023-0268.

†Toulouse School of Economics, University of Toulouse Capitole, Toulouse, France. Email: stefan.lamp@tse-fr.eu

‡HEC Montreal. Email: mario.samano@hec.ca

§Hertie School Berlin. Email: tiedemann@hertie-school.org

1 Introduction

Renewable energy (RE) investment is seen as a key component to reach stringent emission reduction targets set by policy makers worldwide.[1] To accelerate technology deployment and reduce subsidy costs, fixed subsidy schemes, common in the early 2000s, have largely been replaced by market-based support mechanisms such as RE auctions. As of 2019, more than 100 countries have held such auctions.[2] However, while RE auctions have been widely adopted, the determinants of the market participants' bidding behavior have not been empirically studied to the same extent. This holds significant relevance for the deployment costs associated with these technologies, particularly in the current landscape of increased climate change mitigation efforts and revised investment targets for RE.

In this paper, we study the role of auction design when there is no risk of government default, and the role of cost and market factors that influence observed price developments. The first has been a central question in studies of government procurement for construction (e.g., Bajari and Ye, 2003; Krasnokutskaya and Seim, 2011) and spectrum allocation for telecommunications (e.g., Cramton, 2013; Fox and Bajari, 2013), among other industries. The second helps us understand whether the regulatory setting is conducive to achieve the goals set by the policy itself.

The objective of RE auctions is to identify the most cost-efficient suppliers of renewable generation capacity and to determine the level of the per unit output subsidy once the plant is built. The auctioneer, in this case, the government, announces the desired volume of capacity in advance, creating a perfectly inelastic demand curve. The auction rules allow participants to submit multiple quantity-price pairs (bids) in the same auction round, and several bids can be awarded, this is known as multi-unit auctions. The auctioneer collects

[1]The Inflation Reduction Act in the US provides numerous examples (`https://bit.ly/3RLZ2sF`) and the Renewable Energy Directive in the EU sets specific targets for RE (`https://bit.ly/3Q13vqf`).

[2]In 2017-2018, about 50 countries used auctions to procure RE-based electricity. The total number of countries that have held RE auctions is 100 (IRENA, 2019). Since 2017, the European Union (EU) requires that competitive tenders for RE subsidies replace incentives previously set by the state.

all the submissions and sorts the bids by price in ascending order to obtain the aggregate supply curve. The market clearing price and the specific quantities per bidder are determined by the intersection of this curve with the government demand curve. This intersection also determines the level of the individual subsidy, which can be either based on the uniform auction price or implemented as a pay-as-bid pricing rule.

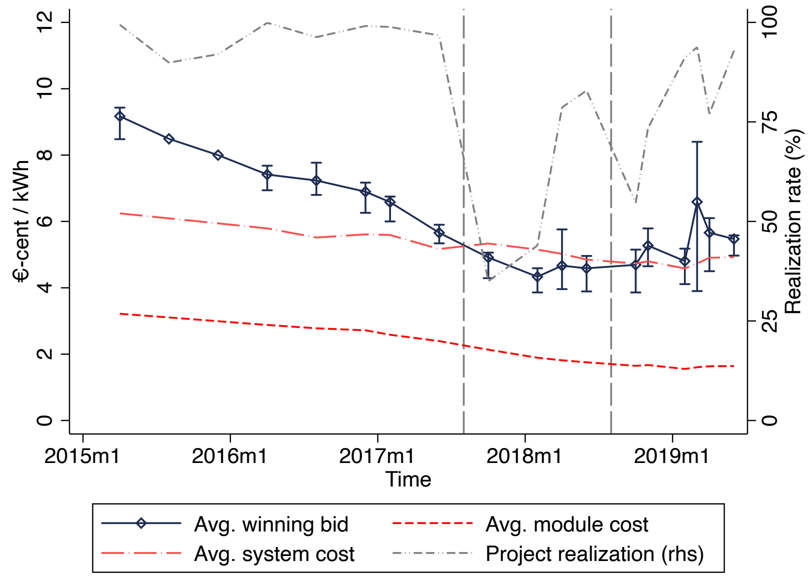
Our first research question is to understand the extent to which the winning bidders' production subsidy is determined − under uniform or pay-as-bid pricing rule − has implications for the levels of market power exercised by the participants. Depending on the underlying cost of each quantity segment (RE project), the price-cost gap will be different in each auction format because the market clearing price may change. Our second objective is to identify the market and cost factors that influence firms' bidding behavior in these type of auctions. Specifically, we analyze the relationship between a large set of observable and non-observable bid characteristics and the price at which they are submitted. This analysis quantifies some of the regulatory concerns about the size of the government demand and the location of sites.

To achieve these goals, we make use of unique bid-level data from German RE auctions held between 2015 and 2019, with a focus on solar photovoltaic (solar) technology. Germany is a particularly interesting case to study as the country experimented with both uniform pricing (UP) and pay-as-bid (PAB) pricing rules in an initial pilot phase, and then opted for a PAB format only. Moreover, all auctions were over-subscribed, making them well-suited for analyzing bidding behavior.[3] Our dataset includes bid quantities and prices from all bidders of winning and losing bids in each auction round. Additionally, we have information on the geographical location of each bid, enabling us to match bids with covariates such as solar irradiation and distance to the electricity network.

An initial observation is that the average price of winning bids decreased in the first three years after the introduction of the auction in 2015. However, prices have stagnated since then.

[3]Also, many RE auction design elements that are common in Europe and other developed economies can be found in the German auction design (Del Río and Kiefer, 2021).

Figure 1: Winning bids, average costs, and project realization rates in German solar auctions



Notes: Average quantity-weighted winning bid prices in €-cent / kilowatt-hour (kWh) together with min/max accepted winning bids in pay-as-bid (PAB) auctions. The second and third auction rounds were implemented with uniform pricing rules and only a single market clearing price is reported. Average solar module costs and system costs for ground-mounted installations converted to €-cent / kWh assuming a lifetime of 25 years and an annual discount rate of 10%. Project realization rates for winning bids only.

Figure 1 shows those trends together with cost indicators for large, ground-mounted solar installations, which have been decreasing over time.[4] However, in the second half of 2017, the average winning bid price fell below the system cost, and only recovered in late 2018. We use this observation to distinguish between three periods during the PAB auction rounds implemented from 2016 to 2019. In Periods 1 and 3, average winning prices are above or equal to system costs. In Period 2, average winning prices are below system costs. This suggests that profit margins must have decreased in Period 2 relative to Period 1. This observation is also consistent with the ex-post project realization rates of winning bids, which show a large drop during Period 2, and a recovery in later rounds (see Figure 1). We argue in this paper

[4] *Avg. module cost* represents the average cost of solar modules, and is based on monthly observations from PV Exchange. *Avg. system cost* includes additional hardware and installation cost and is based on quarterly survey data from the German Solar Industry Association. Both cost indicators refer to installations in the following 12 months.

that this is related to a change in the extent to which bidders exercise market power in the auctions after 2017, and that factors such as bidder size are strongly correlated with bidding behavior.

We build on the literature of multi-unit auctions (Hortaçsu and McAdams, 2010; Kastl, 2011) to obtain measures of bidders' costs taking into account the auction format and the specific context of RE subsidies, which rely on expectations about future market payoffs. With a resampling technique used by the aforementioned authors, we simulate a large set of residual demand curves to determine market-clearing prices. By substituting those prices into a closed-form expression for the costs, we obtain estimates for the underlying cost of each bid. Using the estimated costs we compute measures of market power, conduct an analysis of factors that influence bidding behavior, and construct counterfactuals for the auction format. We find that the density of margins shifted to the left during the time where system costs were equal or above the levels of average winning bids –Period 2. After this period, the density remained in almost the same location thereafter.

We then use linear regressions to identify the key factors associated with bidding behavior. We find that the estimated costs are strongly correlated with system costs, solar irradiation, and the proximity of the site to the nearest high-voltage electricity interconnection node. Moreover, bid prices exhibit a robust and positive correlation with estimated costs, suggesting a pass-through effect of between 0.1 and 0.3 €-cent/ kiloWatthour (kWh) for every 1 €-cent/kWh increase in costs. Interestingly, larger bidders show a higher propensity to pass-through their costs compared to smaller bidders. In addition, our analysis delves into the temporal and size-based heterogeneity of pass-through behavior.

Next, we use the model to run a first counterfactual, asking what would have happened to bidder revenues and subsidy payments if the policymaker had conducted all auctions under uniform pricing rule rather than PAB pricing. Since the theoretical literature does not provide a clear ranking on either efficiency or revenue grounds, this is an empirical question (Ausubel et al., 2014; Hortaçsu and McAdams, 2018). We take advantage of the fact that two auction rounds were implemented with uniform pricing rules in an initial pilot phase to estimate costs and average markups from this setting. For the counterfactual, we then either assume that bidders under uniform pricing would have had similar markups throughout −fixed markup obtained from UP estimates− or that they would bid their costs instead of the observed bids −truthful bidding−. In either case, the auctioneer aggregates these bids to obtain the new supply curve of bidders, which determines a new market clearing price for each auction round. If all winning bids receive the same clearing price, this approximates a non-discriminatory auction setup. Our results indicate that under truthful bidding, quantity-weighted average margins would have been lower than under the PAB format in most rounds. In the fixed markup case, the market clearing prices are instead closer to the average PAB prices. Neither of theses results is mechanical, since the marginal bid depends on the convexity of both the cost and bid curves at the intersection with the perfectly inelastic demand curve.

We proceed by calculating the subsidy payments under each auction format. Under UP, subsidies are determined by the market clearing price common to all bidders, while under PAB, they are determined by the bids themselves. We show that, depending on the shape of the aggregate bid curve and cost curve, either format may lead to a lower total amount of subsidy payments, necessitating further empirical investigation. Our analysis shows that subsidies under truthful bidding are consistently equal to or lower than those under PAB in almost all auction rounds. The only exceptions to this trend occur in rounds where the margins under uniform pricing are significantly larger or close to those under the PAB format. In the fixed markup case, the subsidy amounts are closer to each other. Detailed summary statistics of the differences in subsidies relative to the PAB setting show that the UP format would have lowered government costs in the early part of the sample period, but this advantage eroded toward the end due in part to the change in the size of the markups.

Finally, as a second counterfactual, we calculate the inverse elasticity resulting from an increase in auction volume. This analysis is motivated by the over-subscription observed in all auction rounds and the fact that governments have updated their policy objectives in recent years, leading to a demand for accelerated technology deployment. Our results indicate that under truthful bidding, a 10% increase in government demand leads to a 1.5% increase in the market clearing price, while under PAB, it corresponds to a 2.8% increase in the marginal price.

Related Literature. We contribute to three main strands of the literature. First, we systematically quantify market power for the procurement of RE capacity in the context of multi-unit auctions and document the factors associated with bid prices and bidder costs. The analysis of multi-unit auctions has long been an active area of research, particularly comparing the efficiency of auction formats such as uniform vs. discriminatory pricing, the latter also referred to as pay-as-bid. While Vickrey (1961) proved that the revenue equivalence theorem holds in single-item auctions, Ausubel et al. (2014) showed that there is no clear ranking of sellers' revenues in multi-unit auctions. Instead, such a ranking is an empirical question that has been addressed mostly in the context of treasury auctions (Kang and Puller, 2008; Cassola et al., 2013; Elsinger et al., 2019) and to some extent in electricity markets.[5]

The development of empirical methods to determine bidders' valuations or, in the case of procurement auctions, bidders' costs, has mostly been done in the field of government bond allocation (Hortaçsu and McAdams, 2010, 2018; Kastl, 2011). Some other applications of these techniques in electricity-related markets include Wolak (2003, 2007), Reguant (2014), Ryan (2021), and Kim (2022). The only application of these techniques to RE auctions that we are aware of is Ryan (2021), who uses data from solar auctions in India to estimate a structural model, focusing on the role of counter-party risk in procurement. In comparison to his work, our paper aims to analyze the importance of auction design and the factors that influence bidding behavior in an environment with virtually no default risk. While solar technology is well-established in Germany (thanks to generous policy support since the early

[5] There is also a strand of mostly theoretical literature that examines the electricity generation sector to compare the two auction formats. Federico and Rahman (2003) found that, under certain conditions, market power is higher in a UP auction than in a PAB auction. Holmberg (2009) uses a supply function approach to obtain comparisons. Fabra et al. (2011) builds on a duopoly model with investment and finds that PAB leads to lower prices than the UP auction while keeping capacity fixed. Willems and Yueting (2023), show that PAB auctions are inefficient in the context of electricity generation because they incentivize a portfolio mix without sufficient base load capacity. In contrast to this literature, our paper examines procurement and therefore capacity is not fixed.

2000s), we show that even in this market, fundamentals evolve, and different types of bidders may respond heterogeneously to shifting policy paradigms.

Second, we extend the model for multi-unit auctions mentioned above to estimate costs from supply schedules instead of valuations from demand curves in a setting with discounted future payoffs. The latter captures the net present value of the stream of uncertain future payments, the sliding premia over the lifetime of the project. We consider a setting with both independent private values and common price expectations, similar to Gupta and Lamba (2023) in the context of treasury auctions.

Finally, we contribute to the literature evaluating auction designs in the RE context. The question of how to best design auctions has been studied empirically, but only for auctions that run for a short period of time and rarely by considering the impact of design elements on different market factors (Winkler et al., 2018; Matthäus, 2020; Fabra and Montero, 2023). Several studies on RE auctions have highlighted a lack of empirical evidence on the effectiveness of auctions in reducing support costs and efficiently selecting producers (see Del Río, Pablo and Kiefer, Christoph P., 2023, for a review), mostly due to the general unavailability of detailed bid-level auction data in this context, a limitation that this paper circumvents. In the absence of robust empirical studies, the literature on RE auctions refrains from making conclusive arguments about the performance of auctions, but rather argues that performance, both in terms of deployment and efficiency/cost, depends on the level of competition and the specific choice of eligibility criteria and bid bonds (e.g., Bayer et al., 2018; Matthäus, 2020; Anatolitis et al., 2022). On the other hand, the evidence on the impact of RE auctions on market concentration and bidder diversity is mixed. Our analysis highlights that factors such as the size of bidders are strongly correlated with bidding behavior.[6]

The rest of this paper is structured as follows. Section 2 introduces the German RE

[6]Grashof (2019) argues that auctions are likely to disadvantage smaller bidders, which would discourage policy acceptance and risk capacity expansion. However, Batz Liñeiro and Müsgens (2021), focusing on winning projects in German solar auctions, find no apparent difference in the level of support between large and small bidders.

auctions, while Section 3 describes the data. Section 4 presents the structural model for multi-unit auctions used to recover bidders' costs and the regression framework to decompose bid prices and costs. Finally, Section 5 presents counterfactuals regarding the auction format and Section 6 concludes.

2 Institutional Background

In 2015, the German government introduced auctions for large scale solar projects to steer capacity additions and to reduce subsidy payments.[7] Moreover, the *Renewable Energy Act* (*EEG*, for its letters in German) explicitly aims at maintaining a diverse actor landscape in the German solar market, which is deemed necessary for the acceptance of the energy transition (Bundesregierung, 2014). While 2015 and 2016 were considered the initial pilot phase, auctions became mandatory for large scale solar with the 2017 reform of the EEG in line with EU regulation.

The renewable energy targets, defined by the EEG, are converted into a fixed auction volume and distributed over several rounds per year. As the pilot phase was considered successful, the government increased the annual volume demanded by making the auctions more frequent. Bidders with solar projects above 100 kilowatt (kW) (since 2017 restricted to $\geq$ 750 kW) and below 20 megawatt (MW) are invited to submit one quantity-price bid per project, but are not restricted on the number of projects (bids) they supply. All formally eligible bids are ranked according to their bid price and awarded until the cumulative volume exceeds the auction volume of the round. In general, the auction applies discriminatory pricing (pay-as-bid). Exemptions are the second and third auction rounds (both in 2015) in which awarded projects received the bid price of the last accepted bid (uniform pricing). The ex-post subsidy payments depend not only on the bid price, but also on the realized market

[7] Furthermore, the government was aiming to overcome information asymmetries which, in the past, led to support levels that were considered as 'too high' creating unforeseen capacity additions in 2009 to 2012, or that were considered as 'too low' leading to fewer than expected installations in 2013 to 2015 (see also Online Appendix O.3).

value of solar, as described below. Finally, German RE auctions are generally technology-specific, i.e., there is a specific auction for solar and another one for wind. Yet, several auction rounds from 2018 onwards have been run as joint auctions in which solar and wind were allowed to bid simultaneously.[8] The auctions are implemented by the Federal Network Agency, which however does not have significant power to alter the auction rules despite adjusting the ceiling prices in line with the provisions in the law (Tiedemann et al., 2019). Appendix Table A.1 lists the auction dates, volume, and the price ceilings per auction round. Online Appendix O.3 provides additional details on specific auction rules that apply only to a subset of rounds.

Bid eligibility and obligations. Bids are eligible as long as they are below the published ceiling price. Also, bidders need to submit proof of having advanced in the planning process of the project and submit a bid bond.[9] The bid bond depends on the volume of the bid and the planning status of the project: bids in the initial planning phase need to pay (or show proof of a bank security over) 50 €/kW, bids for projects that are developed further need to pay only 25 €/kW.[10] The main purpose of the bid bond is to discourage spontaneous bidders in the auction. Successful bids have 24 months to realize the projects, otherwise the total security is withheld. Furthermore projects that are commissioned later than 18 months after the auction date get a bid price deduction of 0.3 €-cent/kWh. Note that projects are location and bidder specific. Won projects can therefore not be resold on a secondary market and if a project changes its location a penalty of 0.3 €-cent/kWh applies.

Subsidy payments. The subsidy is a direct payment for every unit of electricity produced. The EEG guarantees that the transmission system operator provides a monthly payment to

[8]During our sample period, wind bids in these auctions were not competitive and solar was the single winning technology. We therefore exclude wind bids from our analysis.

[9]Contrary to many international auction designs (Del Río and Kiefer, 2021), no restrictions in terms of size and capabilities of the firm or the level of experience apply.

[10]Note that in practice the bid bond is split in two: upon submitting the bid, bidders have to pay/show proof of 5 €/kW. Only successful bids need to increase the security within three weeks after receiving notice of their success to the full amount.

the investor for a period of 20 years after the project has been connected to the grid. The EEG defines the payment as the bid price reduced by the monthly average of hourly revenue on the wholesale electricity market by all solar plants in Germany, i.e., the monthly market value or average *capture price of solar*.[11] In the literature on RE support schemes this subsidy design is called a *sliding market premium* (e.g., Klobasa et al., 2013) or more recently *one-sided contract for difference* (e.g., Beiter et al., 2021). Specifically, the subsidy is defined as

$$\text{subsidy}_{i,t} = \begin{cases} b_i - cp_t & \text{if } b_i > cp_t \\ 0 & \text{if } b_i \leq cp_t \end{cases} \tag{1}$$

where $\text{subsidy}_{i,t}$ is the payment per unit of electricity in month t to bidder i, b_i is the bid price (or the award price for rounds with uniform pricing), and cp_t is the average capture price of solar in month t.

This subsidy design effectively guarantees a minimum revenue for the production and thereby shields bidders from the long-term risk of low wholesale prices. Since the bid price is not indexed to inflation, the significance of the insurance effect reduces over the years.

3 Data and Descriptive Statistics

Our data consist of all bids submitted to solar auctions in Germany held between the introduction of the German RE auctions in 2015 and June 2019, covering 18 auction rounds with a total of 1,791 bids.[12] We focus on solar installations only and exclude the 19 bids for wind projects in auctions where both technologies were admissible.[13] If not otherwise mentioned, we exclude non-eligible bids which make up 11% of the total number of obser-

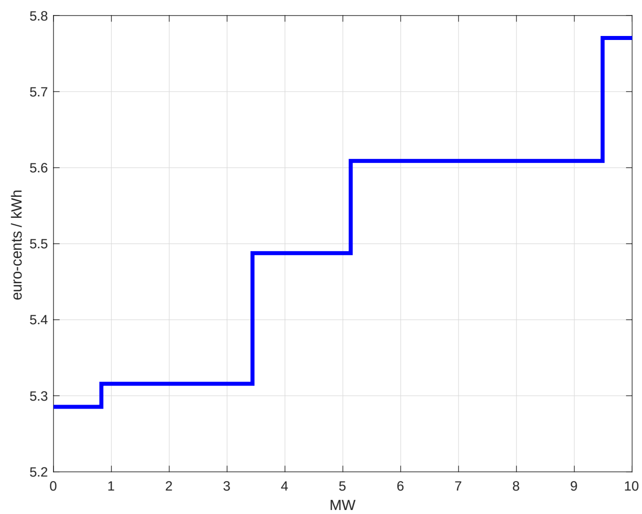
[11] The transmission system operator calculates the monthly capture prices and publish them online `https://www.netztransparenz.de/EEG/Marktpraemie/Marktwerte`.

[12] The bidding data are anonymized, but given identifiers we are able to follow individual bidders over time. We would like to thank the Federal Ministry of Economic Affairs and Energy for making these data available for research.

[13] Note that in the three auction rounds that were implemented as joint solar and wind auctions solar was the single winning technology.

vations. Moreover, we exclude the first auction round (132 observations) from our analysis, as bidders did not have any previous experience in participating in these type of auctions. Our final dataset consists of 1,441 individual bids, of which 235 belong to the two uniform auction rounds held in August and December 2015, and 1,206 observations belong to PAB auctions (April 2016 through June 2019). A common feature of multi-unit auctions is that bidders are not restricted to submit a single bid in the auction. Figure 2 shows an example of a bidding curve of a bidder that submits multiple projects. The dataset reveals that there is a wide variety of bidding patterns across firms and across time periods.

Figure 2: An example of a bid curve



Notes: Example of a bid curve of a bidder that submits multiple projects. We omit the bidder indicator as well as the round number in order to comply with the anonymization of the data. In this case, there are five different quantity-price pairs (bids) submitted by this bidder.

Table 1 summarizes our data pooling all observations first and then splitting the sample into subgroups: the initial UP rounds and the three periods in our main estimation sample for PAB rounds, defined whether the average winning bid prices are above or below the average system costs (see Figure 1). In addition to the bid related variables (bid value, bid volume, land type, and location), we match information on average system costs, solar irradiation, distance to the nearest high-voltage network node, and define an indicator variable for large bidders, that is based on the size of the projects submitted.[14] We elaborate on the data sources and construction of these covariates in Online Appendix O.1.

Table 1 also shows that there were some differences between the initial UP rounds and the PAB rounds. Submitted bids in the former were only admissible if they were located adjacent to railway or roads or sites with previous usage and hence the average project size (bid volume) is slightly smaller. At the same time, more bidders have been active in the first auction rounds with a larger number of total bids submitted, leading to lower market concentration measures.[15] On the other hand, the summary statistics show that in the PAB rounds, Period 2 (when the average winning bid prices were below the average system costs) exhibits some noticeable differences relative to the rest of the PAB auctions. In particular, we find that the average project size (bid volume) was slightly larger in line with the fact that there were more bids allowed on agricultural land. We also find that during this period the share of large bidders was higher and that the market was much more concentrated, as indicated by the HHI and C1-C3 indices. Projects were otherwise similar in terms of average solar irradiation and distance to nearest high-voltage network node.

To get a better sense of how competition evolved over time, Figure 3 shows the evolution of the number of bidders, the degree of over-subscription (defined as the ratio of bid volume to auction volume), as well as the HHI and C3 indices for individual auction rounds. While there is some variation in the number of bidders and the volume provided in each auction, all auction rounds have been over-subscribed.[16]

[14] We define large bidders on the ex-post distribution of average project sizes by bidder, using the 90th percentile over all rounds. This classifies 22 out of 202 bidders as "large". The average number of bid steps (std. dev.) is 4.19 (5.52) for large bidders, and 1.97 (1.79) for small bidders, respectively. In the Online Appendix we perform a robustness check concerning the definition of large bidders.

[15] We report C1 to C3 as well as the Herfindahl-Hirschman Index (HHI). C3 is the sum of the submitted capacity shares of the three largest bidders by capacity size in a given round. Similarly for C1 (largest) and C2 (two largest). The HHI is defined as the sum of the squares of the submitted capacity shares in a given round.

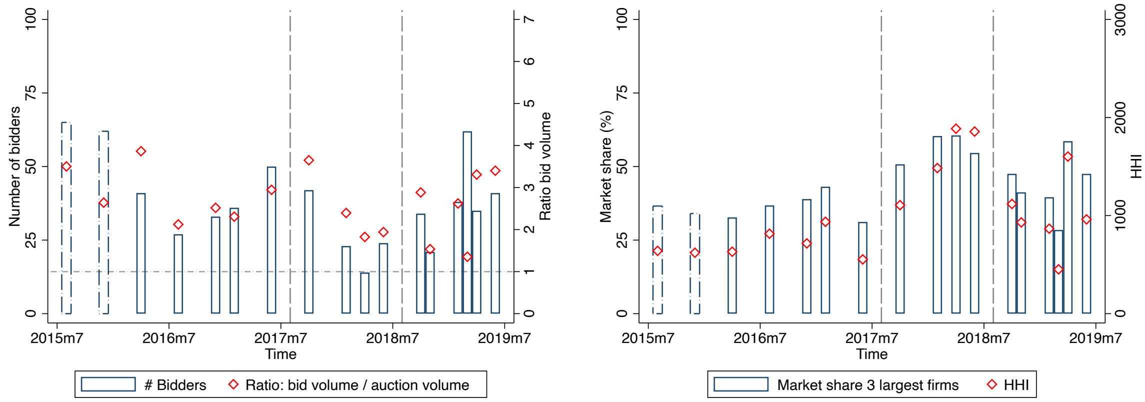
[16] Moreover, the stipulated ceiling price (see Appendix Table A.1) has not been binding in solar auctions. This is an important difference to other RE auctions held during the same time period, e.g., for wind technology, which have been under-subscribed.

Table 1: Summary statistics - German solar auctions

	All	UP	PAB		
			Period 1	Period 2	Period 3
Bid value (€-2019 c/kWh)	6.80	8.78	7.47	5.14	6.19
	(1.58)	(1.23)	(1.02)	(0.55)	(1.15)
Bid volume (MW)	5.68	4.48	5.25	6.95	5.94
	(5.93)	(2.99)	(3.25)	(7.23)	(7.52)
System cost (€-2019 c/kWh)	5.39	6.33	5.79	5.23	4.72
	(0.66)	(0.28)	(0.34)	(0.29)	(0.20)
Solar irradiation (kWh/m^2)	1096.93	1095.30	1093.49	1101.99	1097.92
	(43.98)	(42.30)	(39.85)	(45.47)	(46.86)
Distance to network (km)	20.39	20.29	21.47	19.41	20.06
	(11.26)	(11.95)	(11.37)	(10.49)	(11.19)
Land types (share):					
- Agriculture or grassland	0.22	0.00	0.17	0.38	0.28
	(0.41)	(0.00)	(0.38)	(0.49)	(0.45)
- Non-conventional buildings	0.11	0.00	0.10	0.15	0.15
	(0.31)	(0.00)	(0.29)	(0.36)	(0.36)
- Government land	0.07	0.00	0.06	0.06	0.12
	(0.26)	(0.00)	(0.24)	(0.23)	(0.33)
- Adjacent to railway or road	0.30	0.44	0.28	0.21	0.30
	(0.46)	(0.50)	(0.45)	(0.41)	(0.46)
- Site with previous usage	0.29	0.56	0.39	0.20	0.15
	(0.46)	(0.50)	(0.49)	(0.40)	(0.35)
1(large bidder, project size)	0.22	0.19	0.17	0.39	0.17
	(0.41)	(0.39)	(0.38)	(0.49)	(0.38)
Share of eligible bids	0.91	0.89	0.88	0.92	0.92
	(0.05)	(0.01)	(0.04)	(0.09)	(0.05)
# bids per round	84.76	117.50	84.00	64.75	87.83
	(29.43)	(4.95)	(23.63)	(28.27)	(32.85)
# bidders per round	38.12	63.50	37.40	25.75	38.50
	(14.83)	(2.12)	(8.68)	(11.73)	(13.40)
# bidders awarded per round	16.29	21.50	12.60	11.75	20.67
	(10.74)	(6.36)	(1.52)	(2.22)	(17.10)
HHI	1010.75	630.98	730.82	1583.71	988.64
	(446.59)	(13.47)	(150.81)	(366.76)	(374.20)
C1, bid volume per round (%)	23.38	18.44	19.33	32.26	22.47
	(7.81)	(0.09)	(3.60)	(7.77)	(7.65)
C3, bid volume per round (%)	43.69	35.31	36.56	56.60	43.83
	(10.41)	(1.80)	(4.82)	(4.77)	(10.07)
C5, bid volume per round (%)	55.39	44.86	47.93	68.57	56.33
	(11.27)	(3.56)	(5.81)	(6.58)	(10.52)
Observations	1,441	235	420	259	527
Number of auction rounds	17	2	5	4	6

Notes: Individual bids from German solar auctions held between August 2015 and June 2019. The data exclude the first auction round held in April 2015 and non-eligible bids. Uniform price (UP) auctions: August and December 2015. Pay-as-bid (PAB) auctions: April 2016 - June 2019. Period 1 covers auction rounds 4 to 8, Period 2 includes rounds 9 to 12, and Period 3 includes rounds 13 to 18. See Appendix Table A.1 for a detailed overview of each auction rounds.

Figure 3: Evolution of competition in German solar auctions



Notes: Number of bidders per auction round and ratio of bid volume to auction volume in the left panel. Market share of three largest firms (C3) and Herfindahl-Hirschman Index (HHI) in the right panel. UP auction rounds represented in dash-dotted lines.

4 Empirical Strategy

In the following section we adapt a model of multi-unit auctions to the context of RE procurement with a stream of future subsidy payments. We build on Hortaçsu and McAdams (2010) and Kastl (2011) who develop an empirical method to estimate valuations in multi-unit auctions based on Wilson (1979), taking into account the discreteness of bids. We use the model to recover costs that we employ in a second step to analyze observed bidding behavior. In Section 5, we then quantify the effect of the auction format on bidders' margins and total subsidy payments.

4.1 Bidding Model for Multi-unit Auctions

Model set-up. There are R auction rounds indexed by τ, where each auction is a discriminatory auction of Q_τ divisible units (total solar capacity demanded by the government). In each individual auction round $\tau = 1, \ldots, R$, there are N_τ bidders. As in Kastl (2011), we allow for bidder asymmetries by introducing G different groups of bidders, denoted by g, such that $N_\tau = \sum_{g=1}^{G} N_\tau^g$. Bidders are assumed to be symmetric conditional on belonging to group g. Otherwise, bidders are risk-neutral with independent private values (IPV). Similar to the context of treasury-bill auctions (e.g., Hortaçsu and Kastl, 2012; Elsinger et al., 2019), we claim that IPV is a good assumption in the context of RE auctions, as it can be argued that firms have idiosyncratic shocks to the project cost (e.g., land cost, financing, etc.).[17] However, as there is a common payoff uncertainty resulting from the evolution of the capture prices, we model this additional component as in Gupta and Lamba (2023). The main differences in our setting relative to the aforementioned literature is that firms face residual demand curves instead of residual supply curves and bidders maximize the expected net present value (NPV) over the lifetime of the projects.

Assume that each firm has a cost $c_i(q_{i,k}, s_i)$ that is increasing in s_i, the private signal, which is independent and identically distributed across bidders and auctions and $q_{i,k}$, the k-th quantity segment bid by firm i. Note that we dropped the auction index τ to improve readability. The firm submits the non-decreasing supply schedule

$$y_i(p; s_i) = \sum_{k}^{K_i} q_{i,k} \mathbb{1}[p \in (b_{i,k}, b_{i,k+1}]]$$

that consists of a step function where each step k has for length the quantity offered $q_{i,k}$, for height the price offered $b_{i,k}$, and K_i is the number of steps of bidder i's submission.[18]

Payoff under pay-as-bid payment rule. The total expected NPV over the lifetime of the projects in the supply curve taking into account the subsidy scheme in each time period under PAB is

$$E\Pi_i(s_i) = E_{cp_t, s_i|s_{-i}} \int_0^{Q_i(\boldsymbol{y}^{-1}(\cdot;\boldsymbol{s}))} \pi_i \; dq_i$$

[17]A similar assumption is made in Ryan (2021), who studies solar investment in India.

[18]We assume that bidder i submits bid b_i which is associated to the cumulative quantity q_i (both vectors of size K_i), where $1 \leq k < K_i$, $q_{i,k} < q_{i,k+1}$, and $b_{i,k} < b_{i,k+1}$. Bidders' actions therefore include choices regarding the bid value and the quantity (project size).

where

$$\pi_i = \sum_{k=1}^{K_i} \left[\sum_{t=13}^{T=252} \underbrace{\delta^t \left[\mathbb{1}(b_{i,k} > cp_t)(b_{i,k} - c_{i,k}) + \mathbb{1}(b_{i,k} \leq cp_t)(cp_t - c_{i,k}) \right]}_{\text{Discounted future profits}} \right] \mathbb{1}(q_{i,k} \leq q_i < q_{i,k+1}) \tag{2}$$

and $Q_i(\boldsymbol{y}^{-1}(\cdot; \boldsymbol{s}))$ is the total quantity awarded to bidder i as a function of the other bidders' supply curves and their private signals. Expectations are also drawn with respect to the capture price. Note that the total auction volume is pre-announced and therefore known to the bidders ex-ante. The discounted future profits term includes a monthly discount rate $\delta = 0.83\%$[19] and two possible revenues determined by the policy: either the subsidy is active because the capture price cp_t is too low or the producer receives cp_t, according to Equation 1. We include uncertainty about the common price component, cp_t, by considering the combination of discretized levels of growth paths and levels of volatility and then take the average over the equilibrium outcomes for each of those scenarios (Gupta and Lamba, 2023).[20]

To implement the model empirically, we need to make additional assumptions about the timing when the solar plant is built and starts to produce electricity as well as the evolution of the capture prices that are relevant for the ex-post auction payoffs. In line with the data, we assume that the solar plants are being built one year after the auction date, which means that they start producing at 13 months. Profits are guaranteed for 20 years, the policy horizon.[21] Moreover, we assume that the expectations concerning the evolution of the capture price

[19] This is equivalent to an annual discount rate of 10% as in Ryan (2021). We justify the discount rate by a 3% social discount factor for public projects as it is commonly used in Europe and 7% capital depreciation. The capital depreciation takes into account solar panel deterioration, but also other factors such as maintenance and operation costs, insurance, and replacement investment for sub-components, e.g., inverters.

[20] In addition to the NPV setup presented here, Online Appendix Section O.2.1 develops a version of the multi-unit auction model without future payoffs and no common uncertainty, confirming our main findings.

[21] Time to build is not exactly the same for all projects. There are a few installations built within three months after the auction date and several are completed only after 18 months. Yet, the 12 month span is representative of this distribution, and in addition, we do not observe all plants completion date. Therefore, we abstract from uncertainty on this parameter and assume it fixed at 12 months.

(cp_t) are common to all bidders and evolve according to the following equation:

$$Ecp_t = cp_0 \times \phi_t \times \sigma_t$$

where cp_0 refers to the price level of the capture price in the year of investing, ϕ_t is a time trend (with both linear and quadratic terms), and σ_t is the expected volatility. The assumption about the common beliefs for the future payoffs can be justified by the fact that project developers need to forecast the capture price at a monthly frequency for a 20 year period. Typically, these market forecasts are available from professional associations or for-profit businesses and are based on model predictions about future states of the electricity market, as well as long-term policy scenarios. As we do not have information on individual cp_t forecasts, we calibrate the expectations in line with observed price levels and volatility at the time of investment and make some assumptions on expected price growth and increase in volatility over time based on government reports and policy documents. To account for uncertainty, we consider different price and volatility levels relative to the baseline scenario, over which we aggregate. Further details on the modeling of the capture price can be found in Online Appendix O.3.3.

Recovering costs. We can group the terms inside the square brackets of the profits expression in Equation 2 by whether the subsidy is active or not,

$$\sum_{k=1}^{K} \underbrace{\left(\sum_{t|b_{i,k}>cp_t} \delta^t (b_{i,k} - c_{i,k}) + \sum_{t|b_{i,k}\leq cp_t} \delta^t (cp_t - c_{i,k}) \right)}_{\equiv \pi_{i,k}} \mathbb{1}(q_{i,k} \leq q_i < q_{i,k+1}).$$

If the bidder knew the capture price with certainty, she could calculate both sums in $\pi_{i,k}$. We take this approach and present the optimality conditions for a given realization of the capture price. Therefore, there is a numerical expectation taken over all the recovered costs as a final step. The two sums represent the NPV of one unit of capacity installed aggregated over all the steps from bidder i's submission. We further group those terms as follows:

$$\begin{aligned}
\pi_{i,k} &\equiv \sum_{t|b_{i,k}>cp_t} \delta^t (b_{i,k} - c_{i,k}) + \sum_{t|b_{i,k}\leq cp_t} \delta^t (cp_t - c_{i,k}) \\
&= b_{i,k} \sum_{t|b_{i,k}>cp_t} \delta^t - c_{i,k} \sum_{t=13}^{T=252} \delta^t + \sum_{t|b_{i,k}\leq cp_t} \delta^t cp_t \\
&= L_{1,k}(cp_t, b_{i,k}) b_{i,k} - L_2 c_{i,k} + L_{3,k}(cp_t, b_{i,k})
\end{aligned}$$

where

$$\begin{aligned}
L_{1,k}(cp_t, b_{i,k}) &= \sum_{t|b_{i,k}>cp_t} \delta^t, \\
L_2 &= \frac{\delta^{13} - \delta^{T+1}}{1-\delta}, \\
L_{3,k}(cp_t, b_{i,k}) &= \sum_{t|b_{i,k}\leq cp_t} \delta^t cp_t,
\end{aligned}$$

and only $L_{1,k}$ and $L_{3,k}$ are functions of the time series of capture price forecasts and of the bid step. To recover the cost $c_{i,k}$ we extend the perturbation argument in Kastl (2011, 2012) for optimal bidding to our empirical setting.[22] In particular, there is a set of necessary conditions for each step k at which the estimated cost is continuous in q given by Equation 3 below. While the market clearing price $p_c(\boldsymbol{y}(\cdot;\boldsymbol{s}))$ is a function of all the submitted bid schedules and the signals, we omit these dependencies in what follows to improve readability, the optimality condition is:

$$\begin{aligned}
\underbrace{\Pr(b_{i,k} < p_c < b_{i,k+1})}_{\equiv M_1} \pi_{i,k} &= \underbrace{\Pr(b_{i,k+1} \leq p_c)}_{\equiv M_2} (L_{1,k+1}(cp_t, b_{i,k+1}) b_{i,k+1} - L_{1,k}(cp_t, b_{i,k}) b_{i,k} \\
&+ L_{3,k+1}(cp_t, b_{i,k+1}) - L_{3,k}(cp_t, b_{i,k})), \qquad (3)
\end{aligned}$$

where $L_{1,k+1}(cp_t, b_{i,k+1}) = \sum_{t|b_{i,k+1}>cp_t} \delta^t$ and similarly for $L_{3,k+1}(cp_t, b_{i,k+1})$. From that expression we can solve for $c_{i,k}$,

$$c_{i,k} = \frac{1}{L_2} \left[L_{1,k} b_{i,k} + L_{3,k} - \frac{M_2}{M_1} (L_{1,k+1} b_{i,k+1} - L_{1,k} b_{i,k} + L_{3,k+1} - L_{3,k}) \right]. \qquad (4)$$

[22] In Online Appendix Section O.2.1, we also present a version of this model without considering future payoffs.

Equation 3 describes the trade-off that a bidder is facing at each step k regarding potential gains and losses from offering a lower quantity $q_{i,k}$. The argument is as follows. Assume that the market clearing price $p_c(\boldsymbol{y}(\cdot;\boldsymbol{s}))$ occurs at a vertical segment of the individual supply curve. Then, by reducing the quantity by a small amount, bidder i losses $\pi_{i,k}$ times the small reduction in quantity and only if the price is indeed between the k-th and the $k+1$-th steps (given by $\Pr(b_{i,k} < p_c < b_{i,k+1})$). This shift of the supply curve to the left makes the step $b_{i,k+1}$ marginal and brings gains of $b_{i,k+1} - b_{i,k}$ in every time period where the subsidy is active, i.e., $b_{i,k+1} > cp_t$, as long as the new clearing price is at least $b_{i,k+1}$. This occurs with probability $\Pr(b_{i,k+1} \leq p_c)$. Those gains must be properly weighted by the functions $L_{1,k}$ and $L_{3,k}$ only, since L_2 is a constant. Note that in time periods where $b_{i,k+1} \leq cp_t$, the firm gets paid the capture price on all its inframarginal units regardless of the cost level. If losses and gains from bid shading are not equalized, then there exists a potential deviation in the bid schedule that leads to higher expected payoffs, so the bidding strategy cannot be optimal.

The payoff function for the uniform auction rounds is different since it directly depends on the uniform market clearing price. To estimate costs under the uniform auction rules, we develop a net present value formula in Online Appendix Section O.2.2 that extends the single-period expression found by Kastl (2011, 2012).

Equilibrium. The set of all supply schedules in $\boldsymbol{y}(p;\boldsymbol{s})$ is a Bayesian Nash equilibrium if each firm i maximizes its expected value of Π_i. Finally, the horizontal sum of other bidders' supply curves ($\sum_{j\neq i} y_j(p;s_j)$) and the total demand for solar installations (Q) determine the residual demand RD_i faced by bidder i:

$$RD_i(p;s_i) = Q - \sum_{j\neq i} y_j(p;s_j).$$

The intersection of $RD_i(p;s_i)$ with $y_i(p;s_i)$ for each i gives a market clearing price denoted by p_c.

4.1.1 Estimation

We use a non-parametric estimator for resampling bids based on Hortaçsu and McAdams (2010) and Kastl (2011). To relax the symmetry assumption in the model, we separate bidders into two groups $G = \{1, 2\}$ based on size and assume symmetry only within each of the groups. We define a large bidder as a bidder whose cumulative submitted capacity over the entire sample period is in the top ten percentile of the distribution of all bidders. This separation is correlated and statistically significant with bid values (see Appendix Table A.2). We also tried alternative definitions of size with similar results.[23] For a given round, let N represent the number of bidders. For each bidder in the round, we implement the following steps.

1. Fix bidder i from group $g \in G$ and its observed supply schedule $\{b_{i,k}\}$.
2. From the n_g bidders in group g, draw a random subsample of $n_g - 1$ bid vectors with replacement, assigning a weight of $1/n_g$ to each bid vector from group g.[24]
3. Repeat the previous step for the other group $h \in G \setminus \{g\}$, drawing n_h bid vectors, assigning a weight of $1/n_h$ to each bid vector from group h.
4. Construct bidder i's realized residual demand $RD_i(p; s_{-i})$ to determine the realized market-clearing price.

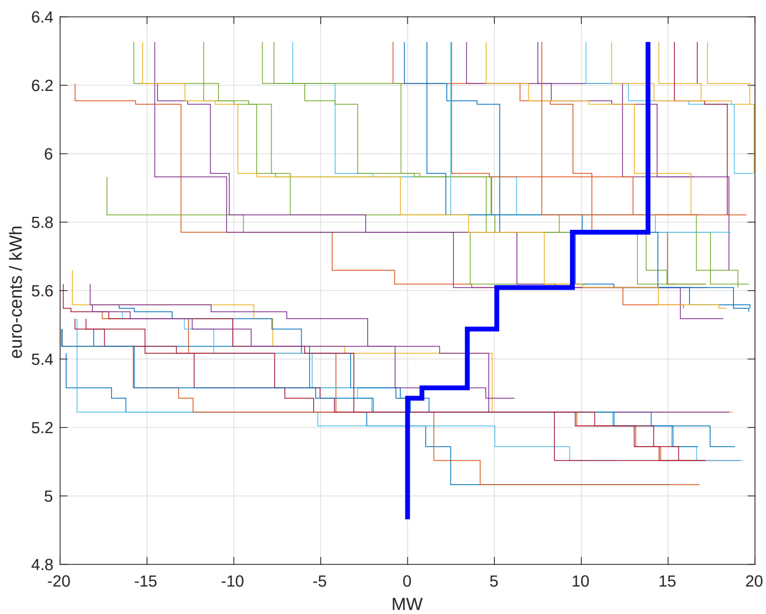
By repeating the above steps several times, we obtain a sample of market clearing prices, which can then be used to consistently estimate each bidder's winning probability using Equation 3. At each step, we obtain several residual demand curves, each intersecting one of

[23] In particular, we define bidders as large in case they submit more than two bids on average over all auction rounds in which they participate. The results are presented in Online Appendix O.4.3 and Figure O.5 shows the results when assuming symmetry across all bidders.

[24] Unlike the literature that uses this algorithm for treasury auctions, we resample only from within the same round since rounds can be different one from another in several dimensions, e.g., number of competitors, the volume requested by the government, and by the expectations on future electricity prices. Online Appendix Figure O.6 provides robustness for our results, pooling several rounds based on a three-dimensional kernel and confirms our main findings.

the observed supply curves, as shown in Figure 4. Each of those intersections gives a value for the price that can be used to evaluate the ratio in Equation 3, which in turn allows us to obtain the cost for each of the steps in the bid function. In a few cases, the recovered costs are negative or do not exist if the denominator is numerically very small.[25] In those cases we impute the cost with the observed bid price, thus artificially imposing a zero margin in those cases and potentially underestimating market power. In Section 4.2 we discuss how this imputation of values does not represent an important difference in the results when compared to a restricted sample of non-imputed values.

Figure 4: Simulated residual demand curves and observed supply schedule



Notes: Each residual demand curve is obtained using a random sub sample of bid vectors with replacement. Each intersection results in a market clearing price.

4.1.2 Costs estimates

We present the kernel densities of the estimated costs in Figure 5 together with the kernel densities of the observed bids for the UP rounds (Panel a) and each of the three periods in

[25]As there is a non-negligible number of bidders with single bids ($k = 1$), we smooth the resulting distribution of market clearing prices to ensure that the resulting probabilities exist.

PAB (Panels b to d). To do so, we aggregate individual bids and costs by bidder and period using quantity-weighted averages. The density of costs is shifted to the left relative to the density of the observed bids due to the existence of profit margins and that of market power. Interestingly, Panel (a) shows that the median bid and cost estimates are relatively close in the uniform auction rounds 2 and 3.[26] Yet, the gap widens considerably under PAB in Period 1 (auction rounds 4 to 8). Nevertheless, we find that also under this auction format the overall probability mass for both distributions shifted to the left in Periods 2 and 3 relative to Period 1.

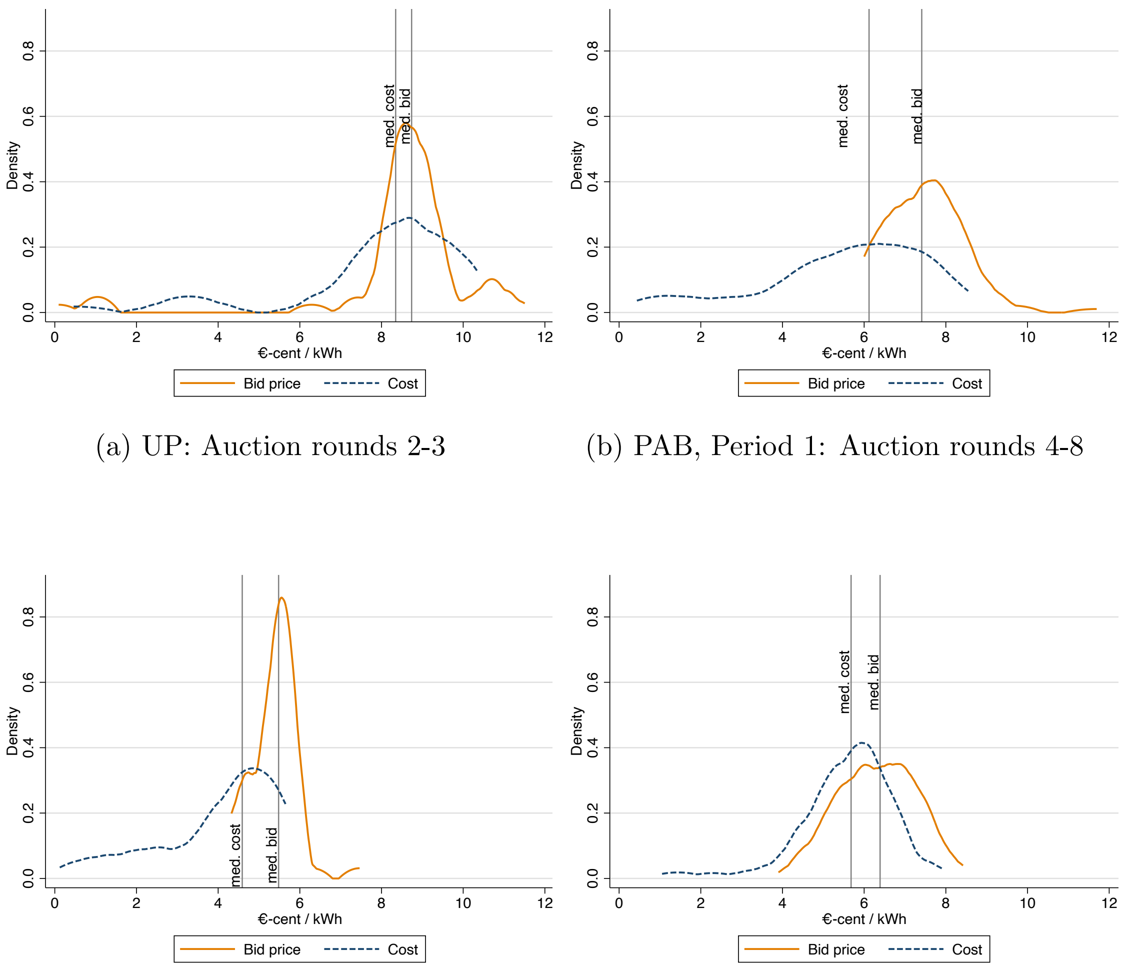
In Figure 6 we plot the densities of the margins $(b_i - c_i)$ for UP and the three PAB periods separately. Under PAB, Period 1 has the largest margins among the three while Periods 2 and 3 have very similar densities that are also aligned with the UP rounds. The median margins for all our estimates are between 0 and 2 €-cent/kWh, which are in line with the vertical difference between bid prices and system costs shown in Figure 1. This is a remarkable result since no information on costs was provided as an input to the structural model. The estimated costs are recovered by inverting the optimality condition using only the observed bids as inputs.

4.2 Analyzing Bidding Behavior

To analyze market participants' bidding behavior more in detail, in this section we examine the correlation between auction outcomes and a rich set of *bid* and *market characteristics* focusing on the PAB auction rounds 4 to 18. In particular we test whether the estimates of cost and the bids differ for bidders of different size, whether the probability of winning is related to size and costs, and the correlation to the distance from the electricity network. We estimate several different versions of linear models of auction outcomes on a variety of controls and combinations of land-type, state, year, and bidder fixed effects. In all versions

[26] To ensure that this difference is not driven by other time-varying factors, in Appendix Figure A.2, we plot the margins comparing the UP rounds 2 and 3 with the adjacent PAB rounds 4 and 5 only and found a difference in medians of more than 1 €-cent/kWh.

Figure 5: Estimated costs and observed bids densities



(a) UP: Auction rounds 2-3

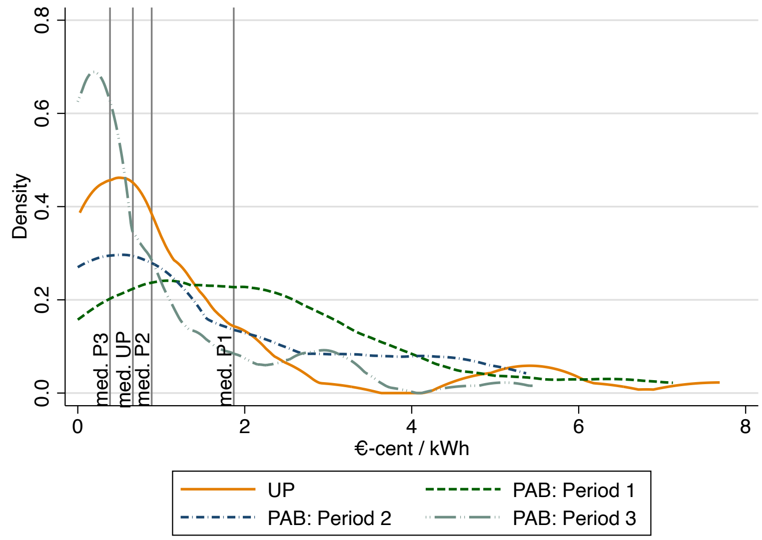
(b) PAB, Period 1: Auction rounds 4-8

(c) PAB, Period 2: Auction rounds 9-12

(d) PAB, Period 3: Auction rounds 13-18

Notes: Kernel densities of the costs obtained from Equation 4 (PAB, panels b to d) and subsection O.2.2 (uniform auction rounds, Panel a). Individual bids are aggregated by bidder and period using quantity-weighted averages.

Figure 6: Margins



Notes: Margins defined as $b_i - c_i$. For each bidder and period, we subtract the average cost from the average bid (quantity-weighted) and plot the result as a kernel density.

of these regressions, standard errors are clustered at the bidder level.

Among the *market factors* we consider is the distance to the nearest high-voltage electricity network node, which is motivated by the market and regulatory concerns regarding the interconnection costs as a barrier of entry for renewable capacity.[27] We also consider an aggregate measure of system costs, solar irradiation, and auction volume.[28] At the *bid level*, we control for the land type and for whether the bidder is "large", according to the aforementioned definition of project size. We also experiment with an alternative definition of size regarding the number of projects submitted, with similar results (see Online Appendix O.4.3).

[27]See for instance Davis et al. (2023). We calculate the distance as the direct line from the centroid of the 5-digit zip code where the solar plant is located and the nearest high voltage network node (see Appendix Figure A.1).

[28]See Section 3 for a detailed data discussion. We include a dummy variable for when the volume demanded by the government exceeded 200 MW. The auction volume was typically between 125 and 200 MW (see Appendix Table A.1). Yet, one auction round had a significantly larger volume of 500 MW. Therefore, we treat this round separately. Results are robust to including the actual auction volume as a regressor instead of a binary variable.

Bidders' costs. Table 2 shows the results from four different specifications where the dependent variable is the estimated cost. The main motivation is to understand in how far the estimated costs reflect aggregate observed costs and market factors.[29] Across all specifications a few patterns emerge. Distance to network and system costs are positively correlated with estimated costs. A higher auction volume leads to higher cost bids being selected (in Columns 1 and 2) and solar irradiation is generally negatively correlated, indicating that more productive sites have lower costs. Finally, developing large projects (large bidder = 1) does not have any significant impact on bidders' costs, indicating that there are no economies of scale for this size class of solar installations. Interestingly, the distance between the solar site and the closest interconnection loses statistical significance once we increase the number of fixed effects. This result speaks to the debate on interconnection costs as a barrier to entry for renewable generation sources in some markets.[30] One possibility is that the network is more dense in this market compared to some of the North American markets where distances are much bigger (Figure A.1). Alternatively, plants might connect to lower voltage network nodes which, are even more densely located than the high voltage nodes.

In general, as we add more fixed effects, most of the observable market and bid factors lose their statistical significance. In our most stringent specification in Column 5, only the coefficient on system costs remains significant (capturing the within-year cost decline of hardware costs), indicating that the estimated cost is not significantly correlated with other bid and market factors once we control for a rich enough set of fixed effects. We are thus confident to use it as an exogenous regressor in the analysis of bid prices, on which we focus next.[31]

[29] The number of observations drops slightly from 1,206 in the original sample to 1,111 since for a few bids we cannot assign an estimated cost. Therefore, we omit these observations from the analysis.

[30] See `https://emp.lbl.gov/queues` for the US markets and Lamp and Samano (2023) for a discussion on interconnection costs in Germany.

[31] It is possible that some of the factors examined in this paragraph are correlated not only with the estimated costs but also with the markups reflected in the bid values. Given that these are not causal regressions, concern about this overlap is unwarranted.

Table 2: DV: Bidders' costs

	(1)	(2)	(3)	(4)
Distance to network	1.237**	1.117**	0.969*	0.529
	(0.483)	(0.480)	(0.518)	(0.548)
System costs	4.886**	4.870**	4.316	5.297*
	(2.137)	(2.104)	(2.687)	(2.745)
1(auction volume > 200MW)	0.624***	0.637***	-0.092	-0.121
	(0.237)	(0.243)	(0.268)	(0.320)
Solar irradiation		-3.752**	-2.849	-0.443
		(1.513)	(2.584)	(3.114)
1(large bidder: size, p90)		0.031	0.170	
		(0.126)	(0.107)	
N	1,111	1,111	1,111	1,111
Adjusted R2	0.03	0.03	0.14	0.24
Mean DV	5.92	5.92	5.92	5.92
Land FE	No	No	Yes	Yes
State FE	No	No	Yes	Yes
Year FE	No	No	Yes	Yes
Bidder FE	No	No	No	Yes

Notes: DV: estimated costs. Regressions include a constant term. System costs represent the aggregate industry price trends for large scale ground-mounted solar in Germany. Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Bid values. In Table 3 we assess whether the observed bid values correlate in an intuitive manner with our estimated costs. In all of our five specifications the coefficient on costs is positive and highly statistically significant. We take this finding as a strong signal that the auction model and the estimates are consistent with economic theory. Columns 1 - 3 suggest a pass-through of between 0.12 and 0.30 €-cent/kWh for a 1 €-cent/kWh in costs. In Columns 4 and 5 we examine whether the pass-through is related to the size of the bidder. While the coefficient on costs decreases only slightly relative to Columns 2 - 3, we find that there is an additional pass-through from large bidders of about 0.21 €-cent/kWh relative to the small bidders. Using Column 5, the total pass-through for a large bidder is about 5% of the mean of bid values.[32]

[32] We provide an alternative fixed effects structure for the main results (Columns 4 and 5) in Appendix Table A.3 including round and bidder fixed effects with largely unchanged results.

The coefficient related to auction volume is not statistically significant. Including auction volume as a control variable in these regressions aims to assess how the cost and bidding curves respond as more volume is requested. It appears that the cost curve is more sensitive to changes in volume compared to the bidding curve. We will further explore this phenomenon in Section 5.3.

Table 3: DV: Bid values

	(1)	(2)	(3)	(4)	(5)
Estimated cost	0.300***	0.120***	0.122***	0.105***	0.094***
	(0.052)	(0.025)	(0.026)	(0.024)	(0.025)
Distance to network			0.512*	0.528*	0.623*
			(0.281)	(0.272)	(0.337)
1(large bidder: size, p90)			-0.449***	-1.681***	
			(0.131)	(0.201)	
1(auction volume > 200MW)			-0.199	-0.206	-0.190
			(0.136)	(0.137)	(0.142)
1(large bidder: size, p90) × cost				0.205***	0.216***
				(0.035)	(0.032)
N	1,111	1,111	1,111	1,111	1,111
Adjusted R2	0.18	0.65	0.67	0.68	0.75
Mean DV	6.50	6.50	6.50	6.50	6.50
Land FE	No	Yes	Yes	Yes	Yes
State FE	No	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes
Bidder FE	No	No	No	No	Yes

Notes: DV: bid values. Regressions include a constant term. Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Heterogeneity of pass-through. Table 4 further decomposes the pass-through over time and bidders size. Columns 1 and 2 contain dummies for Periods 2 and 3 and their interactions with costs plus some additional controls. Relative to Period 1, the pass-through in Period 2 is about the same, but in Period 3 the pass-through is about 0.13 €-cent/kWh higher relative to a mean of bid prices of 6.5 c/kWh, e.g., 2%.

However, that heterogeneity over time masks yet another layer in Column 3. When we interact the bidder size with dummies for Periods 2 and 3, we find that the pass-through is stronger in Period 2, which is the time period when the average of winning bids fell below system costs. In other words, large bidders seemed more skilled than small bidders to navigate a time of unattractive clearing prices and relatively high costs. Yet, this result only holds when we do not include bidder fixed effects. Using the within bidder variation over time (Column 4), we find that large bidders consistently have a larger pass-through, as indicated by the main interaction term for 1(large bidder) $\times$ *cost*.

In order to get a decomposition not only across the three periods exogenously defined by our data but at the round level, we estimate a similar regression to that in Columns 2 and 3 from Table 4 but we interact the cost with a dummy for each auction round. We plot the coefficients (total effects by auction round) from that two-way interaction in Figure 7. The left panel shows the overall results of pass-through by round and the right panel of Figure 7 distinguishes between large and small bidders. While during Period 1, the pass-through was very close to zero – and even turned negative during the first auction round in Period 2 – the overall pass-through stabilized at positive values in Period 3 (with one exception). There has been a clear upward trend over time until the most recent periods, indicating that bids have been more informed by cost towards the second half of our sample. Focusing on the pass-through by bidder type, we see that the aggregate pattern is mostly driven by small bidders. Large bidders do not show this type of variation in pass-through, although individual effects are more noisily estimated and we cannot reject the null hypothesis of equal pass-through in most rounds.

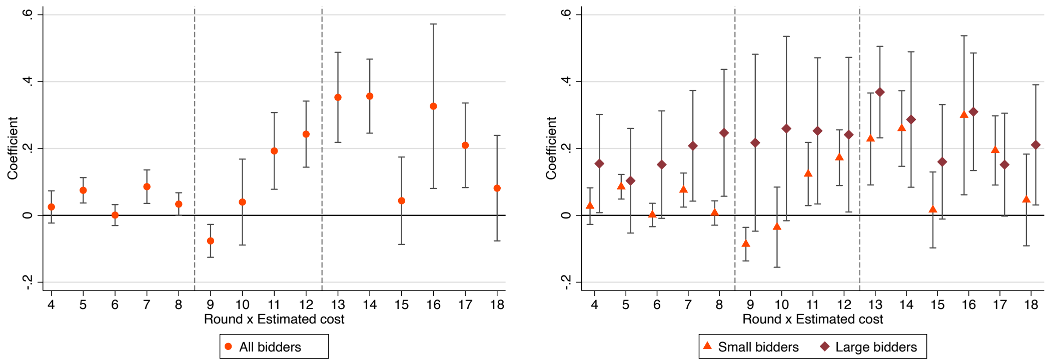
Probability of winning. Finally, we also estimate a linear probability model for the awarded bids. The results, shown in Table 5, confirm the trade-off between a higher bid price and a lower probability of winning (Column 1). Columns 2 - 5 add the rest of controls from the previous regressions but without the bid price since we already examined its correlation with market and bidders characteristics. Bidders' costs are negative and significant in most specifications, indicating that the auction selects lower cost bids. The negative and significant

Table 4: DV: Bid values

	(1)	(2)	(3)	(4)
Estimated cost	0.146***	0.063**	0.062**	0.049**
	(0.029)	(0.025)	(0.026)	(0.023)
1(Period=2)	-1.800***	-0.901***	-0.754***	-0.857***
	(0.263)	(0.165)	(0.151)	(0.181)
1(Period=3)	-2.034***	-1.354***	-1.278***	-1.392***
	(0.557)	(0.359)	(0.388)	(0.469)
1(Period=2) × cost	-0.063	-0.008	-0.031	-0.007
	(0.045)	(0.030)	(0.031)	(0.030)
1(Period=3) × cost	0.160*	0.163**	0.138**	0.134*
	(0.085)	(0.066)	(0.069)	(0.070)
1(auction volume > 200MW)		-0.168	-0.158	-0.128
		(0.130)	(0.133)	(0.138)
1(large bidder: size, p90)		-0.356***	-0.099	
		(0.134)	(0.624)	
1(Period=2) × 1(large bidder)			-1.440**	0.670
			(0.726)	(0.729)
1(Period=3) × 1(large bidder)			-1.451	0.135
			(0.899)	(0.971)
1(large bidder) × cost			-0.030	0.182***
			(0.073)	(0.068)
1(Period=2) × 1(large bidder) × cost			0.234**	-0.109
			(0.091)	(0.131)
1(Period=3) × 1(large bidder) × cost			0.248**	0.030
			(0.113)	(0.123)
N	1,111	1,111	1,111	1,111
Adjusted R2	0.52	0.71	0.72	0.78
Mean DV	6.50	6.50	6.50	6.50
Land FE	No	Yes	Yes	Yes
State FE	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
Bidder FE	No	No	No	Yes

Notes: DV: Bid values. Regressions include a constant term. Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 7: Total pass-through over time and by bidder type



Notes: Coefficients and 90% confidence intervals from the interaction term between bidders' costs and an auction round dummy. Left panel: all bidders. Right panel: splits observations into large and small bidders. The regression controls for distance to network, solar irradiation, system costs, auction volume, and for land-type, state, and year fixed effects. Standard errors clustered at the bidder level.

coefficient on system costs in Column 5 suggests that the auction mechanism selects low-cost projects, which is desirable for overall efficiency. As expected, when government demand increases, the probability of winning increases because more bids end up to the left of the demand curve. A less obvious result is that large bidders are more likely to win in the auctions, even conditional on estimated costs. Yet, adding the interaction term in Column 5 yields a negative and significant coefficient, compensating for the main effect.

4.3 Robustness

We perform several robustness checks for the reduced form regression results to show that the main data patterns hold independently of whether or not we drop all observations from single step bidders (Online Appendix Tables O.1 and O.2), omit all zero margin bids (Online Appendix Tables O.3 and O.4), or keep only the last appearance of each bid to ensure that each bid is contained only once in the dataset (Online Appendix Tables O.5 and O.6). Similarly, Table O.7 - Table O.9 show the main regression tables with the alternative definition of large bidders, based on the number of submitted projects.

Table 5: DV: Bid awarded (yes/no)

	(1)	(2)	(3)	(4)	(5)
Bid price (deflated)	-0.221***				
	(0.019)				
Estimated cost		-0.024**	-0.023**	-0.022**	-0.015
		(0.010)	(0.011)	(0.011)	(0.010)
1(auction volume > 200MW)			0.776***	0.767***	0.816***
			(0.042)	(0.041)	(0.043)
1(large bidder: size, p90)			0.247***	0.250***	
			(0.086)	(0.088)	
Solar irradiation				0.180	0.226
				(0.641)	(0.551)
Distance to network				-0.068	-0.146
				(0.113)	(0.093)
System costs				-1.352	-1.813**
				(0.886)	(0.875)
1(large bidder: size, p90) × cost					-0.071***
					(0.016)
N	1,111	1,111	1,111	1,111	1,111
Adjusted R2	0.16	0.04	0.24	0.24	0.32
Mean DV	0.39	0.39	0.39	0.39	0.39
Land FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Bidder FE	No	No	No	No	Yes

Notes: DV: bid awarded. Linear probability models. Regressions include a constant term. Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In most of the different specifications above, bidder size is statistically significant, this is an indication once again of a potential source of heterogeneity that may violate the symmetry assumption in the structural auction model. However, the results are reasonably similar whether we estimate the model by imposing symmetry across all bidders or whether we separate bidders into two groups by size and draw bidding curves conditional on the size group as explained in Section 4.1.2. We report robustness checks for the estimated margins in Online Appendix O.4.1. We find a large drop for margins in Period 2 compared to Period 1 when assuming symmetric bidders but a less pronounced difference in medians across time periods when allowing to draw supply curves from adjacent rounds using a three dimensional kernel based on the number of bidders, auction round, and volume.[33]

To examine the assumption of independent private signals, we run a regression of the bid prices on publicly available information regarding the auction outcomes of the previous rounds, as well as market and bid-specific factors that are known to the bidders (Appendix Table A.4). We then implement a test on the correlations of residuals between pairs of bidders participating in the same auction rounds. This test follows directly Bajari and Ye (2003).[34] Once the pairwise correlations are transformed into their corresponding z-scores to account for the number of times the two bidders met in the same auction rounds, we obtain a mean value of the z-scores of 0.36 and a corresponding mean of p-values of 0.51, showing that there is no indication that the pairwise residuals are systematically correlated. This test can be also interpreted as no evidence for coordinated behavior of the bidders.[35]

Finally, a similar test can be used to assess the possibility of unobserved auction heterogeneity. To do so, we test for the correlation of average quantity-weighted bid values across auction rounds.[36] We find an average z-score of 2.25, corresponding to a p-value of 0.13.

[33]This result is likely driven by the fact that the kernel does not discriminate between periods and allows for rounds to be merged.

[34]We condition on pairs of bidders that have at least 4 interactions. Bid prices are quantity weighted. This leaves us with a total of 44 bidders and 332 observations.

[35]While there is no general test for collusive behavior in multi-unit auctions, we interpret the fact that bid price residuals are uncorrelated together with the descriptive statistics in Section 3 as evidence against coordinated firm behavior.

[36]We thus mimic the data structure of the structural estimation, where we are treating each auction round

Even with the unconditional data on bid values, we thus cannot reject the null hypothesis of independent bid values.

5 Counterfactual Analysis

We use the structural model to study two counterfactuals. First, we address a long-sought question in economics: how do the outcomes from a pay-as-bid auction compare to those from a uniform auction? Given the lack of theoretical results to rank these two auction designs in multi-unit auctions, our estimates allow us to provide an empirical answer to that question in the present context. This question is also motivated by the actions of the policy maker, who in rounds 2 and 3 experimented with a non-discriminatory auction format. We compute subsidies under each auction format and discuss the effects of the policy parameter that defines the subsidy payments itself: the capture price. Second, we study the supply responsiveness to changes in government demand.

5.1 Auction Format and Size of Subsidies

To test for the impact of the auction format, in a first approximation, we set the bids equal to the estimated costs as the bidders' strategies to simulate a uniform auction format and call this the *truthful bidding* benchmark. This is the equivalent to the truthful bidding case in treasury auctions (see, e.g., Hortaçsu and McAdams, 2010; Elsinger et al., 2019). This circumvents modeling the strategies of each player and simplifies finding the equilibrium.[37] In this auction format, we build the supply curve directly from the estimated costs, intersect it with the inelastic demand curve given by the requested volume in a given auction, and find this way the uniform market clearing price.

In addition, we make use of the bids from the uniform auction rounds, where we esti-

independently.

[37] Similar to the treasury auctions literature, we assume that bidding strategies do not change in the counterfactual simulations, but remain as observed in the data.

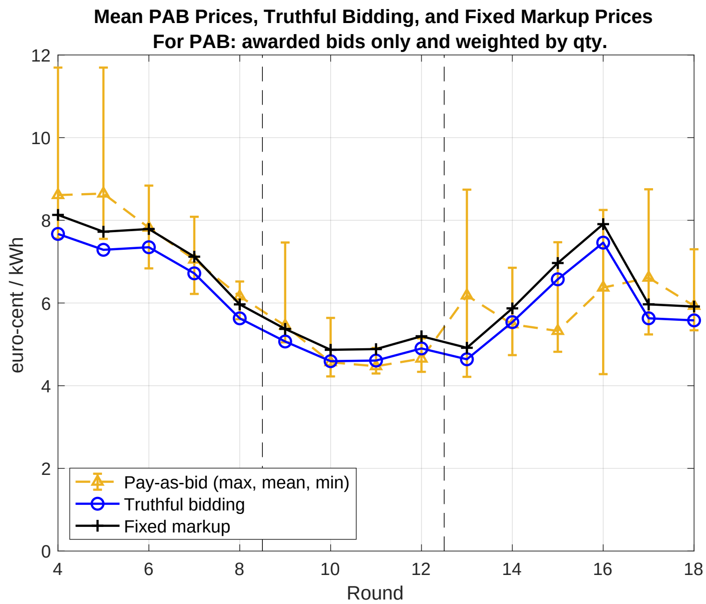
mated a quantity-weighted mean markup of 6%. We consider the case in which there is a fixed markup above costs. Therefore, the assumption is that the level of market power exercised in the two early rounds with uniform pricing is the same in this counterfactual across all subsequent rounds. While the truthful bidding case, which is widely used in the literature, represents the extreme case of no market power, our fixed markup counterfactual is a more realistic scenario based on our own estimates from actual interactions in a uniform price setting in the same market. Yet, the second scenario assumes no changes in bidder composition and market power over time.

Figure 8 shows the clearing prices for truthful bidding and the fixed markup together with the observed PAB prices. For the first we construct the perfectly competitive supply curves directly using the estimated costs ranked from lowest to highest. For the second we use the truthful bidding supply curve and multiply it by a factor of 1.06. As for the PAB prices, we use only the observed awarded bids and construct a quantity-weighted average. The PAB prices in this figure are exactly the same as those shown in Figure 1 except that each round point is equally spaced in the x-axis and we start at round 4.[38] The main difference between the outcomes from the three auction formats is that market clearing prices are lower under truthful bidding and fixed markup than under PAB mostly in Period 1 (the period with the highest profit margins). In Period 2, we find that truthful bidding leads to very similar outcomes than PAB. Finally, in rounds 14 to 16, PAB outperforms the uniform pricing rules. Note, however, that the latter had an unusual high volume and therefore, the market clearing occurs at a point where both the cost curve and the bidding curve are close to each other since markups are lower for high-cost bids.

We compute the margins for each of the winning bids under each format ($p_c - c_i$ in the case of truthful bidding and fixed markup and $b_i - c_i$ in the case of PAB) using the estimated

[38] Since for a few bids we could not estimate their corresponding cost, we discarded those bids. Therefore, the per-round volume does not always perfectly coincide with the observed eligible volume or with the awarded volume. To make the data consistent, we made a normalization so that the weights are relative to the volume of the bids for which a cost was estimated. This selection of bids produces a slightly different set of average and min/max winning bids under PAB than the observed data but it creates a fair comparison with the truthful bidding and the fixed markup counterfactuals.

Figure 8: Pay-as-bid versus truthful bidding

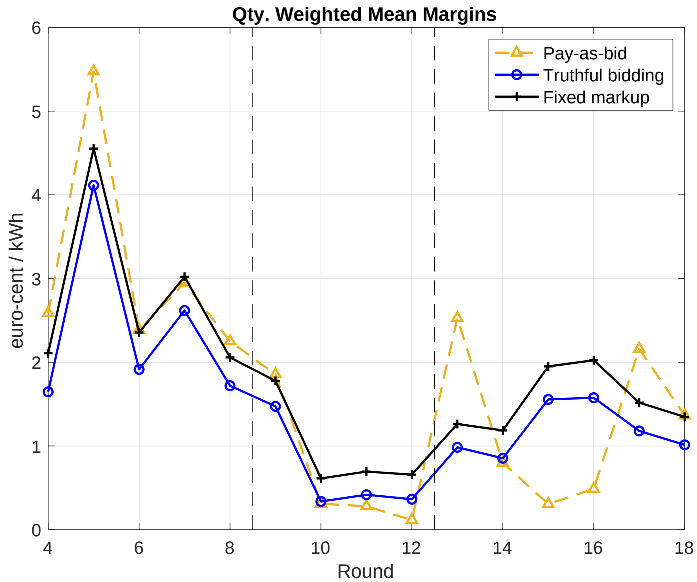


Notes: Truthful bidding is a counterfactual where each firm submits bids that are equal to its estimated costs. Fixed markup adds a constant markup of 1.06 to the cost curve. The PAB line also shows min/max bands. Note that it is possible that the clearing pricing under truthful bidding is higher than the average of winning bids under PAB, but it cannot be higher than the maximum of the winning bids under PAB because that is the marginal bid.

costs. Figure 9 shows the quantity-weighted means of those margins by round. Although it is entirely possible that setting the bids equal to the costs selects the most competitive equilibrium, obtaining lower market power in the uniform price auction is not a mechanical feature of the model since under PAB bidders still face a trade-off between bidding low to get selected and bidding high to maximize their payoff. The truthful bidding setting gives a lower bound on the government expenditure within the class of uniform price auctions, whereas the fixed markup gives a more realistic outcome based on the two early uniform price auctions.[39] Our main finding is that in this market, a uniform auction would have given place to a lower exercise of market power in Period 1, but that this advantage was less clear in the second half of our sample since the estimated margins under PAB were already shrinking over time as shown in Figure 6.

[39] As explained in the Introduction, there are some theoretical results on this issue. See Federico and Rahman (2003), Holmberg (2009), Fabra et al. (2011), and Willems and Yueting (2023).

Figure 9: Margins under different auction formats



Notes: Truthful bidding is a counterfactual where each firm submits bids that are equal to their estimated costs. Fixed markup adds a constant markup of 1.06 to the cost curve. PAB refers to the observed bids. For each round and for each auction format, margins of winning bids used only and graph shows quantity-weighted means.

5.2 Subsidies Under Different Auction Formats

Beyond the effects on market power alone, there is the effect on the size of the subsidy, which depends on the auction format since the market clearing price and the gap between the cost curve and the bid curve do so as well. To evaluate this, we compute the ratio between the quantity-weighted sliding premia at each time period under uniform pricing,

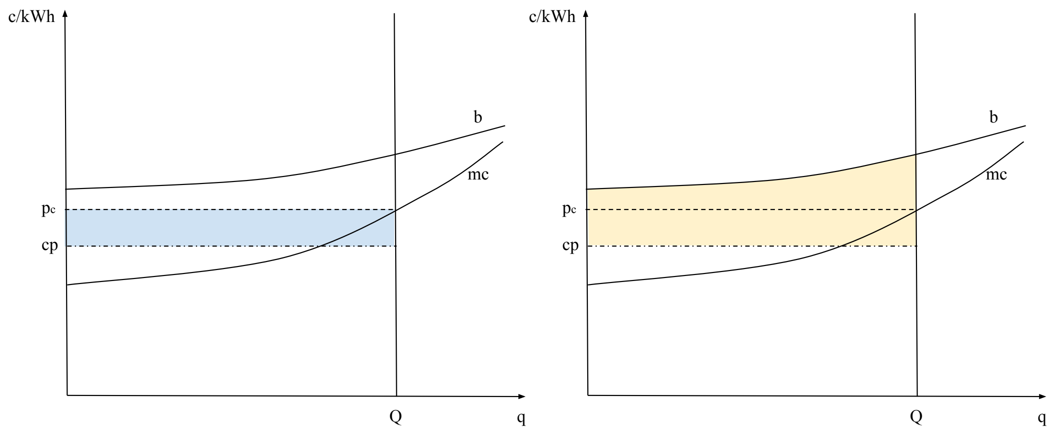
$$S_{U_t} = \sum_i q_i \max\{p_c - cp_t, 0\}$$

and the quantity-weighted sliding premiums under the PAB format,

$$S_{PAB_t} = \sum_i q_i \max\{b_i - cp_t, 0\}.$$

The relationship between the two is an empirical question. Figure 10 shows an example of a bidding curve and its corresponding cost curve where the subsidy under uniform price is lower than the subsidy under PAB.[40] However, it is not difficult to find configurations where the opposite is true. Figure 11 shows one such possibility, which repeats the same configuration than in Figure 10 except that the bidding curve is closer to the cost curve than before. Therefore, the subsidy under uniform pricing does not change but the one for PAB does, and in fact it shrinks relative to the previous configuration.

Figure 10: Subsidy under uniform pricing is lower than under pay-as-bid

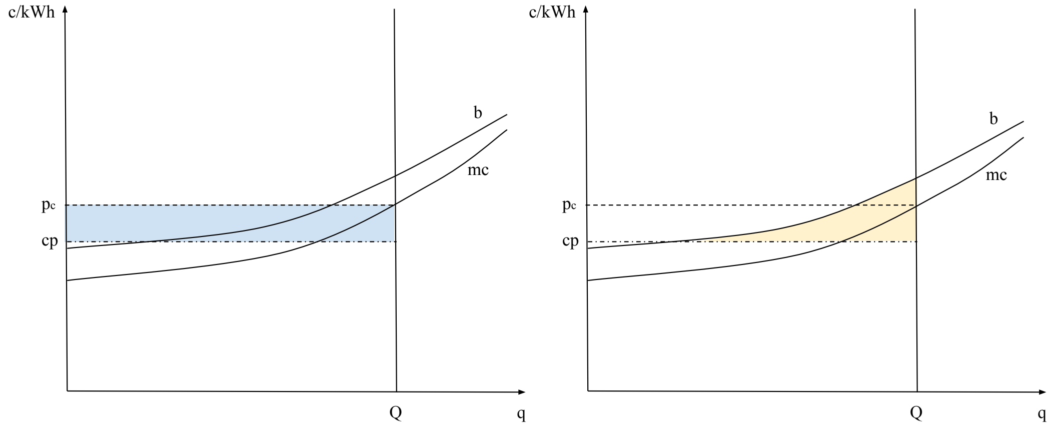


Notes: Both panels are identical except that the blue rectangle (left panel) is the amount of the subsidy under uniform pricing and the yellow area (right panel) is the subsidy under PAB. p_c is the market clearing price assuming uniform pricing can be approximated by the estimated costs curve mc (truthful bidding), cp is the capture price (time subscript omitted here). The uniform price subsidy is defined as $S_U = \sum_i q_i \max\{p_c - cp, 0\}$ over all the quantities up to Q (government demand). The yellow area on the right panel represents the subsidy under PAB defined as $S_{PAB} = \sum_i q_i \max\{b_i - cp, 0\}$ over all quantities awarded, where b on the figure is a smooth version of the set of bids b_i ranked by size, the aggregate bid curve. The blue rectangle is smaller than the yellow area.

Since the two subsidy types cannot be ranked in size in general, we compute the ratio S_U/S_{PAB} of the two subsidies for each auction round averaging over the scenarios defined in the previous section for the monthly evolution of the capture price time series, where S_U is the discounted sum of the per-period subsidy S_{U_t} and similarly for S_{PAB}. Figure 12 presents the results. In most rounds, subsidies under truthful bidding are lower than under PAB.

[40] In order to simplify the exposition of this argument, we use smooth functions instead of step functions but the same reasoning applies to both.

Figure 11: Subsidy under pay-as-bid is lower than under uniform pricing

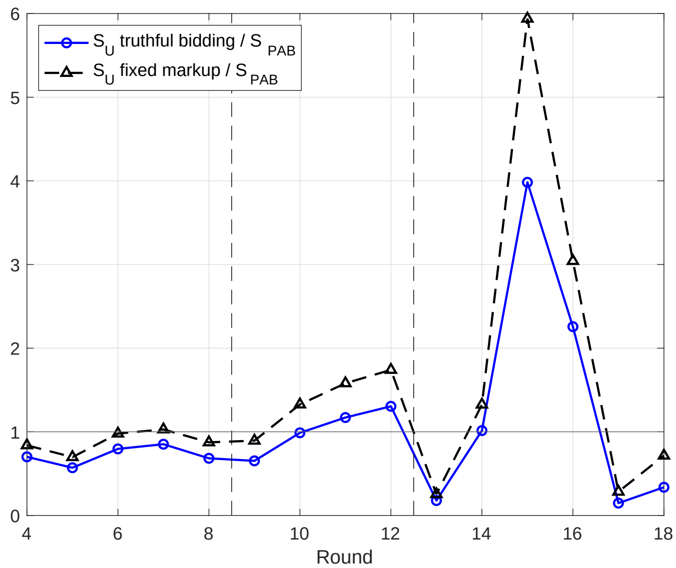


Notes: This is the same as Figure 10 except that the aggregate bid curve b is much closer to the estimated costs curve mc. The subsidy under uniform pricing (blue rectangle, left panel) is greater than under PAB (yellow area, right panel) in this case.

Rounds 14 and 16, which are precisely the two rounds where margins under truthful bidding are larger than under PAB (see Figure 9), show the largest reversal of such observation. The fixed markup case increases the value of this ratio but not as a parallel shift since it is a multiplicative markup on the cost curve. Table 6 expands on these results by showing statistics of the difference in subsidies per unit of capacity installed and in NPV relative to the PAB format.

From both panels we observe that the quantity-weighted mean over all rounds indicates that PAB was more costly in terms of subsidies than the two uniform price formats studied here. However, there is considerable variation across the three time periods consistent with Figure 12. In the beginning of the policy, PAB was extremely costly, but as we transition into Periods 2 and 3 this same format seems to be more favorable. As mentioned earlier, the large change in this differences in Period 3 is related to the large increase in demand. The lower panel of the table reports the same differences but in the fixed markup case. As expected, the disadvantage of the PAB gets diluted and even disappears in the last two periods. For the average project capacity of 5.7 MW (Table 1), the overall difference in subsidies between truthful bidding and PAB is €1,214 over the lifetime of the project. These findings reveal the importance of correctly assessing the degree of market power to correctly assess the RE auction policy.

Figure 12: Subsidies under pay-as-bid and truthful bidding



Notes: Each line represents the ratio of the subsidies under truthful bidding and PAB S_U/S_{PAB} at each auction round, where S_U is the discounted sum of the per-period subsidies $S_{U_t} = \sum_i q_i \max\{p_c - cp_t, 0\}$, p_c is the market clearing price under uniform pricing, q_i are the quantities awarded, S_{PAB} is the discounted sum of the per-period subsidies $S_{PAB_t} = \sum_i q_i \max\{b_i - cp_t, 0\}$, and cp_t is the capture price.

5.3 Increase in Volume

In an environment where each of the auction rounds is over-subscribed, a relevant policy question is to what extent larger volumes required would have increased market clearing prices under each auction format. A shift of the perfectly inelastic government demand curve to the right guarantees a non-decreasing effect on the market clearing price under either of the two auction formats, but the different degree of steepness of the aggregate supply curve of bids and the perfectly competitive supply curve determines the price reactivity. To quantify this we calculate the inverse elasticity from a 10% increase in demand assuming that the supply curve of the PAB case is the one that corresponds to the ordering given by the curve

Table 6: Differences in Subsidies

Δ subsidies (truthful bidding - PAB) in €-cent per kW of capacity				
	All rounds	Period 1	Period 2	Period 3
Mean	-21.38	-50.95	-0.18	-10.87
S.E.	17.59	22.48	5.1	21.84
25th perc.	-21.97	-50.79	-4.76	-9.43
Median	-10.91	-38.48	-0.89	5.39
75th perc.	0.94	-23.34	5.48	18.16

Δ subsidies (fixed markup - PAB) in €-cent per kW of capacity				
	All rounds	Period 1	Period 2	Period 3
Mean	-5.89	-26.73	9.96	0.91
S.E.	19.66	25.06	6.17	24.14
25th perc.	-6.22	-25.39	4.96	2.3
Median	4.85	-13.07	8.83	17.12
75th perc.	16.7	2.06	15.21	29.89

Notes: Each of the panels shows statistics for the difference in subsidies in NPV per unit of output between truthful bidding and PAB and between the fixed markup outcomes and PAB, respectively. Columns Period 1, Period 2, and Period 3 report the results conditional on each of those rounds periods. The standard error are calculated using a bootstrap with 100 iterations and all statistics are quantity-weighted and averaged over the different scenarios of capture prices.

of estimated costs. In other words, we do not compute a new set of strategies, but rather we use the supply curves from the perfectly competitive setting –the marginal curve itself– and the inherited ordering of observed bids stemming from the estimated cost curve. Under truthful bidding, we find a value of 0.15, while under PAB a value of 0.28. In each case, the reported value is the simple average over the per-round elasticities. This means that a 10% increase in government demand is associated to an increase of 1.5% of the clearing price under truthful bidding and a 2.8% under PAB. Given more stringent RE investment targets, one potential change in the policy is a more aggressive government demand. However, both the cost curve and the bidding curve are flat enough that an increase in demand would not have a strong effect on the market clearing price.

6 Conclusion

This paper outlines key findings regarding auctions distributing payments to solar power electricity producers in Germany. Acknowledging the constraints of a reduced-form analysis, we employ a structural multi-unit auction model to infer the unobservable costs of bidders. Subsequently, these costs are leveraged to compute metrics of market power and conduct counterfactual analyses, exploring the implications of alternative auction formats. As the energy transition progresses, understanding the ramifications of different auction mechanisms for selecting producers and incentivizing them appropriately lies at the heart of economics and public finance.

References

Anatolitis, V., Azanbayev, A., and Fleck, A.-K. (2022). How to design efficient renewable energy auctions? Empirical insights from Europe. *Energy Policy*, 166:112982.

Ausubel, L. M., Cramton, P., Pycia, M., Rostek, M., and Weretka, M. (2014). Demand reduction and inefficiency in multi-unit auctions. *The Review of Economic Studies*, 81(4):1366–1400.

Bajari, P. and Ye, L. (2003). Deciding between competition and collusion. *Review of Economics and Statistics*, 85(4):971–989.

Batz Liñeiro, T. and Müsgens, F. (2021). Evaluating the German PV auction program: The secrets of individual bids revealed. *Energy Policy*, 159:112618.

Bayer, B., Schäuble, D., and Ferrari, M. (2018). International experiences with tender procedures for renewable energy – A comparison of current developments in Brazil, France, Italy and South Africa. *Renewable and Sustainable Energy Reviews*, 95:305–327.

Beiter, P., Kitzing, L., Spitsen, P., Noonan, M., Berkhout, V., and Kikuchi, Y. (2021). Toward global comparability in renewable energy procurement. *Joule*, 5(6):1485–1500.

Bundesregierung (2014). Entwurf eines Gesetzes zur grundlegenden Reform des Erneuerbare-Energien-Gesetzes und zur Änderung weiterer Bestimmungen des Energiewirtschaftsrechts.

Cassola, N., Hortaçsu, A., and Kastl, J. (2013). The 2007 subprime market crisis through the lens of European Central Bank auctions for short-term funds. *Econometrica*, 81(4):1309–1345.

Cramton, P. (2013). Spectrum auction design. *Review of Industrial Organization*, 42:161–190.

Davis, L. W., Hausman, C., and Rose, N. L. (2023). Transmission Impossible? Prospects for Decarbonizing the US Grid. Technical report, National Bureau of Economic Research.

Del Río, P. and Kiefer, C. P. (2021). Analysing patterns and trends in auctions for renewable electricity. *Energy for Sustainable Development*, 62:195–213.

Del Río, Pablo and Kiefer, Christoph P. (2023). Academic research on renewable electricity auctions: Taking stock and looking forward. *Energy Policy*, 173:113305.

Elsinger, H., Schmidt-Dengler, P., and Zulehner, C. (2019). Competition in treasury auctions. *American Economic Journal: Microeconomics*, 11(1):157–84.

Fabra, N. and Montero, J.-P. (2023). Technology-neutral versus technology-specific procurement. *The Economic Journal*, 133(650):669–705.

Fabra, N., von der Fehr, N.-H. M., and de Frutos, M.-Á. (2011). Market design and investment incentives. *The Economic Journal*, 121(557):1340–1360.

Federico, G. and Rahman, D. (2003). Bidding in an electricity pay-as-bid auction. *Journal of Regulatory Economics*, 24(2):175–211.

Fox, J. T. and Bajari, P. (2013). Measuring the efficiency of an FCC spectrum auction. *American Economic Journal: Microeconomics*, 5(1):100–146.

Grashof, K. (2019). Are auctions likely to deter community wind projects? And would this be problematic? *Energy Policy*, 125:20–32.

Gupta, S. and Lamba, R. (2023). Treasury auctions during a crisis. *Available at SSRN 4251675*.

Holmberg, P. (2009). Supply function equilibria of pay-as-bid auctions. *Journal of Regulatory Economics*, 36:154–177.

Hortaçsu, A. and Kastl, J. (2012). Valuing dealers' informational advantage: A study of Canadian treasury auctions. *Econometrica*, 80(6):2511–2542.

Hortaçsu, A. and McAdams, D. (2010). Mechanism choice and strategic bidding in divisible good auctions: An empirical analysis of the Turkish treasury auction market. *Journal of Political Economy*, 118(5):833–865.

Hortaçsu, A. and McAdams, D. (2018). Empirical work on auctions of multiple objects. *Journal of Economic Literature*, 56(1):157–84.

IRENA (2019). Renewable Energy Auctions: Status and Trends beyond Price. Technical report.

Kang, B.-S. and Puller, S. L. (2008). The effect of auction format on efficiency and revenue in divisible goods auctions: A test using korean treasury auctions. *The Journal of Industrial Economics*, 56(2):290–332.

Kastl, J. (2011). Discrete bids and empirical inference in divisible good auctions. *The Review of Economic Studies*, 78(3):974–1014.

Kastl, J. (2012). On the properties of equilibria in private value divisible good auctions with constrained bidding. *Journal of Mathematical Economics*, 48(6):339–352.

Kim, H. (2022). Heterogeneous impacts of cost shocks, strategic bidding, and pass-through: evidence from the new england electricity market. *American Economic Journal: Microeconomics*, 14(2):370–407.

Klessmann, C., Tiedemann, S., Wigand, F., Kelm, T., Winkler, J., Ragwitz, M., Haufe, M.-C., and Ehrhart, K.-M. (2015). Ausschreibungen für PV-Freiflächenanlagen: Auswertung der ersten zwei Runden: im Auftrag des BMWi. Berlin.

Klobasa, M., Winkler, J., Sensfuß, F., and Ragwitz, M. (2013). Market integration of renewable electricity generation: The German market premium model. *Energy & Environment*, 24(1/2):127–146.

Krasnokutskaya, E. and Seim, K. (2011). Bid preference programs and participation in highway procurement auctions. *American Economic Review*, 101(6):2653–2686.

Lamp, S. and Samano, M. (2023). (Mis) allocation of Renewable Energy Sources. *Journal of the Association of Environmental and Resource Economists*, 10(1):195–229.

Matthäus, D. (2020). Designing effective auctions for renewable energy support. *Energy Policy*, (142):111462.

Reguant, M. (2014). Complementary bidding mechanisms and startup costs in electricity markets. *The Review of Economic Studies*, 81(4):1708–1742.

Ryan, N. (2021). Holding up green energy. Technical report, National Bureau of Economic Research.

Schlesinger, M., Hofer, P., Kemmler, A., Kirchner, A., Koziel, S., Ley, A., Piégsa, A., Seefeldt, F., Straßburg, S., Weinert, K., et al. (2014). Entwicklung der energiemärkte–energiereferenzprognose. *Projekt Nr. 57/12. Studie im Auftrag des Bundesministeriums für Wirtschaft und Technologie. Basel/Köln/Osnabrück: ewi/gws/prognos*.

Tiedemann, S., Bons, M., Sach, T., Jakob, M., Klessmann, C., Anatolitis, V., Billerbeck, A., Winkler, J., Höfling, H., Kelm, T., Metzger, J., Jachmann, H., Bangert, L., Maurer, C., Tersteegen, B., Hirth, L., Reimann, J., Ehrhart, K.-M., and Hanke, A.-K. (2019). Evaluierungsbericht: Ausschreibungen für Erneuerbare Energien nach dem ErneuerbareEnergien-Gesetz (EEG) und dem Windenergie-auf-See-Gesetz (WindSeeG): Erstellt im Auftrag des Bundesministeriums für Wirtschaft und Energie (BMWi). Berlin.

Vickrey, W. (1961). Counterspeculation, auctions, and competitive sealed tenders. *The Journal of Finance*, 16(1):8–37.

Willems, B. and Yueting, Y. (2023). Bidding and investment in wholesale electricity markets: Discriminatory versus uniform-price auctions.

Wilson, R. (1979). Auctions of shares. *The Quarterly Journal of Economics*, 93(4):675–689.

Winkler, J., Magosch, M., and Ragwitz, M. (2018). Effectiveness and efficiency of auctions for supporting renewable electricity – what can we learn from recent experiences? *Renewable Energy*, (119):473–489.

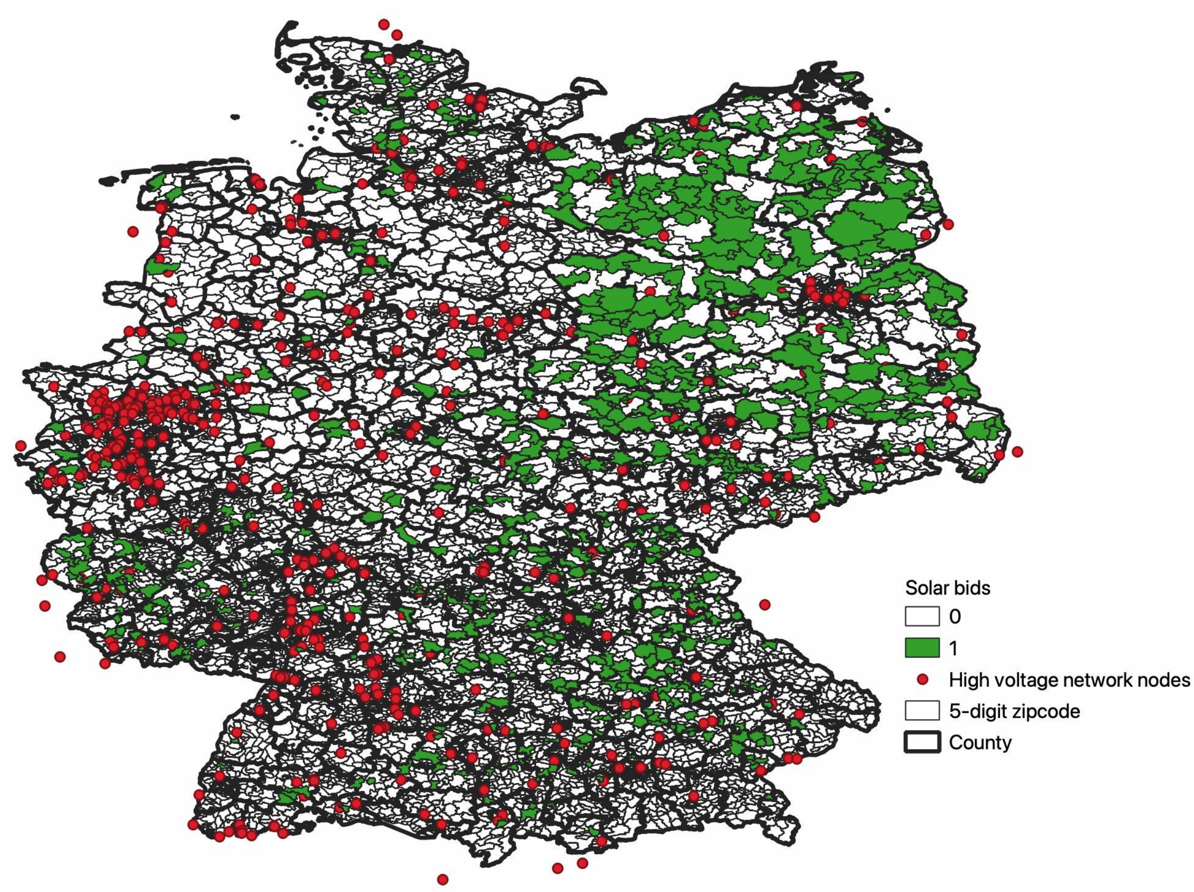
Wolak, F. A. (2003). Measuring unilateral market power in wholesale electricity markets: The california market, 1998–2000. *American Economic Review*, 93(2):425–430.

Wolak, F. A. (2007). Quantifying the supply-side benefits from forward contracting in wholesale electricity markets. *Journal of Applied Econometrics*, 22(7):1179–1209.

Appendix

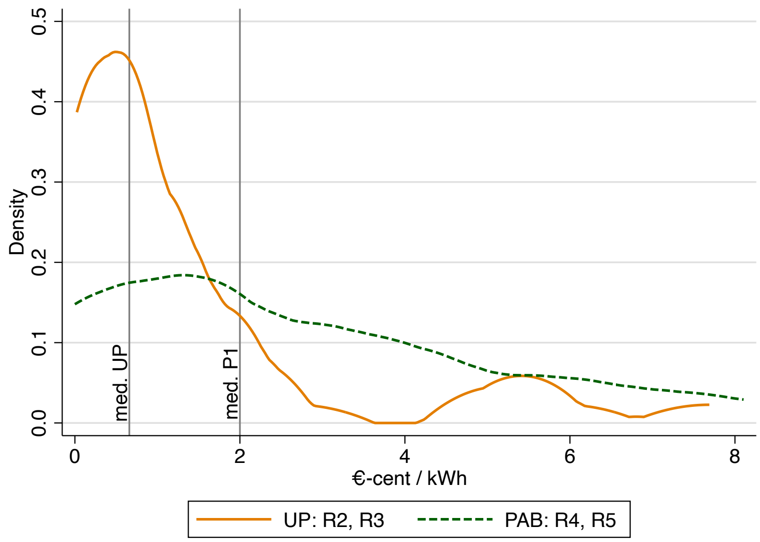
A Additional Figures and Tables

Figure A.1: Solar bids and network nodes



Notes: Map of Germany indicating the zip codes for which a bid has been submitted in at least one auction round and the access points (nodes) to the high voltage electricity network. Note that the average zip code size is larger in former East Germany.

Figure A.2: Margins: UP versus PAB pricing (auction rounds 2 - 5)



Notes: Margins defined as $b_i - c_i$. For each bidder and period, we subtract the average cost from the average bid (quantity-weighted) and plot the result as a kernel density. Auction rounds 2 to 5 only.

Table A.1: German solar auctions, 2015-2019

# Round	Date	Technology	Pricing rule	Volume (MW)	Ceiling price (€-cent/kWh)
1	15/04/2015	Solar	pay-as-bid	150	11.29
2	01/08/2015	Solar	uniform pricing	150	11.18
3	01/12/2015	Solar	uniform pricing	200	11.09
4	01/04/2016	Solar	pay-as-bid	125	11.09
5	01/08/2016	Solar	pay-as-bid	125	11.09
6	01/12/2016	Solar	pay-as-bid	160	11.09
7	01/02/2017	Solar	pay-as-bid	200	8.91
8	01/06/2017	Solar	pay-as-bid	200	8.91
9	01/10/2017	Solar	pay-as-bid	200	8.84
10	01/02/2018	Solar	pay-as-bid	200	8.84
11	01/04/2018	Solar / Wind	pay-as-bid	200	8.84
12	01/06/2018	Solar	pay-as-bid	182	8.84
13	01/10/2018	Solar	pay-as-bid	182	8.75
14	01/11/2018	Solar / Wind	pay-as-bid	200	8.75
15	01/02/2019	Solar	pay-as-bid	175	8.91
16	01/03/2019	Solar	pay-as-bid	500	8.91
17	01/04/2019	Solar / Wind	pay-as-bid	200	8.91
18	01/06/2019	Solar	pay-as-bid	150	7.50

Notes: List of German solar auctions: April 2015 to June 2019. Solar was single winning technology in case bids from wind were admitted in the same auction round. Annual auction volume is determined by the government's RE goals and broken down into auction rounds. The price ceiling is the maximum allowed bid price in each auction round.

Table A.2: DV: Bid values

	(1)	(2)	(3)	(4)
1(large bidder: size, p90)	-0.622***	-0.695***	-0.438***	
	(0.200)	(0.203)	(0.133)	
System costs	10.843***	10.720***	3.678*	5.316**
	(1.343)	(1.261)	(1.992)	(2.051)
1(auction volume > 200MW)	0.652***	0.652***	-0.191	-0.184
	(0.205)	(0.192)	(0.149)	(0.149)
Distance to network		0.698*	0.607**	0.617*
		(0.355)	(0.288)	(0.372)
Solar irradiation		-4.302***	-0.963	-1.685
		(1.063)	(1.293)	(1.023)
N	1,111	1,111	1,111	1,111
Adjusted R2	0.26	0.28	0.65	0.73
Mean DV	6.50	6.50	6.50	6.50
Land FE	No	No	Yes	Yes
State FE	No	No	Yes	Yes
Year FE	No	No	Yes	Yes
Bidder FE	No	No	No	Yes

Notes: DV: bid values. Regressions include a constant term. Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: DV: Bid values

	(1)	(2)	(3)	(4)
Estimated cost	0.197***	0.183***	0.101***	0.088***
	(0.026)	(0.030)	(0.021)	(0.021)
Distance to network	0.430	0.370	0.454*	0.549*
	(0.318)	(0.368)	(0.254)	(0.303)
1(auction volume > 200MW)	0.381**	0.328*	-1.854***	-1.956***
	(0.158)	(0.166)	(0.189)	(0.220)
1(large bidder: size, p90)	-3.011***		-1.090***	
	(0.432)		(0.156)	
1(large bidder: size, p90) × cost	0.397***	0.380***	0.117***	0.124***
	(0.065)	(0.075)	(0.038)	(0.041)
System costs	8.392***	8.417***		
	(1.105)	(1.679)		
N	1,111	1,111	1,111	1,111
Adjusted R2	0.49	0.58	0.76	0.84
Mean DV	6.50	6.50	6.50	6.50
Land FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Round FE	No	No	Yes	Yes
Bidder FE	No	Yes	No	Yes

Notes: DV: bid values. Regressions include a constant term. Columns 1 and 2 include average system costs to control for decreasing cost trends over time. Columns 3 and 4 include auction round FEs. Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4: DV: Bid values

	(1)	(2)	(3)
# bids, prev. auction	-0.003***	-0.002*	-0.002*
	(0.001)	(0.001)	(0.001)
Median winning bid, prev. auction	0.564***	0.537***	0.517***
	(0.111)	(0.104)	(0.102)
Max. winning bid, prev. auction	0.259***	0.236***	0.240***
	(0.074)	(0.069)	(0.069)
System costs	-1.830	-1.621	-1.376
	(1.211)	(1.110)	(1.063)
Distance to network	0.547**	0.489**	0.481*
	(0.275)	(0.242)	(0.285)
Solar irradiation	-2.774***	-1.534	-1.177
	(0.849)	(0.979)	(1.207)
1(auction volume > 200MW)	0.653***	0.586***	0.609***
	(0.175)	(0.177)	(0.169)
1(large bidder: size, p90)	-0.347*	-0.359**	-0.354**
	(0.204)	(0.174)	(0.147)
Capture price (last three years)	1.973***	1.992***	2.004***
	(0.294)	(0.282)	(0.282)
Landtype			
Buildings		0.345**	0.340*
		(0.151)	(0.201)
Other		0.310***	0.329**
		(0.108)	(0.142)
Adjacent road or railway		0.452***	0.420***
		(0.080)	(0.081)
Site, prev. usage		0.413***	0.396***
		(0.070)	(0.126)
N	1,111	1,111	1,111
Adjusted R2	0.693	0.708	0.712
Mean DV	6.502	6.502	6.502
State FE	No	No	Yes

Notes: DV: bid values. Regressions include a constant term. Landtype: all estimates with respect to agricultural land (omitted category). Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Online Appendix

O.1 Data Background

Irradiation data. We control for the available sunshine at the location of the solar installation, the irradiation. Higher irradiation levels lead to a higher generation per unit of capacity installed and hence should lead to lower unit costs and lower bid values. We use irradiation data between 2010 and 2016 at the county level provided by the German Weather Service.[41]

Solar cost indicators. We also use two aggregate solar cost indicators, the module price index in Euros per kilowatt (€/kW) provided by PVxchange and a system price index provided by the German Solar Association (BSW). Both indicators measure average cost factors for typical installations of large ground-mounted solar in Europe and Germany. From 2014 until the end of 2020 the solar module costs decreased almost linearly, from roughly 500 €/kW in 2015 to 250 €/kW in 2020 (see Figure 1). The same is true when considering the solar system costs, which decreased from roughly 1000 €/kW in 2015 to 750 €/kW in 2019. To calculate the module cost and system cost measures and to account for price expectations at the time of the auction, we take the average expected costs in the next 12 months. To convert the installation capacity (in €/kW) to €/kWh, we assume a lifetime of 25 years and an annual discount factor of 10%. Moreover, we use capacity factors (based on annual observed production) for realized bids at the solar installation level.

Interconnection costs to the electricity grid. To proxy for the interconnection costs, we calculate the distance between the solar installation and the electricity grid as direct line from the centroid of the 5-digit zip code in which the solar installation is located and the nearest high voltage network node (see Appendix Figure A.1).

[41] Climate Data Center of the German Weather Service (DWD). `https://cdc.dwd.de/portal/`.

O.2 Alternative Model Specifications

O.2.1 Multi-unit auction model without future payoffs

Pay-as bid auction. An alternative to the main estimation that takes into account expectations on future payoffs due to the subsidy design is to model bidding as a one-time payment in which bidders maximize expected profits from the auction and disregard the evolution of the capture prices. The following builds direct on the setup in Hortaçsu and McAdams (2010) and Kastl (2011). The firm maximizes the expected value of its profits as a function of the private signal s_i

$$\Pi_i(s_i) = \int_0^{Q_i(\boldsymbol{y}^{-1}(\cdot;\boldsymbol{s}))} \sum_{k=1}^{K_i} (b_{i,k} - c_i(q_{i,k}; s_i))\mathbb{1}(q_{i,k} \le q_i < q_{i,k+1}) dq_i,$$

where $Q_i(\boldsymbol{y}^{-1}(\cdot; \boldsymbol{s}))$ is the quantity firm i is awarded when all firms' supply schedules are the vector $\boldsymbol{y}(p; \boldsymbol{s})$. The set of all supply schedules in $\boldsymbol{y}(p; \boldsymbol{s})$ is a Bayesian Nash equilibrium if each firm i maximizes its expected value of Π_i. This profit function reflects specifically the pay-as-bid auction format.

We use a perturbation argument similar to that in Kastl (2011, 2012) to find an expression for the costs without using the first order conditions from the expression for profits above. For the bid to be optimal, the following equation must hold for each step k,

$$\Pr(b_{i,k} < p_c < b_{i,k+1})[b_{i,k} - c_i(q_{i,k}; s_i)] = \Pr(b_{i,k+1} \le p_c)(b_{i,k+1} - b_{i,k}),$$

where p_c is the market clearing price.[42]

This equation can be rearranged to obtain a closed-form expression for the cost for each

[42] The argument works as follows. Assume that the clearing price occurs at a vertical segment of the individual supply curve. Then, a small reduction in quantity (bid shading) makes the bidder lose $b_{i,k} - c_i(q_{i,k}; s_i)$ times the small reduction in quantity and only if the price is effectively in the vertical segment between the k-th and the $(k+1)$-th steps ($\Pr(b_{i,k} < p_c < b_{i,k+1}) > 0$), where p_c is the market clearing price. At the same time, this quantity reduction shifts the bidder's supply curve to the left therefore, the step b_{k+1} now becomes marginal and produces gains of $b_{i,k+1} - b_{i,k}$ as long as the new clearing price is effectively at least $b_{i,k+1}$. If losses and gains from bid shading are not equalized, then there exists a potential deviation in the bid schedule that leads to higher expected payoffs, so the bidding strategy cannot be optimal.

step k of the firm's supply curve,

$$c_i(q_{i,k}; s_i) = b_{i,k} - \frac{\Pr(b_{i,k+1} \leq p_c)}{\Pr(b_{i,k} < p_c < b_{i,k+1})}(b_{i,k+1} - b_{i,k}).$$

Our goal is to estimate $c_i(q_{i,k}; s_i)$ by using the supply curves $b_{i,k}$ observed in data and by simulating residual demand curves to find $\Pr(b_{i,k+1} \leq p_c)$ and $\Pr(b_{i,k} < p_c < b_{i,k+1})$.

This expression is the equivalent of a pricing equation in a Bertrand-Nash game where the marginal costs can be recovered from the prices and a markup term that depends on the own market share and the substitution effects. Similarly, our expression for the cost is equal to the bid value minus a term that depends on the probability of winning and on how that probability is affected by the clearing price.

Uniform auction. In the uniform price setting without future payoffs, the bidder receives the market clearing price if the capture price falls below the bid and it receives the capture price otherwise. Therefore, the bidder's objective function is

$$E\Pi_i(s_i) \quad = \quad \int_0^{Q_i(\boldsymbol{y}^{-1}(\cdot;\boldsymbol{s}))} \sum_{k=1}^{K_i} (p_c(\boldsymbol{y}(\cdot;\boldsymbol{s})) - c_i(q_{i,k}; s_i))\mathbb{1}(q_{i,k} \leq q_i < q_{i,k+1}) dq_i,$$

where $p_c(\boldsymbol{y}(\cdot;\boldsymbol{s}))$ is the market clearing price.

We obtain an optimality condition following the argument in Kastl (2011) but adapted to the case of bidders that submit supply curves instead of demand curves. Assume that the residual demand curve crosses between the k-th and the $(k+1)$-th steps. If bidder i reduces her marginal quantity by one unit, she losses $p_c - c_{i,k}$ with some probability. Note that we have simply written p_c without its dependencies on the signals and the vector of bids to make the notation lighter. At the same time she would gain the increase in the clearing price multiplied by the inframarginal quantity because all inframarginal quantities are paid the same price. Since a decrease in quantity causes an increase in price, and vice-versa, we write a negative sign on the right-hand side to put the derivative in terms of gains.

$$\underbrace{\Pr(b_{i,k} < p_c < b_{i,k+1})}_{\equiv M_1}[E(p_c | b_{i,k} < p_c < b_{i,k+1}) - c_{i,k}] = -\underbrace{q_{i,k}\frac{\partial E(p_c \mathbb{1}(b_{i,k} \leq p_c \leq b_{i,k+1}))}{\partial q_{i,k}}}_{\equiv M_2}$$

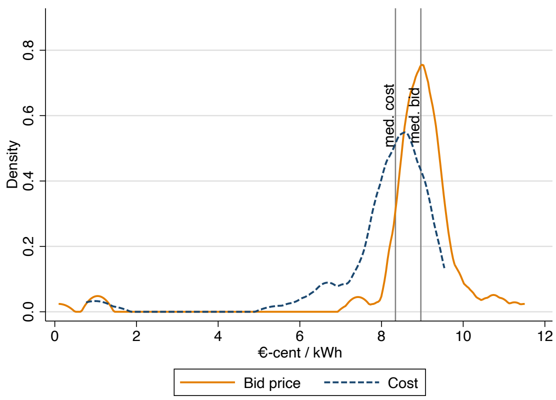
Solving for the costs gives

$$c_{i,k} = E(p_c | b_{i,k} < p_c < b_{i,k+1}) + \frac{M_2}{M_1},$$

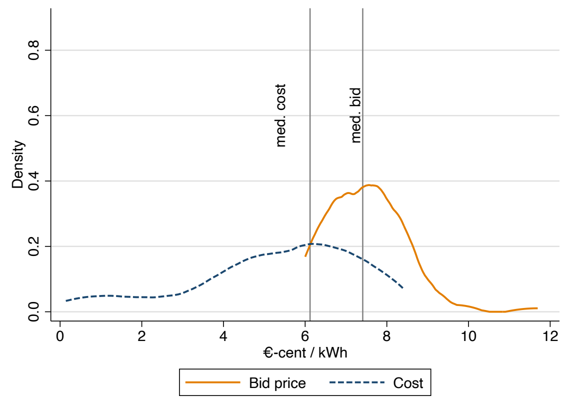
which has the usual interpretation of a uniform price setting where the cost is the price minus a markup since $\frac{M_2}{M_1} < 0$ and therefore, costs are lower than p_c.

We show the estimated costs and margins densities using this model with no future payoffs in Figure O.1 and Figure O.2. The main difference with respect to the full model is that the margins density for PAB in Period 3 has more mass over higher margins, highlighting the importance of considering a comprehensive model to assess market power.

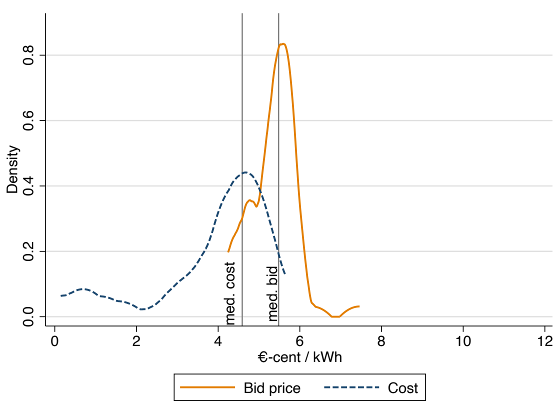
Figure O.1: Estimated costs and observed bids densities: no future payoffs



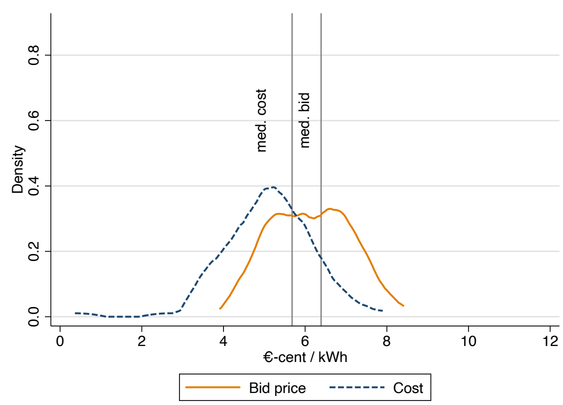
(a) UP: Auction rounds 2-3



(b) PAB, Period 1: Auction rounds 4-8



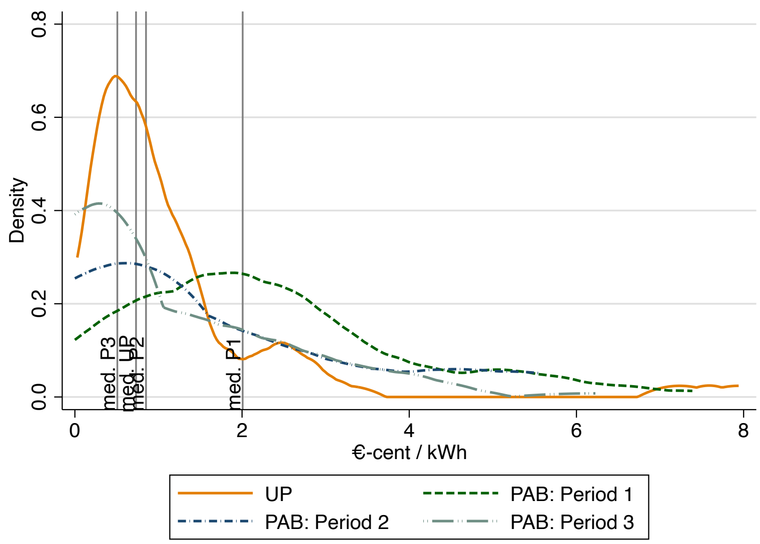
(c) PAB, Period 2: Auction rounds 9-12



(d) PAB, Period 3: Auction rounds 13-18

Notes: Kernel densities of the costs obtained from a model that only considers 'static' auction payoffs and from the observed bids. Individual bids are aggregated by bidder and period using quantity-weighted averages. Panel (a): uniform auction rounds. Panels (b) to (d): pay-as-bid auction rounds.

Figure O.2: Margins: no future payoffs



Notes: Margins defined as $b_i - c_i$. For each bidder and period, we subtract the average cost from the average bid (quantity-weighted) and plot the result as a kernel density.

O.2.2 Uniform price auction, considering future payoffs

The structure of the UP case is the same as for PAB except that the expression for π_i −the expression inside the integral− in Equation 2 is different,

$$\begin{aligned}\pi_i &= \sum_{k=1}^{K_i}\left[\sum_{t=13}^{T=252}\underbrace{\delta^t\left[\mathbb{1}(p_c(\boldsymbol{y}(\cdot;\boldsymbol{s}))>cp_t)(p_c(\boldsymbol{y}(\cdot;\boldsymbol{s}))-c_{i,k})+\mathbb{1}(p_c(\boldsymbol{y}(\cdot;\boldsymbol{s}))\leq cp_t)(cp_t-c_{i,k})\right]}_{\text{Discounted future profits}}\right]\\ &\times \mathbb{1}(q_{i,k}\leq q_i<q_{i,k+1})\end{aligned}$$

where K_i is the number of bid steps and the contribution from a single step k is

$$\begin{aligned}\pi_{i,k} &\equiv \sum_{t|p_c>cp_t}\delta^t(p_c-c_{i,k})+\sum_{t|p_c\leq cp_t}\delta^t(cp_t-c_{i,k})\\ &= p_c\sum_{t|p_c>cp_t}\delta^t-c_{i,k}\sum_{t=13}^{T=252}\delta^t+\sum_{t|p_c\leq cp_t}\delta^t cp_t\\ &= L_1(cp_t,p_c)E(p_c|b_{i,k}<p_c<b_{i,k+1})-L_2c_{i,k}+L_3(cp_t,p_c)\end{aligned}$$

where

$$\begin{aligned}L_1(cp_t,p_c) &= \sum_{t|p_c>cp_t}\delta^t\\ L_2 &= \frac{\delta^{13}-\delta^{T+1}}{1-\delta}\\ L_3(cp_t,p_c) &= \sum_{t|p_c\leq cp_t}\delta^t cp_t\end{aligned}$$

and we have written p_c without its dependencies on the signals and the vector of bids to make the notation lighter.

Assuming once again that the residual demand curve crosses between the steps k and $k+1$, if the bidder reduces her bid by one unit she loses $\pi_{i,k}$. Since by reducing the length of the k-th step the intersection of the vertical segment and the residual demand occurs at a higher point p'_c and this new price will affect all inframarginal units, the bidder gains p'_c-p_c over each unit won properly scaled for the NPV. We write a minus sign on the right-hand side because price increases when quantity is reduced. Assume further that $L_3(cp_t,p'_c)-L_3(cp_t,p_c)=0$

since at best the change in p_c does not affect which terms in the NPV sum are activated in L_3 and if there is a change in the number of terms that go inside this sum they are very small terms since $\delta^t < 0.01$ for $t \geq 50$. Then the optimality condition becomes

$$\underbrace{\Pr(b_{i,k} < p_c < b_{i,k+1})}_{\equiv M_1} \pi_{i,k} = -\underbrace{q_{i,k} L_1(cp_t, p_c) \frac{\partial E(p_c \mathbb{1}(b_{i,k} \leq p_c \leq b_{i,k+1}))}{\partial q_{i,k}}}_{\equiv M_2}.$$

After solving for $c_{i,k}$ and recalling that M_2 contains the function L_1:

$$c_{i,k} = \frac{1}{L_2} \left[L_1(cp_t, p_c) E(p_c | b_{i,k} < p_c < b_{i,k+1}) + L_3(cp_t, p_c) + \frac{M_2}{M_1} \right].$$

The results from this model are shown and discussed in the main text in Figure 5 and Figure 6.

O.3 Additional Institutional Details

O.3.1 The German solar market before the introduction of auctions

The market for large scale solar in Germany was rather unstable in the years prior to the introduction of the auction mechanism in 2015. First, module prices had declined more rapidly than anticipated by the policy maker, leading to an unexpected surge in capacity (and related subsidy payments) and windfall profits to investors. The government responded to these developments by reducing the governmental set subsidy (feed-in tariff, FIT) and reducing supply (excluding the possibility to construct solar on agricultural land, and introducing a maximum size of 10 MW of capacity per plant, EEG 2012). Furthermore, the government introduced a dynamic reduction of FITs as a function of the total added solar capacity. However, module prices stagnated in the following years mainly due to the import tariffs on Chinese modules imposed by the European Union, leading to low uptake. While the annual total installed capacity for ground-mounted solar exceeded 3 gigawatt (GW) in 2012 (representing 40% of total new solar capacity), it declined dramatically to around 1.2 GW in

2013 and further to about 0.6 GW in 2014 (Tiedemann et al., 2019; Klessmann et al., 2015). Given this uncertainty in the market environment and the difficulty to set the 'correct' FIT rates, the government began to implement auctions for large solar and wind installations, with the objective to lower the total subsidy cost, while providing sufficient incentives for RE investment.

O.3.2 Special auction rules

In addition to the auction rules discussed in the main text, there are some special rules that only apply to a subset of rounds in our sample.

First, during the pilot auction phase (2015-2016), the auctioneer restricted the number of awards per year for bids on agricultural land to 10. Once this quota was reached, bids on agricultural land could only be awarded in the following year. From 2017 onward, however, several states changed that rule, which de facto lifted the quota for projects in Bavaria, Baden-Wuerttemberg, Hesse, Rhineland Palatinate, and Saarland. In most states and years these quotas have been non-binding.

Second, for two auction rounds (April and November 2018) bids were ranked not only according to their bid value, but bids from counties with a high penetration of RE relative to load received a penalty on their bid value (malus). Ranking was performed according to these updated values.

Third, the second auction of 2019 was significantly larger than the other auction rounds. This change in auction volume (demand) was unexpected and is related to an amendment to the EEG Act increasing the annual volume to 1,800 MW (from about 500 MW in the preceding years), which is more than threefold the initial annual auction volume. This amendment also increased the auction frequency from a quarterly auction format to more frequent auctions (up to monthly).

Finally, while RE auctions in Germany are generally technology-specific, i.e., there is a specific auction for solar and another one for wind, three auction rounds between January 2018 and June 2019 have been implemented as joint auctions in which solar and wind were allowed to bid at the same time (see also Figure 3). Note however that wind bids in these auctions were not competitive and solar was the single winning technology. We therefore exclude wind bids from our analysis and treat these auction rounds the same as other solar auctions in the rest of our sample.

O.3.3 Data and prediction of the capture prices

In order to calculate the expected profits over the lifetime of the project (20-year policy horizon), we need to make assumptions about the future evolution of capture prices. We do so in the following way.

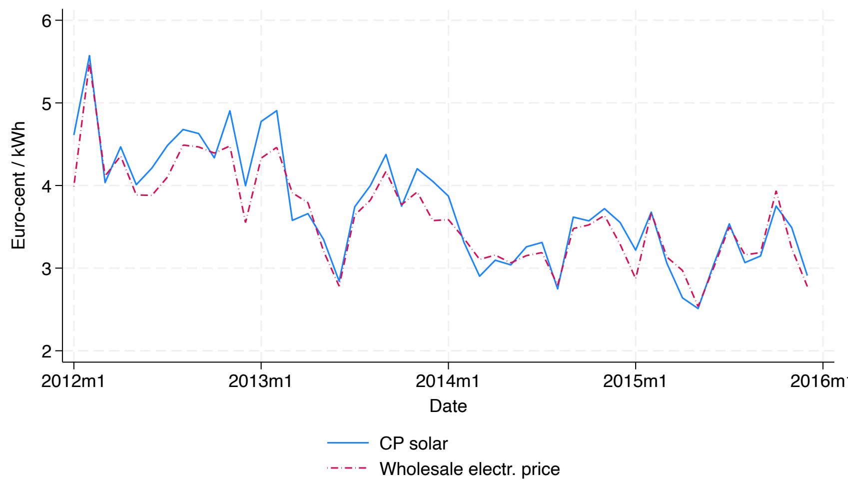
At the moment of the auction participation, the investor has information on past capture prices and wholesale electricity market prices for the years leading up to the auction. This information is publicly available on the website of the German Network Transmission Operators (https://www.netztransparenz.de/). We assume that the investors take past prices (average capture prices over the four years leading up to the auction) as the initial guess. Similarly, the monthly variation in capture prices is equal to the observed variation over the previous four years. The uncertainty regarding future capture prices is therefore mainly related to the time trend and evolution of volatility of the same.

To account for these elements, we use information from policy reports that are publicly available and that make long-term price forecasts about the level and volatility of wholesale electricity prices.[43] Note that the wholesale electricity prices and the capture price are highly correlated. In the period prior to the first auction round included in our sample, January

[43] In particular, Schlesinger et al. (2014) and vbw / Prognos Strompreisprognose 2023 (accessible here: https://www.vbw-bayern.de/Redaktion/Frei-zugaengliche-Medien/Abteilungen-GS/Wirtschaftspolitik/2023/Downloads/vbw_Strompreisprognose_Juli-2023-3.pdf). We thus make the implicit assumption that the capture rate, the ratio between the capture price and the wholesale electricity price remains constant over time. Nevertheless, we allow for differential growth trends by month of year in our sample.

2012- December 2015, the two monthly time series show a correlation coefficient of $\rho = 0.96$ (see Figure O.3).

Figure O.3: Monthly capture price and wholesale electricity price in Germany, 2012-2015



The main driving forces for the long-term price evolution of wholesale electricity prices in Germany are discussed in a White Paper published by the German government in 2017 'Electricity 2030: long-term trends - tasks for the coming years'.[44] The most relevant factors include i) increased electricity demand (stemming mostly from electrification in industry and transportation), ii) decreased electricity supply (nuclear and coal phase out), and iii) increase in RE capacity (according to RE targets set by the government). While i) and ii) have an increasing impact on prices, iii) will lead to lower price levels, but likely will result in higher price volatility as renewable output of plants is highly correlated.

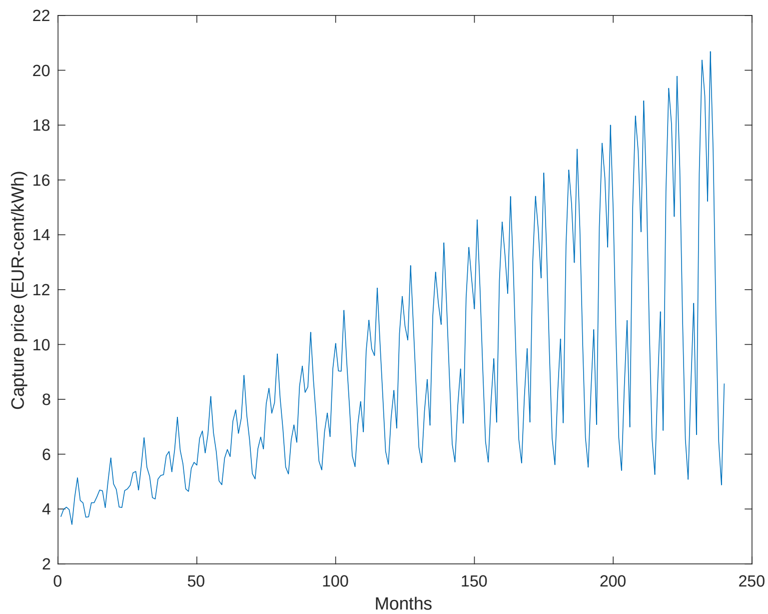
To capture the long-term price trend, we use the baseline scenario for nominal price evolution in Schlesinger et al. (2014) and interpolate linearly between reported years.[45] To account for the increase in volatility, we use the final volatility estimates in vbw / Prognos Strompreisprognose (2023) for the year 2035 and perform linear interpolation at the monthly level with respect to the baseline volatility measures.

[44] https://www.bmwk.de/Redaktion/EN/Publikationen/electricity-2030-concluding-paper.html

[45] We use nominal prices as the bid price in the policy is not indexed to inflation.

We parameterize the time series of capture prices to simulate the evolution over 240 months (20 years), starting at month 13 after each auction date. Figure O.4 shows, as example, the main scenario for the capture price relevant for auction round 4, held in April 2016. For reference, the quantity-weighted average bid price of winning bids was 7.14 €-cents/kWh in this auction round.

Figure O.4: Simulation of capture price paths for 20 years, auction round 4: April 2016

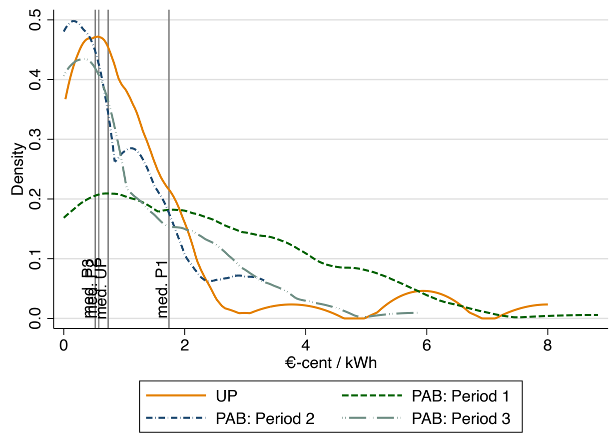


Finally, to account for uncertainty in the capture price time series, we simulate a total of nine scenarios, multiplying the baseline growth rate and the volatility measures by the following factors: 0.9, 1, and 1.1, respectively.

O.4 Additional Robustness Checks

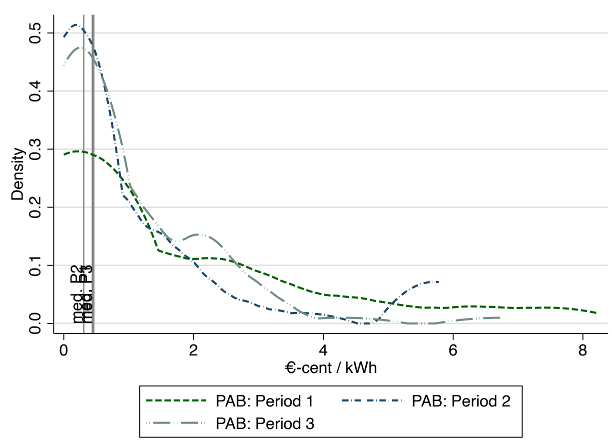
O.4.1 Model estimates with symmetric bidders

Figure O.5: Margins with symmetric bidders



Notes: Margins defined as $b_i - c_i$. Analogous figure to Figure 6 in the main text. Yet, we do not assume heterogeneous bidder types.

Figure O.6: Margins with symmetric bidders, pooling adjacent auction rounds



Notes: Margins defined as $b_i - c_i$. Analogous to Figure 6 in the main text. Yet, we do not assume heterogeneous bidder types and we allow for several rounds to be pooled according to a three dimensional kernel based on the number of bidders, auction round, and auction volume. Bids can be drawn from adjacent rounds (PAB auction rounds 4-18, only). The average markups for Periods 1 to 3 are 1.58, 1.04, and 0.89, respectively.

O.4.2 Robustness checks for main regression results

We perform several robustness checks for the reduced form regression results to show that the main data patterns hold independently of whether or not we drop all observations from single step bidders (Tables O.1 and O.2), omit all zero margin bids (Tables O.3 and O.4), or keep only the last appearance of each bid to ensure that each bid is contained only once in the dataset (Tables O.5 and O.6). We report the tables for whether the bid was awarded and the heterogeneous cost pass-through by bidder size and periods. Additional results are available from the authors upon request.

Table O.1: No single step bidders. DV: Bid awarded (yes/no)

	(1)	(2)	(3)	(4)	(5)
Bid price (deflated)	-0.219***				
	(0.019)				
Estimated cost		-0.057***	-0.050***	-0.049***	-0.038***
		(0.018)	(0.017)	(0.016)	(0.012)
1(auction volume > 200MW)			0.752***	0.744***	0.799***
			(0.060)	(0.059)	(0.049)
1(large bidder (size, p90))			0.285***	0.287***	
			(0.080)	(0.083)	
Solar irradiation				0.126	0.020
				(0.783)	(0.601)
Distance to network				-0.158	-0.116
				(0.113)	(0.104)
System costs				-0.815	-1.382
				(1.120)	(0.950)
Large bidder (size, p90) × cost					-0.077***
					(0.016)
N	809	809	809	809	809
Adjusted R2	0.16	0.06	0.26	0.26	0.34
Mean DV	0.41	0.41	0.41	0.41	0.41
Land FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Bidder FE	No	No	No	No	Yes

Notes: DV: bid awarded. Linear probability models. Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table O.2: No single step bidders. DV: Bid values

	(1)	(2)	(3)	(4)
Estimated cost	0.247***	0.110***	0.112***	0.090***
	(0.051)	(0.040)	(0.041)	(0.033)
1(Period=2)	-1.591***	-0.712**	-0.514*	-0.567*
	(0.435)	(0.271)	(0.281)	(0.327)
1(Period=3)	-1.589**	-1.252**	-1.132*	-1.059*
	(0.734)	(0.526)	(0.587)	(0.629)
1(Period=2) × cost	-0.058	-0.023	-0.057	-0.037
	(0.067)	(0.043)	(0.042)	(0.038)
1(Period=3) × cost	0.116	0.180*	0.151	0.112
	(0.107)	(0.090)	(0.096)	(0.085)
1(auction volume > 200MW)		-0.118	-0.109	-0.078
		(0.162)	(0.168)	(0.175)
1(large bidder (size, p90))		-0.417***	-0.283	
		(0.106)	(0.537)	
1(large bidder (size, p90)) × cost			-0.019	0.120*
			(0.079)	(0.072)
1(Period=2) × 1(large bidder (size, p90))			-0.930	0.160
			(0.643)	(0.737)
1(Period=3) × 1(large bidder (size, p90))			-1.321*	-0.538
			(0.762)	(0.972)
1(Period=2) × 1(large bidder (size, p90)) × cost			0.158*	-0.044
			(0.086)	(0.120)
1(Period=3) × 1(large bidder (size, p90)) × cost			0.233**	0.117
			(0.112)	(0.128)
N	809	809	809	809
Adjusted R2	0.55	0.73	0.73	0.78
Mean DV	6.46	6.46	6.46	6.46
Land FE	No	Yes	Yes	Yes
State FE	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
Bidder FE	No	No	No	Yes

Notes: DV: Bid values. Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$.

Table O.3: No zero margin bids. DV: Bid awarded (yes/no)

	(1)	(2)	(3)	(4)	(5)
Bid price (deflated)	-0.189***				
	(0.022)				
Estimated cost		-0.028***	-0.033***	-0.031***	-0.035***
		(0.009)	(0.010)	(0.010)	(0.009)
1(auction volume > 200MW)			0.832***	0.820***	0.874***
			(0.053)	(0.052)	(0.047)
1(large bidder (size, p90))			0.344***	0.345***	
			(0.097)	(0.099)	
Solar irradiation				-0.146	0.130
				(0.584)	(0.658)
Distance to network				-0.133	-0.167
				(0.106)	(0.110)
System costs				-1.639**	-2.021***
				(0.822)	(0.689)
1(large bidder (size, p90)) × cost					-0.057***
					(0.014)
N	857	857	857	857	857
Adjusted R2	0.16	0.07	0.34	0.35	0.42
Mean DV	0.32	0.32	0.32	0.32	0.32
Land FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Bidder FE	No	No	No	No	Yes

Notes: DV: bid awarded. Linear probability models. Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table O.4: No zero margin bids. DV: Bid values

	(1)	(2)	(3)	(4)
Estimated cost	0.142***	0.079***	0.078***	0.076***
	(0.030)	(0.024)	(0.026)	(0.025)
1(Period=2)	-1.672***	-0.646***	-0.511***	-0.540***
	(0.285)	(0.144)	(0.135)	(0.168)
1(Period=3)	-1.553***	-0.802**	-0.723*	-0.900*
	(0.573)	(0.379)	(0.406)	(0.523)
1(Period=2) × cost	-0.089**	-0.039	-0.053*	-0.045*
	(0.045)	(0.028)	(0.031)	(0.027)
1(Period=3) × cost	0.087	0.097	0.075	0.076
	(0.089)	(0.065)	(0.069)	(0.068)
1(auction volume > 200MW)		-0.111	-0.100	-0.133
		(0.147)	(0.152)	(0.161)
1(Large bidder (size, p90))		-0.464***	0.035	
		(0.157)	(0.649)	
1(large bidder (size, p90)) × cost			-0.061	0.166**
			(0.078)	(0.077)
1(Period=2) × 1(large bidder (size, p90))			-1.456*	0.753
			(0.752)	(0.902)
1(Period=3) × 1(large bidder (size, p90))			-1.679	0.146
			(1.058)	(1.058)
1(Period=2) × 1(large bidder (size, p90)) × cost			0.210**	-0.138
			(0.101)	(0.162)
1(Period=3) × 1(large bidder (size, p90)) × cost			0.278**	0.019
			(0.129)	(0.124)
N	857	857	857	857
Adjusted R2	0.49	0.71	0.71	0.79
Mean DV	6.63	6.63	6.63	6.63
Land FE	No	Yes	Yes	Yes
State FE	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
Bidder FE	No	No	No	Yes

Notes: DV: Bid values. Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$.

Table O.5: No repeated bids. DV: Bid awarded (yes/no)

	(1)	(2)	(3)	(4)	(5)
Bid price (deflated)	-0.239***				
	(0.021)				
Estimated cost		-0.019	-0.021*	-0.019*	-0.012
		(0.012)	(0.012)	(0.012)	(0.012)
1(auction volume > 200MW)			0.755***	0.746***	0.811***
			(0.050)	(0.049)	(0.060)
1(large bidder (size, p90))			0.270***	0.274***	
			(0.099)	(0.101)	
Solar irradiation				0.115	0.112
				(0.802)	(0.680)
Distance to network				0.013	-0.104
				(0.111)	(0.089)
System costs				-1.448	-2.047*
				(1.083)	(1.105)
1(large bidder (size, p90)) × cost					-0.080***
					(0.018)
N	908	908	908	908	908
Adjusted R2	0.18	0.05	0.25	0.25	0.36
Mean DV	0.47	0.47	0.47	0.47	0.47
Land FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Bidder FE	No	No	No	No	Yes

Notes: DV: bid awarded. Linear probability models. Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table O.6: No repeated bids. DV: Bid values

	(1)	(2)	(3)	(4)
Estimated cost	0.149***	0.069***	0.072***	0.060**
	(0.032)	(0.026)	(0.027)	(0.026)
1(Period=2)	-1.941***	-0.979***	-0.806***	-0.910***
	(0.356)	(0.223)	(0.185)	(0.238)
1(Period=3)	-1.664***	-1.171***	-1.068***	-1.258**
	(0.593)	(0.380)	(0.386)	(0.498)
1(Period=2) × cost	-0.030	0.008	-0.028	-0.002
	(0.063)	(0.040)	(0.036)	(0.042)
1(Period=3) × cost	0.108	0.124*	0.081	0.086
	(0.090)	(0.072)	(0.070)	(0.072)
1(auction volume > 200MW)		-0.163	-0.161	-0.142
		(0.147)	(0.150)	(0.174)
1(large bidder (size, p90))		-0.313**	-0.227	
		(0.143)	(0.401)	
1(large bidder (size, p90)) × cost			-0.017	0.166**
			(0.052)	(0.077)
1(Period=2) × 1(Large bidder (size, p90))			-2.167***	-0.416
			(0.734)	(0.610)
1(Period=3) × 1(large bidder (size, p90))			-2.142**	-0.681
			(1.074)	(1.450)
1(Period=2) × 1(large bidder (size, p90)) × cost			0.415***	0.106
			(0.117)	(0.097)
1(Period=3) × 1(large bidder (size, p90)) × cost			0.397***	0.181
			(0.141)	(0.198)
N	908	908	908	908
Adjusted R2	0.51	0.71	0.72	0.78
Mean DV	6.48	6.48	6.48	6.48
Land FE	No	Yes	Yes	Yes
State FE	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
Bidder FE	No	No	No	Yes

Notes: DV: Bid values. Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$.

O.4.3 Robustness check: Alternative definition of large bidders

Analogously to the baseline size definition, we define 'large' bidders in an alternative manner according to the number of projects submitted in each auction in which the bidder is present. Specifically, we define a bidder as 'large' if the average number of submitted bids is larger than two. This alternative definition classifies 44 bidders as 'large', which roughly represent 70% of all bids. The omitted category are 'small bidders' with fewer project bids.

To obtain the regression tables, we first run the model with the alternative group definition, and in a second step, estimate the linear regressions. Size of individual coefficients and direction of estimates are similar to the main regressions, yet, the alternative group definition leads to lower statistical significance for the interaction terms.

Table O.7: DV: Bid values

	(1)	(2)	(3)	(4)	(5)
Estimated cost (cost)	0.253***	0.065***	0.068***	0.009	0.046
	(0.038)	(0.022)	(0.021)	(0.022)	(0.029)
Distance to network			0.675**	0.686**	0.634*
			(0.293)	(0.292)	(0.329)
1(large bidder (> 2 bids p. round))			-0.101	-0.568**	
			(0.114)	(0.223)	
1(auction volume > 200MW)			-0.208	-0.210	-0.251*
			(0.166)	(0.165)	(0.143)
1(large bidder (> 2 bids p. round)) × cost				0.082**	0.040
				(0.035)	(0.040)
N	1,129	1,129	1,129	1,129	1,129
Adjusted R2	0.15	0.63	0.64	0.64	0.73
Mean DV	6.49	6.49	6.49	6.49	6.49
Land FE	No	Yes	Yes	Yes	Yes
State FE	No	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes
Bidder FE	No	No	No	No	Yes

Notes: DV: bid values. Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table O.8: DV: Bid awarded (yes/no)

	(1)	(2)	(3)	(4)	(5)
Bid price (deflated)	-0.220***				
	(0.018)				
Estimated cost (cost)		-0.008	-0.014	-0.015	0.009
		(0.012)	(0.012)	(0.011)	(0.017)
1(auction volume > 200MW)			0.741***	0.731***	0.804***
			(0.049)	(0.049)	(0.044)
1(large bidder (> 2 bids per round))			0.092	0.098	
			(0.067)	(0.064)	
Solar irradiation				0.519	0.432
				(0.718)	(0.556)
Distance to network				-0.090	-0.125
				(0.109)	(0.101)
System costs				-1.369*	-2.001**
				(0.793)	(0.957)
1(large bidder (> 2 bids per round)) × cost					-0.036
					(0.023)
N	1,129	1,129	1,129	1,129	1,129
Adjusted R2	0.16	0.03	0.20	0.20	0.31
Mean DV	0.39	0.39	0.39	0.39	0.39
Land FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Bidder FE	No	No	No	No	Yes

Notes: DV: bid awarded. Linear probability models. Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table O.9: DV: Bid values

	(1)	(2)	(3)	(4)
Estimated cost (cost)	0.151***	0.039	0.034	0.038*
	(0.028)	(0.025)	(0.024)	(0.023)
Period=2	-1.626***	-0.782***	-0.420	-0.752***
	(0.223)	(0.207)	(0.260)	(0.198)
Period=3	-1.177***	-0.962***	-0.794**	-1.169**
	(0.438)	(0.322)	(0.318)	(0.475)
Period=2 × cost	-0.093**	-0.044	-0.118**	-0.039
	(0.036)	(0.039)	(0.049)	(0.035)
Period=3 × cost	0.014	0.080	0.025	0.084
	(0.070)	(0.054)	(0.055)	(0.089)
1(auction volume > 200MW)		-0.228	-0.223	-0.248*
		(0.168)	(0.172)	(0.146)
1(large bidder (> 2 bids per round))		-0.095	-0.262	
		(0.100)	(0.222)	
1(large bidder (> 2 bids per round)) × cost			0.013	0.003
			(0.040)	(0.040)
Period=2 × 1(large bidder (> 2 bids per round))			-0.495	-0.105
			(0.334)	(0.324)
Period=3 × 1(large bidder (> 2 bids per round))			-0.164	-0.016
			(0.501)	(0.698)
Period=2 × 1(large bidder (> 2 bids per round)) × cost			0.104	0.022
			(0.064)	(0.051)
Period=3 × 1(large bidder (> 2 bids per round)) × cost			0.065	0.011
			(0.083)	(0.109)
N	1,129	1,129	1,129	1,129
Adjusted R2	0.49	0.68	0.68	0.76
Mean DV	6.49	6.49	6.49	6.49
Land FE	No	Yes	Yes	Yes
State FE	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
Bidder FE	No	No	No	Yes

Notes: DV: Bid values. Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$