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

Stefan Lamp† Mario Samano‡ Silvana Tiedemann§

April 2, 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. This paper makes use of unique bid-level data from German RE pay-as-bid auctions (2015-2019) to document bidding behavior of firms in this newly established market and recover bidders' costs by estimating a structural model of multi-unit auctions. We show that bidding behavior has changed over time and explore alternative mechanisms driving the observed price evolution and conduct counterfactual analyses to examine the impact of implementing a non-discriminatory auction format. Our primary findings indicate that adopting a non-discriminatory auction would have resulted in reduced subsidy expenses and mitigated market power. By identifying the factors influencing bidding prices and costs, our empirical insights offer guidance for the design of environmental policies aimed at fostering the adoption of RE.

JEL codes: D44, L51, Q42, Q48

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

---

*We thank Riccardo Camboni, Alan Crawford, Natalia Fabra, Harim Kim, Mario Liebensteiner, Stan Reynolds, Eric Richert, Morten Saethre, Philipp Schmidt-Dengler, Matthias Wrede, and participants at the Bergen Competition Policy Conference, EAERE, Mannheim Energy Conference, Southern Economic Association Conference, Toulouse Conference on the Economics of Energy and Climate, 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".

†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 been largely replaced by market-based support mechanisms such as RE auctions. As of 2019, over 100 countries have held these auctions.[2] However, while RE auctions have been widely adopted, the determinants of the market participants' bidding behavior has not been equally studied from an empirical perspective. This holds significant relevance for the deployment costs associated with these technologies, particularly within the current landscape of intensified efforts towards climate change mitigation policies and revised investment objectives for RE.

In this paper we study the role of auction design when there is no risk of default by the government and that of cost and market factors that influence observed price developments. The first has been a central question in studies on 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 established by the policy itself.

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

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

[2]During 2017-2018, around 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.

participants can simultaneously submit individual supply curves with the possibility of submitting just one quantity-price pair. The auctioneer collects 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 by bidder are determined by the intersection of this curve and the government's demand curve. This intersection also determines the maximum level of the subsidy, which consists of a per-unit of output payment equal to the price submitted in the auction, i.e., a pay-as-bid auction.

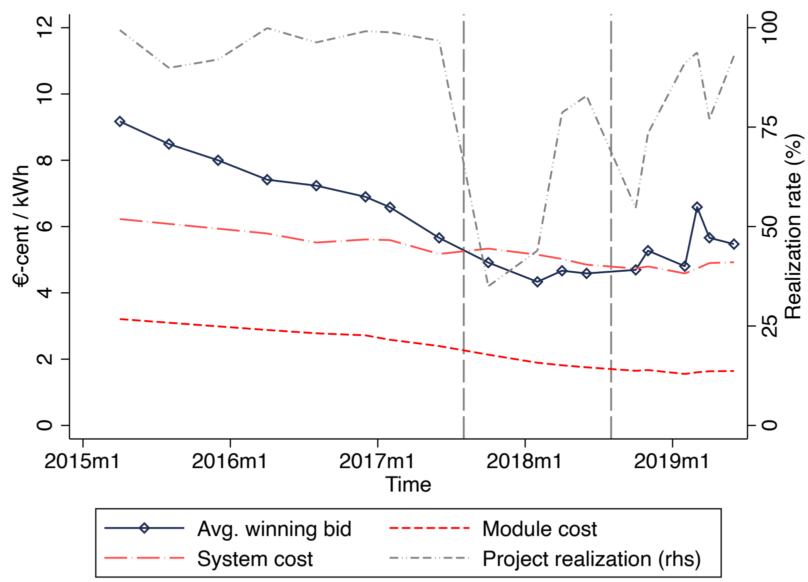
Our first research question is to understand the extent to which the particular way in which winning bidders' production subsidy is determined, the pay-as-bid system, has implications for the levels of market power exercised by the participants relative to an auction design in which the production subsidy is non-discriminatory. Therefore, depending on the underlying cost of each quantity segment, the price-cost gap will be different in each auction format because the market clearing price will not necessarily be the same. Our second main 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 vast set of observable and non-observable bids characteristics and the price at which they were submitted. This analysis quantifies some of the regulatory concerns regarding the size of the government's demand, the location of the sites, and the frequency at which the bidders are allowed to participate over time.

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. Our dataset includes bid quantities and prices from all bidders in each auction round. Additionally, we have information on the geographical location of each bid, enabling us to match covariates, such as solar irradiation and distance to the electricity network. The German solar auctions are particularly well-suited to analyze bidding behavior of firms, as these auctions have been competitive (over-subscribed) and the design elements are very exemplary for other RE auctions as they have been implemented in Europe and other developed economies.[3]

[3] Del Río and Kiefer (2021) map the evolution of design variants of RE auctions over time, technology,

An initial observation is that the average auction winning prices in Germany have been decreasing for the first three years after introducing the auction mechanism in 2015 in line with international developments.[4] Yet, prices have stagnated after that period.

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



Notes: Average quantity-weighted winning bid prices (€-cent / kWh) together with average solar module costs and solar system costs (in the next 12 months) for ground mounted installations. To convert the EUR / kW cost measures into EUR / kWh we assume a lifetime of 25 years and an annual discount factor of 10%, as in Ryan (2021), using observed capacity factors at the plant level. The figure also plots project realization rates (up to 24-months after the auction date) for winning bids. The vertical dashed gray lines represent the split of the sample into three periods depending on whether mean bid prices are below or above average system costs.

Figure 1 shows these trends together with cost indicators for ground mounted solar installations, which have been decreasing over time.[5] However, in the second half of 2017 average winning bid prices fell below the system costs for several auction rounds, and recovered only in late 2018. We use this observation to distinguish between three periods in our sample. In

and country, and find that governments navigated towards common design elements, almost all of which are found in the German solar auction.

[4]See Online Appendix Figure O.1.

[5]Solar *module cost* represents only the cost of solar panels and is based on monthly observations from PV Exchange. *System cost* includes additional hardware and installation costs and are based on quarterly survey data from the German Solar Industry Association. Both cost indicators refer to ground mounted installations in the next 12 months.

Periods 1 and 3 average winning prices are above system costs. In Period 2 average winning prices are below system costs. This indicates that profit margins must have fallen in Period 2 relative to Period 1. This observation is also in line with 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 that this is related to a change in the extent that bidders exercise market power in the auctions after 2017 and that factors such as the size of bidders are strongly correlated with bidding behavior.

We follow the literature on multi-unit auctions (Hortaçsu and McAdams, 2010; Kastl, 2011) to obtain measures of bidders' costs and we apply those tools to our context in a similar manner as Ryan (2021). With a resampling technique used by the aforementioned authors over a set of the firms' bidding curves, we simulate a large set of residual demand curves to determine simulated market-clearing prices. By substituting those prices into a closed-form expression for the costs, we obtain estimates for the underlying costs for each bid. Using the estimated costs we compute measures of market power, conduct an analysis of factors that influence bidding behavior and counterfactuals. 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– and this density remained in almost the same location thereafter.

We then determine, through linear regressions the key factors that are related to bidding behavior. We find that the estimated costs are strongly correlated with system costs and solar irradiation. However, we do not find a significant correlation between costs and proximity to the nearest high-voltage electricity interconnection node. Moreover, bid prices exhibit a robust correlation with estimated costs, indicating a pass-through effect ranging between 0.15 and 0.37 c/kWh for every 1 c/kWh increase in costs. Interestingly, larger bidders demonstrate a higher propensity to pass-through a greater proportion of their costs compared to smaller bidders. Furthermore, our analysis delves into the temporal and size-based heterogeneity of pass-through behavior. Notably, during periods of low average winning bid prices, larger bidders exhibit a greater inclination to pass on costs compared to their smaller counterparts.

Next, we use the model to perform a first counterfactual, assuming that bidders submit their costs instead of the observed bids. We call this the *truthful bidding* case. The auctioneer aggregates these bids to obtain the equivalent of a perfectly competitive supply curve of bidders' costs, which determines a new market clearing price for each auction. When all the winning bids get paid that same clearing price, this approximates a non-discriminatory auction setup, which is different from the pay-as-bid format currently implemented by the regulator. Our results indicate that under truthful bidding, in all but one auction round quantity-weighted average margins would have been lower than under the pay-as-bid format. This is not a mechanical result because it depends on the degree of convexity of the cost and the bidding curves at the intersection point with the perfectly inelastic demand curve.

We proceed by calculating the subsidy payments under each auction format. In the uniform auction format, subsidies are determined by the market clearing price, while in the pay-as-bid format, they are dictated by the bids themselves. To illustrate, we present stylized examples showcasing instances where either auction format may yield a lower total subsidy amount, necessitating further empirical investigation. To this end, we analyze subsidies under each format across three levels of the capture price.[6] Our analysis reveals that subsidies under uniform pricing consistently remain equal to or less than those under pay-as-bid in nearly all auction rounds. The only exceptions to this trend occur in rounds where margins under uniform pricing are notably larger or closely aligned with those under the pay-as-bid format. Additionally, we observe that as the capture price increases, subsidies under uniform pricing generally decrease relative to pay-as-bid subsidies across the majority of rounds, as higher capture prices diminish the protective advantage conferred by auction prices.

Finally, we calculate the inverse elasticity resulting from an increase in auction volume (government demand). This analysis is prompted by the over-subscription observed across all auction rounds. Our findings indicate that under uniform pricing, a 1% rise in government demand causes a 0.12% uptick in the market clearing price, while under pay-as-bid, it

[6] The capture price refers to the wholesale price of electricity used to compute the level of subsidies. We describe it in detail in section 2.

corresponds to a 0.13% increase in the marginal price.

We contribute to two main strands of literature. First, we systematically quantify market power for the procurement of RE capacity in the context of multi-unit auctions and in addition, we document the factors associated with bidding 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) has shown that the revenue equivalence theorem holds in single-item auctions, Ausubel and Cramton (2002) have shown that there is no clear ranking of sellers' revenues in multi-unit auctions. Instead, such a ranking is an empirical question.[7] 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 recent applications of these techniques in electricity-related markets include 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 bid data from solar auctions in India to estimate a structural model, focusing on the role of counterparty risk in procurement. Compared to his work, our paper aims to analyze the importance of market design and factors that influence bidding behavior in an environment with virtually no default risk. Also, while solar technology is well-established in Germany (thanks to generous policy support since the early 2000s), we show that even in this market, fundamentals evolve and different types of bidders may respond heterogeneously to these changes when the policy paradigms change.

Second, we contribute to the literature evaluating auction designs in the RE context, with the objective to find the most efficient auction design. The question how to best design

[7] There is a strand of the literature studying the electricity generation sector to compare both formats. Federico and Rahman (2003) found that under some conditions, market power is higher in a uniform price auction than in a pay-as-bid auction. Holmberg (2009) used a supply function approach to obtain comparisons. Fabra et al. (2011) used a duopoly model with investment and found that pay-as-bid resulted in lower prices than the uniform price auction while keeping capacity fixed. Willems and Yueting (2023), using a theoretical model, found that pay-as-bid auctions are inefficient in the context of electricity generation because they incentivize a portfolio mix without sufficient baseload capacity. Compared to this literature, our paper examines procurement and therefore capacity is not fixed.

auctions has been studied empirically but only for auctions that run for a short period of time and seldom by taking the impact of the design elements on different market factors into account (Winkler et al., 2018; Matthäus, 2020; Fabra and Montero, 2023). Several studies on renewable energy auctions have highlighted a dearth of empirical evidence regarding auctions' effectiveness in reducing support costs and efficiently selecting producers (see Del Río, Pablo and Kiefer, Christoph P., 2023, for a review), which is mostly linked to the general unavailability of detailed bid-level auction data in this context.[8] In the absence of robust empirical studies, the literature on renewable energy 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 (Bayer et al., 2018; Matthäus, 2020; Anatolitis et al., 2022; Del Río, Pablo and Kiefer, Christoph P., 2023). The pricing rule is considered of minor importance (Matthäus, 2020). On the other hand, the evidence on the impact of renewable energy auctions on market concentration and bidder diversity is mixed.[9] Our analysis highlights that factors such as the size of bidders are strongly correlated with bidding behavior.

The rest of this paper is structured as follows. Section 2 introduces the German RE 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 performs counterfactuals regarding the auction format and section 6 concludes.

[8] Del Río, Pablo and Kiefer, Christoph P. (2023) provide a comprehensive review of the literature on renewable energy auctions. They find that most empirical research consists of descriptive case studies (mostly conducted within two European research projects called AURES I and II. Recent additions include cross-country (panel) comparisons analyzing the impact of auctions on capacity expansion (Bayer et al., 2018; Matthäus, 2020) and on the level of support (Anatolitis et al., 2022). On the theoretical level, Fabra and Montero (2023) provide the theoretical framework to study the equilibrium in renewable energy auctions and Kreiss et al. (2017) and Haufe and Ehrhart (2018) examine the impact of design variants on the auction outcome. Finally, Voss and Madlener (2017) provide simulation results for the design of German RE auctions.

[9] Grashof (2019) argue that auctions are likely to disadvantage smaller bidders, which would discourage policy acceptance and risk capacity expansion. Kruger et al. (2021) find that market concentration hinders competition and increases bid prices. Kiefer and del Río (2024) find that auctions increase market concentration and bidder diversity. 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.

2 Institutional Background

In 2015, the German government introduced auctions for utility-scale solar projects to steer capacity additions and to reduce subsidy payments.[10] 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, set by the government, are converted into a fixed auction volume and distributed over several rounds per year by the Federal Network Agency. 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. The auction applies discriminatory pricing (pay-as-bid), but ex-post subsidy payments depend on the realized market value of solar, as described below. 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). 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.[11] The Federal Network agency has no significant power to alter the auction

[10] 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 Appendix O.2).

[11] 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.

rules despite adjusting the ceiling prices in line with the provisions in the law (Tiedemann et al., 2019). Appendix Figure B.1 shows the auction dates, total auction volume, the distribution of winning bid prices, and the price ceilings. Online Appendix O.2 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.[12] 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 EUR/kW, bids for projects that are developed further need to pay only 25 EUR/kW.[13] 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 will be applied a penalty 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 the penalty of 0.3 cent/kWh applies.

Subsidy payments. The subsidy is a direct payment for every unit of electricity produced. The electricity network operator guarantees the payment to 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 estimated revenue from the wholesale electricity market, i.e., the monthly market value or average *capture price of solar*. The transmission system operators calculate the monthly capture prices and publish them online.[14] In the literature on RE support schemes this subsidy design is called a *sliding market premium* (e.g., Klobasa et al.,

[12] 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.

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

[14] https://www.netztransparenz.de/EEG/Marktpraemie/Marktwerte

2013) or more recently *one-sided contract for difference* (e.g., Beiter et al., 2021). Specifically, the subsidy is defined as

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

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. Even in the case in which firm-specific expectations are such that $b_i \leq cp_t$, the auction will determine who is allowed to participate in the market, so competition in the auction is an important component, even though it may be payoff irrelevant.

3 Data and Descriptive Statistics

The data consist of all bids submitted to solar auctions in Germany held between the introduction of German RE auctions in 2015 and June 2019, covering 18 auction rounds with a total of 1,791 bids.[15] We focus on solar installations only and exclude the 19 bids for wind projects in auctions where both technologies were admissible. If not otherwise mentioned, we exclude non-eligible bids which make up 11% of the total number of observations. Moreover, we exclude the first auction round (132 observations) and the two proceeding rounds in 2015 (pilot phase) that were implemented under uniform price rules (235 observations) from our main sample. Our final dataset consists of 1,206 observations. Table 1 summarizes our data for the pay-as-bid rounds by pooling all observations first and then by splitting the sample

[15] The bid 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.

into three time periods depending on whether the average winning bid prices are above or below the average system costs (see also Figure 1).

In addition to the main 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.[16] We elaborate on the additional data sources and construction of these covariates in Appendix A.

Table 1 shows that during period 2 (the period in which the average winning bid prices have been below the average system cost) the average project size (bid volume) has been slightly larger. Projects are otherwise similar in terms of location (average solar irradiation and distance to nearest high-voltage network node). Yet, we find that in period 2 more large projects have been realized as indicated by both the share of projects on agricultural land and the share of large bidders. In line with these observations, the number of bids and bidders has been slightly lower, and the market concentration indices (HHI and C1-C3) indicate a somewhat more concentrated market during this period.[17]

To get a better sense of how competition has evolved over time, Figure 2 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 and have been considered competitive by the policy maker. In addition, since all eligible bids must be below the stipulated ceiling price, the distribution of winning bids is also below that level (see Appendix Figure B.1). Note that in the three auction rounds that were implemented as joint solar and wind auctions

[16]We define large bidders on the ex-post distribution of average project sizes by bidder, using the 90th percentile over all rounds. This classifies 17 out of 137 bidders as "large". The number of average bid steps submitted is similar for the two types: 4.06 for large and 4.34 for small bidders, respectively. We perform robustness checks concerning this measure.

[17]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 Herfindahl-Hirschman Index (HHI) is defined as the sum of the squares of the submitted capacity shares in a given round.

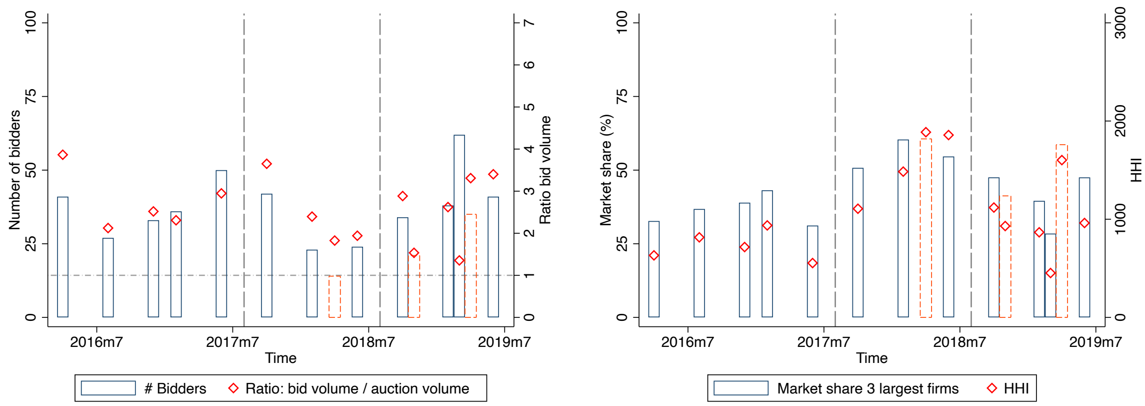
Table 1: Summary statistics - German solar auctions 2016-19

	All		Period 1		Period 2		Period 3	
	mean	sd	mean	sd	mean	sd	mean	sd
Bid-level covariates:								
Bid value (€-2019 c/kWh)	6.41	(1.33)	7.47	(1.02)	5.14	(0.55)	6.19	(1.15)
Bid volume (MW)	5.92	(6.32)	5.25	(3.25)	6.95	(7.23)	5.94	(7.52)
System cost (€-2019 c/kWh)	5.2	(0.54)	5.79	(0.34)	5.23	(0.29)	4.72	(0.20)
Solar irradiation (kWh/m^2)	1097.25	(44.31)	1093.49	(39.85)	1101.99	(45.47)	1097.92	(46.86)
Distance to network (km)	20.41	(11.13)	21.47	(11.37)	19.41	(10.49)	20.06	(11.19)
Land types (share):								
- Agriculture or grassland	0.26	(0.44)	0.17	(0.38)	0.38	(0.49)	0.28	(0.45)
- Non-conventional buildings	0.13	(0.34)	0.1	(0.29)	0.15	(0.36)	0.15	(0.36)
- Government land	0.09	(0.28)	0.06	(0.24)	0.06	(0.23)	0.12	(0.33)
- Adjacent to railway or road	0.27	(0.45)	0.28	(0.45)	0.21	(0.41)	0.3	(0.46)
- Site with previous usage	0.24	(0.43)	0.39	(0.49)	0.2	(0.40)	0.15	(0.35)
Large bidder (project size)	0.22	(0.41)	0.17	(0.38)	0.39	(0.49)	0.17	(0.38)
Round-level covariates:								
Share of eligible bids	0.91	(0.00)	0.88	(0.00)	0.92	(0.01)	0.92	(0.00)
# bids per round	80.4	(28.54)	84	(23.63)	64.75	(28.27)	87.83	(32.85)
# bidders per round	34.73	(12.12)	37.4	(8.68)	25.75	(11.73)	38.5	(13.40)
# bidders awarded per round	15.6	(11.16)	12.6	(1.52)	11.75	(2.22)	20.67	(17.10)
HHI	1061.39	(452.30)	730.82	(150.81)	1583.71	(366.76)	988.64	(374.20)
C1, bid volume per round (%)	24.03	(8.11)	19.33	(3.60)	32.26	(7.77)	22.47	(7.65)
C3, bid volume per round (%)	44.81	(10.59)	36.56	(4.82)	56.6	(4.77)	43.83	(10.07)
C5, bid volume per round (%)	56.79	(11.23)	47.93	(5.81)	68.57	(6.58)	56.33	(10.52)
Observations	1206		420		259		527	
Number of auction rounds	15		5		4		6	

Notes: Main estimation sample: pay-as-bid auctions in 2016 - 2019. Excludes first auction in 2015 and two successive uniform pricing rounds as well as non-eligible bids. Period 1 covers auction rounds 4 to 8, period 2 includes rounds 9 to 12, and period 3 includes rounds 13 to 18.

(orange, dashed bars) solar was the single winning technology and only very few bids for wind had been submitted. We therefore exclude wind related bids from the analysis and treat these auction rounds as the remaining solar auctions.

Figure 2: Evolution of competition in German solar auctions



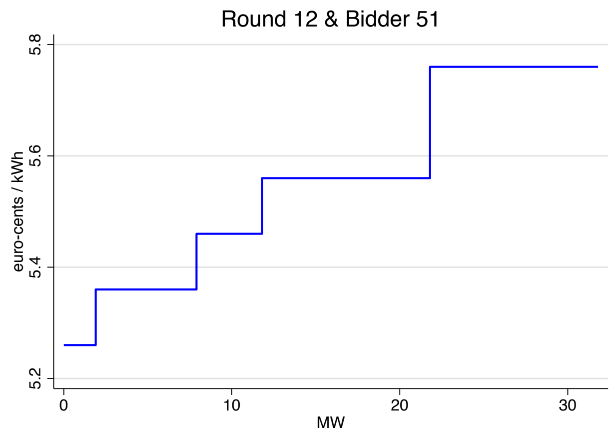
Notes: Number of bidders per auction round and ratio of bid volume to auction volume in the left panel. Market share of three largest firms (C3) and Herfindahl-Hirschman Index (HHI) in the right panel. Solar specific auction rounds in blue, while dashed, orange bars indicate auction rounds implemented as joint wind and solar auctions.

A common feature of multi-unit auctions is that bidders are not restricted to submit a single bid in the auction. Figure 3 shows an example of the bidding curve for bidder 51 in auction round 12. Overall, there is a variety of the type of bidding curves, with about half of the bidders submitting a single quantity-bid pair, some bidders submitting up to 25 different pairs in the same auction round, and the distribution on the number of steps is skewed to the right in period 2 relative to the other periods (see Appendix Figure B.2).

4 Empirical Strategy

In the following section we apply a model of multi-unit auctions to the context of renewable energy procurement. We use the model to recover costs that we employ in a second step to analyze observed bidding behavior.

Figure 3: An example of a bid curve



Notes: Bid curve for bidder 51 in auction round 12. In this case, there are five different quantity-price pairs (bids) submitted by this bidder.

4.1 Bidding Model for Multi-unit Auctions

We follow 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. This method has been mostly used in treasury auctions (e.g., Elsinger et al., 2019), but has also found applications in electricity markets (e.g., Reguant, 2014; Kim, 2022; Ryan, 2021). In the treasury auctions literature, this method is primarily used to estimate underlying valuations from demand schedules. We adapt the method to estimate costs from supply schedules instead.

Model set-up. There are T auction rounds, where each auction is a discriminatory auction of Q_t divisible units (total solar capacity demanded by the government). In each individual auction round t = 1,..., T, there are N_t bidders. As in Kastl (2011), we allow for bidder asymmetries by introducing G different groups of bidders, denoted by g, such that $N_t = \sum_{g=1}^{G} N_t^g$. 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 (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 (land cost, financing, etc.) and furthermore need to form individual expectations about the auction payoff given the subsidy scheme discussed in section 2.

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 t to improve readability.

The firm submits the non-decreasing supply schedule

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

that consists of a step function where each step k has for length the quantity offered $q_{i,k}$ and for height the price offered $b_{i,k}$.[18] The firm maximizes the expected value of its profits as a function of the signal

$$\Pi_i(s_i) = \int_0^{Q_i(\boldsymbol{y^{-1}}(\cdot; \boldsymbol{s}))} [y_i^{-1}(q; s_i) - c_i(q; s_i)]dq,$$

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.

Since auctions can vary on the number of competitors, the volume requested by the government, and by the expectations on future electricity prices that ultimately determine the size of the subsidies, we model each auction round independently from each other.[19]

Equilibrium Price and Bids. 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

[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 $1 \leq k < K_i$, $q_{it} < q_{it+1}$, and $b_{ik} < b_{ik+1}$. Bidders actions therefore include choices regarding the bid value and the quantity (project size).

[19] We have also implemented a version of the model that assumes symmetry (does not split bidders in G groups) and that allows for multiple rounds to be pooled based on observable characteristics (kernel) with qualitatively similar results. We report the results in Online Appendix O.3.1.

by firm 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.

Bidders' costs. 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. The main difference in our setting relative to that in Kastl (2012) is that the firms face residual demand curves instead of residual supply curves. For the bid to be optimal, the following equation has to hold.[20]

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

This equation can be rearranged to obtain a closed-form expression for the cost for each step of the firm's supply curve,

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

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 $\Pr(b_{i,k} < p_c < b_{i,k+1})$. Unlike other multi-unit auctions settings, there is no rationing in these procurement auctions and the last bid is always fully awarded.

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

[20]The argument works as follows. Assume that the clearing price occurs at a vertical segment of the residual demand curve. Then, a small reduction in quantity (bid shading) makes the bidder lose $b_{i,k} - c(q_{i,k})$ 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 ($\Pr(b_{i,k} < p_c < b_{i,k+1}) > 0$). 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.

own market share and the substitution effects. Similarly, our expression for the cost is equal to the bidding value minus a term that depends on the probability of winning and on how that probability is affected by the clearing price.

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 bidding values (see Appendix Table B.1). We also tried alternative definitions of size with similar results.[21] 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.[22]
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.

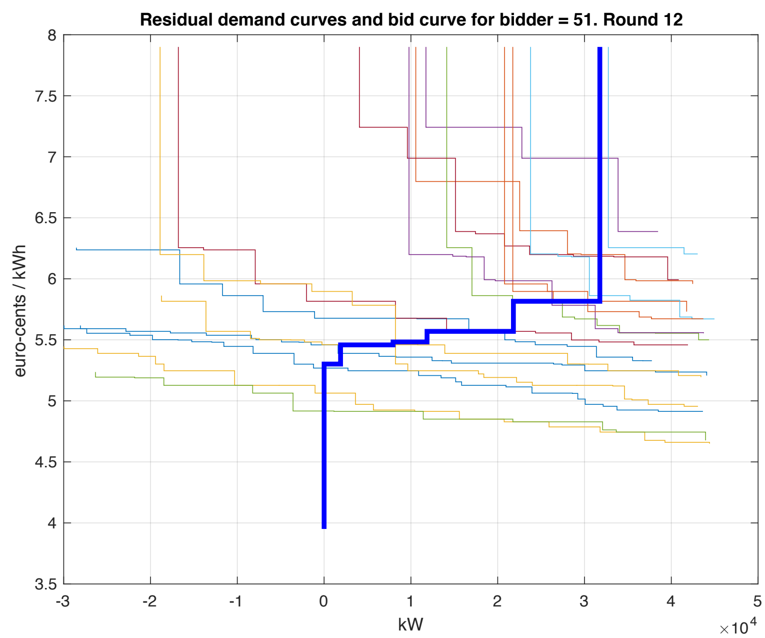
By repeating the above steps several times, we obtain a sample of market clearing prices,

[21] 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.3.3.

[22] 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. Online Appendix Figure O.3 provides robustness for our results, pooling several rounds based on a three-dimensional kernel.

which can then be used to consistently estimate each bidder's winning probability using Equation 1. At each step, we obtain several residual demand curves, each intersecting one of 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 1, 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 in Equation 1 is numerically very small.[23] 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 subsample of bid vectors with replacement. Each intersection results in a market clearing price.

[23]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.

4.1.2 Bidders' costs

We present the kernel densities of the estimated costs in Figure 5 together with the kernel densities of the observed bids for each of the three sample periods. 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 exercise of market power but the overall probability mass for both distributions shifted to the left in Periods 2 and 3 relative to Period 1.

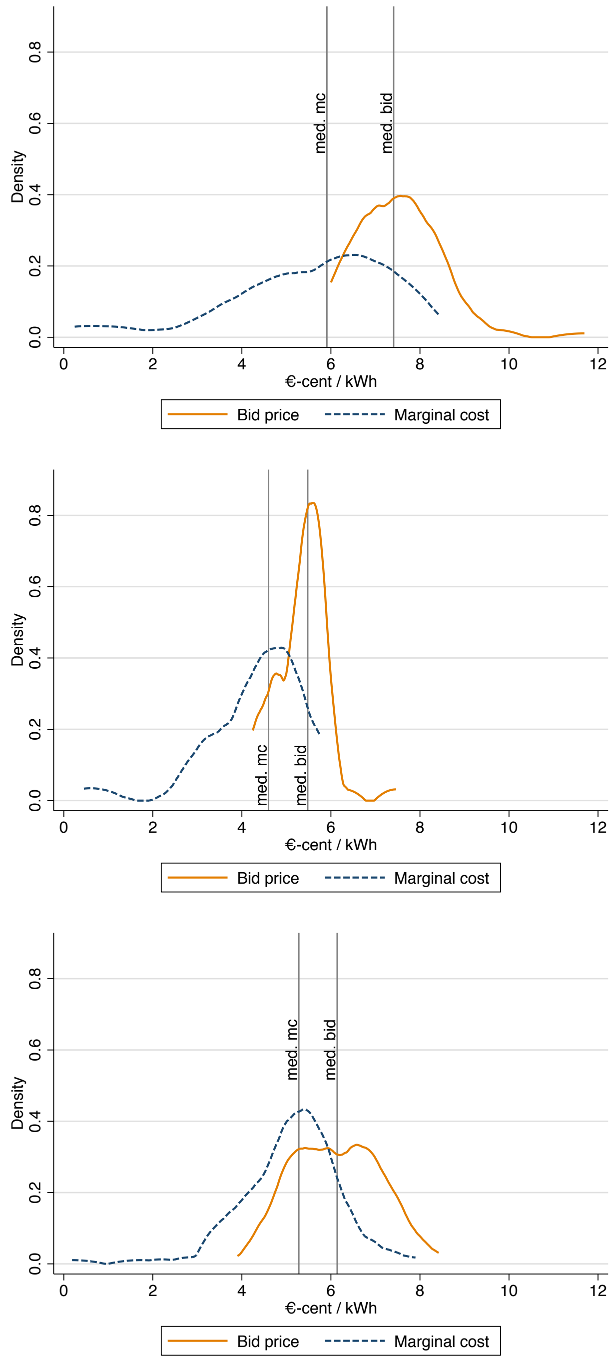
In Figure 6 we plot the densities of the margins $(b_i - c_i)$ for each period separately. Period 1 has the largest margins among the three while Periods 2 and 3 have very similar densities. The median margins for the three periods are between 0 and 2 c/kWh, which are in line with the vertical difference 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

In this section we examine the correlation between auction outcomes and a rich set of bid and market characteristics. 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 of these regressions, standard errors are clustered at the bidder level.

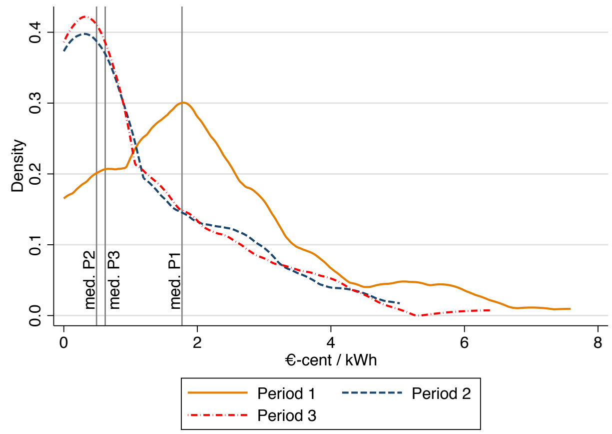
Among the market factors we consider is the distance to the nearest high-voltage electricity network node, which is motivated by the market and regulatory concerns regarding

Figure 5: Estimated costs and observed bids densities



Notes: Kernel densities of the costs obtained from Equation 1 and from the observed bids. Individual bids are aggregated by bidder and period using quantity-weighted averages. From top to bottom: Period 1, Period 2, and Period 3.

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. Margins in Period 1 are higher than in periods 2 and 3.

the interconnection costs as a barrier of entry for renewable capacity.[24] We also consider an observed measure of system costs (see section 3), solar irradiation, and whether the volume requested in the round is greater than 200 MW.[25] At the bidder 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 alternative definitions of size regarding the number of projects submitted, with similar results.

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.[26] Across all specifications a few patterns emerge. System costs are positively related to estimated costs but only in the absence of fixed effects. Solar irradiation is statistically significant and

[24] See for instance Davis et al. (2023). We calculate the distance as the direct line from the centroid of the 5-digit zip code and the nearest high voltage network node (see Appendix Figure B.3).

[25] The auction volume has typically been between 125 and 200 MW (see Appendix B.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.

[26] The number of observations drops slightly from 1,206 in the original sample to 1,143 since for a few bids we cannot assign an estimated cost. Therefore, we omit these observations from the analysis.

with a negative coefficient, indicating that more productive sites have lower costs. Auction volume—the government's demand—is positive and statistically significant as it would be predicted by a demand shift to the right and its corresponding upward pressure on the market clearing price, everything else held constant. Interestingly, the distance between the solar site and the closest interconnection node is almost never statistically significant in any of the specifications. This result speaks to the debate on interconnection costs as a barrier to entry for renewable generation sources in some markets.[27] 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 B.3). Alternatively, plants might connect to lower voltage network nodes (which, however, are even more densely located than the high voltage nodes). Finally, large bidders seem to have slightly higher costs, but this effect is not very robust and it gets absorbed by the bidder fixed effects in the last column.

Bid values. It is possible that some of the market and bidder-specific factors examined in the previous 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. Our objective is merely to assess the plausibility of our cost estimates and to observe patterns in bidding behavior in relation to a variety of factors.

In Table 3 we assess whether the observed bidding 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 0.15 and 0.37 c/kWh for a 1 c/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 remains largely unchanged relative to columns (2) - (3), we find that there is an additional pass-through from large bidders of between 0.19 and 0.24 c/kWh relative to the

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

Table 2: DV: Bidders' costs

	(1)	(2)	(3)	(4)
Distance to network	0.663	0.522	0.405	0.207
	(0.425)	(0.427)	(0.362)	(0.404)
System costs	8.306***	8.278***	2.423	2.390
	(1.880)	(1.855)	(2.666)	(2.880)
Auction volume > 200MW	0.820***	0.865***	0.299	0.516**
	(0.191)	(0.209)	(0.228)	(0.206)
Solar irradiation		-4.588***	-5.515**	-4.365*
		(1.455)	(2.197)	(2.449)
Large bidder (size, p90)		0.110	0.267*	
		(0.141)	(0.150)	
N	1143	1143	1143	1143
Adjusted R2	0.07	0.08	0.20	0.26
Mean DV	5.52	5.52	5.52	5.52
Constant	Yes	Yes	Yes	Yes
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. Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

small bidders. Using column (5), the total pass-through for a large bidder is about 6% of the mean of bidding values.[28] The coefficient related to auction volume is no longer statistically significant, unlike its relationship with estimated costs. 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 (cost)	0.373***	0.152***	0.159***	0.144***	0.128***
	(0.046)	(0.024)	(0.025)	(0.024)	(0.027)
Distance to network			0.483*	0.486*	0.417
			(0.283)	(0.278)	(0.334)
Large bidder (size, p90)			-0.461***	-1.502***	
			(0.125)	(0.223)	
Auction volume > 200MW			-0.114	-0.107	-0.083
			(0.138)	(0.140)	(0.160)
Large bidder × cost				0.185***	0.236***
				(0.046)	(0.040)
N	1143	1143	1143	1143	1143
Adjusted R2	0.25	0.66	0.67	0.68	0.76
Mean DV	6.45	6.45	6.45	6.45	6.45
Constant	Yes	Yes	Yes	Yes	Yes
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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Heterogeneity of pass-through. In Table 4 we further decompose 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

[28] We provide an alternative fixed effects structure for the main results (columns (4) and (5)) in Appendix Table B.2.

in Period 2 is about the same, but in Period 3 the pass-through is between 0.18 and 0.21 c/kWh higher (relative to a mean of bid prices of 6.45 c/kWh).

However, that heterogeneity over time masks yet another layer. When we interact the bidder size with dummies for Periods 2 and 3, we find that the pass-through is stronger in Period 2 (columns (3) and (4)), which is the time period when the average of winning bids fell below system costs. In other words, large bidders were more skilled than small bidders to navigate a time of unattractive clearing prices and relatively high costs.

In order to get a decomposition not only across the three periods exogenously defined in our data but at the round level, we estimate a similar regression to that in columns (2) and (3) from Table 4 but where 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 and the right panel of Table 4 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. There has been a clear upward trend over time. Focusing on the pass-though 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 noisily estimated and we cannot reject the null hypothesis of zero pass-through in most rounds before Period 3.

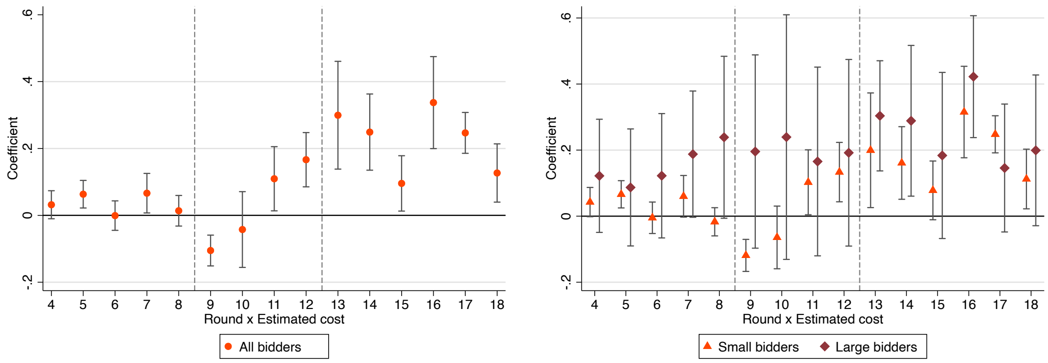
Probability of winning. Finally, we also estimate a linear probability model for the awarded bids. The results, shown in Table 5, confirm the trade-off between a higher bid price and a lower probability of winning (column (1)). Columns (2) - (5) add the rest of controls from the previous regressions but without the bid price since we already examined its correlation with market and bidders characteristics. Bidders' costs do not play an important role in the probability of winning but auction volume, bidder size, and system costs do. As expected, when government demand increases, the probability of winning increases because

Table 4: DV: Bidding values

	(1)	(2)	(3)	(4)
Estimated cost (cost)	0.177***	0.072***	0.071**	0.046*
	(0.031)	(0.025)	(0.027)	(0.024)
Period=2	-1.707***	-0.769***	-0.771***	-1.102***
	(0.262)	(0.210)	(0.206)	(0.236)
Period=3	-2.087***	-1.537***	-1.583***	-1.809***
	(0.311)	(0.224)	(0.227)	(0.260)
Period=2 × cost	-0.079*	-0.036	-0.038	0.030
	(0.047)	(0.041)	(0.044)	(0.039)
Period=3 × cost	0.176***	0.209***	0.188***	0.204***
	(0.053)	(0.043)	(0.044)	(0.048)
Auction volume > 200MW		-0.124	-0.090	-0.077
		(0.130)	(0.135)	(0.151)
Large bidder (size, p90)		-0.357***	-0.294	
		(0.131)	(0.231)	
Large bidder × cost			-0.004	0.136
			(0.041)	(0.087)
Period=2 × Large bidder			-2.889***	-1.596***
			(0.355)	(0.522)
Period=3 × Large bidder			-1.033	-0.035
			(0.676)	(1.138)
Period=2 × Large bidder × cost			0.559***	0.334***
			(0.074)	(0.082)
Period=3 × Large bidder × cost			0.203**	0.061
			(0.100)	(0.149)
N	1143	1143	1143	1143
Adjusted R2	0.55	0.72	0.72	0.80
Mean DV	6.45	6.45	6.45	6.45
Constant	Yes	Yes	Yes	Yes
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: Bidding values. Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 7: Pass-through over time



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

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 auction in addition to be able to pass on a larger fraction of their costs than the small bidders. The negative and significant coefficient on system costs in column (5) suggests that the auction mechanism selects low-cost projects, which is desirable for overall efficiency.

4.3 Robustness checks

Table O.1 - Table O.3 in the Online Appendix repeat the same analysis as above but keeping only the observations that have not been replaced with the observed bid price (see section 4.1.2 for details). All of our results hold even in this subsample. Similarly, Table O.4 - Table O.6 show the main regression tables with the alternative definition of large bidders, based on the number of submitted projects.

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, as explained above, the results are

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

	(1)	(2)	(3)	(4)	(5)
Bid price (deflated)	-0.214***				
	(0.018)				
Estimated cost (cost)		0.011	0.003	0.003	0.004
		(0.012)	(0.009)	(0.009)	(0.011)
Auction volume > 200MW			0.656***	0.648***	0.648***
			(0.053)	(0.051)	(0.067)
Large bidder (size, p90)			0.233***	0.235***	
			(0.076)	(0.077)	
Solar irradiation				-0.255	-0.397
				(0.554)	(0.495)
Distance to network				-0.082	-0.089
				(0.109)	(0.114)
System costs				-1.442	-1.875**
				(0.884)	(0.934)
N	1143	1143	1143	1143	1143
Adjusted R2	0.16	0.04	0.19	0.19	0.26
Mean DV	0.40	0.40	0.40	0.40	0.40
Constant	Yes	Yes	Yes	Yes	Yes
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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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.3.1. We consistently find a large drop for margins in Period 2 compared to Period 1.

Even though there is no suggestive evidence of any type of coordinated behavior, we implement a test on the correlations of residuals between pairs of bidders participating in the same auction rounds from a regression of log prices on cost and market factors. This test follows directly Bajari and Ye (2003). 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 -0.02 and a corresponding mean of p-values of 0.72, showing that there is no indication that the pairwise residuals are systematically correlated.

5 Auction Format and Size of Subsidies

We use the structural model to study a series of 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. Then we compute subsidies under each auction format and discuss the effects of the policy parameter that defines the subsidy itself: the capture price. Finally, we study the supply responsiveness to changes in government demand.

5.1 Changing the format of the auction

Similarly to Hortaçsu and McAdams (2010) and Elsinger et al. (2019) we set the bids equal to the estimated costs –valuations in their case studies– as the bidders' strategies to simulate a uniform auction format. We call this the truthful bidding benchmark. This circumvents modeling the strategies of each player and simplifies finding the equilibrium.[29] In the truthful bidding auction, we build the supply curve directly from the estimated valuations, 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.

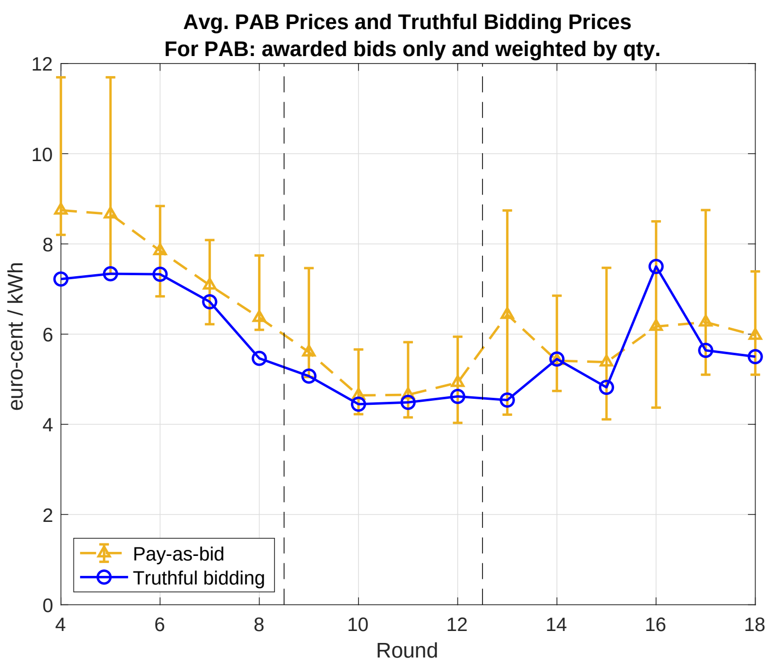
Figure 8 shows the truthful bidding clearing prices together with the observed pay-as-bid prices. For the former we construct the perfectly competitive supply curves directly using the estimated costs ranked from lowest to highest. As for the pay-as-bid prices, we use only the observed awarded bids and construct a quantity-weighted average. The pay-as-bid prices in this Figure are exactly the same as those shown in Figure 1 and Figure B.1 except that each round point is equally spaced in the x-axis and we start at round 4.[30] The main difference between the outcomes from the two auction formats is that market clearing prices are lower under truthful bidding than under pay-as-bid in almost all rounds except for rounds 14 and 16. The latter had an unusual high volume (see Figure B.1) 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 ($p^* - c_i$ in the case of truthful bidding and $b_i - c_i$ in the case of pay-as-bid) using the estimated costs. Figure 9 shows the quantity-weighted means of those margins by round. Although it is entirely possible

[29] Similar to the treasury auctions literature (see for instance Elsinger et al., 2019), we assume that bidding strategies do not change in the counterfactual simulations, but remain as observed in the data.

[30] 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 again, we made a normalization adjustment 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 pay-as-bid than the observed data but it creates a fair comparison with the truthful bidding counterfactual.

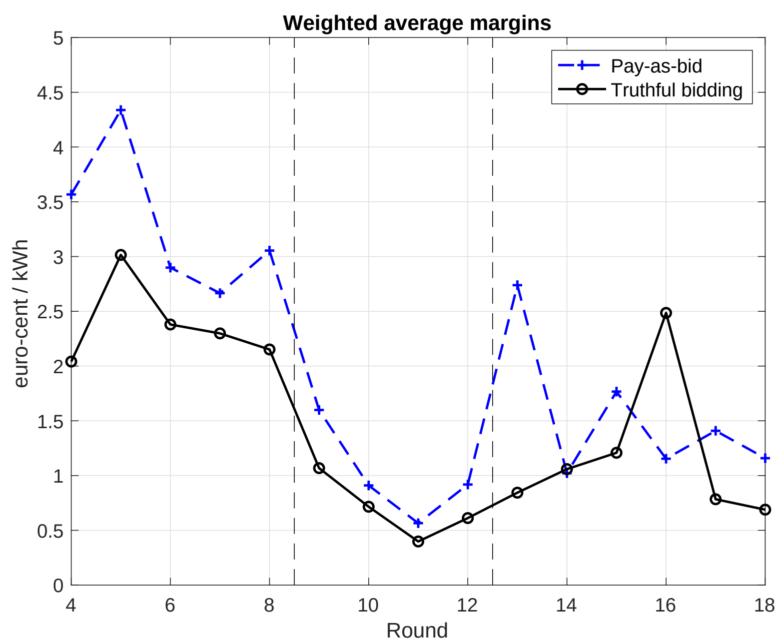
Figure 8: Pay-as-bid versus truthful bidding



Notes: Truthful bidding is a counterfactual where each firm submits bids that are equal to its costs. The pay-as-bid (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.

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 pay-as-bid some bidders could submit very low bids in order to guarantee getting awarded. The truthful bidding setting gives a lower bound on the government expenditure within the class of uniform price auctions.[31] Our main finding is that in this market and with this policy environment, a uniform auction would have given place to a lower exercise of market power than under the currently used auction format.

Figure 9: Margins under different auction formats



Notes: Truthful bidding is a counterfactual where each firm submits bids that are equal to their valuation. Pay-as-bid 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 format auctions

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 underlying cost curve

[31] 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).

do so as well. To evaluate this, we compute the ratio between the quantity-weighted sliding premiums under truthful bidding,

$$S_U = \sum_i q_i \max\{p^* - cp, 0\}$$

and the quantity-weighted sliding premiums under the pay-as-bid format,

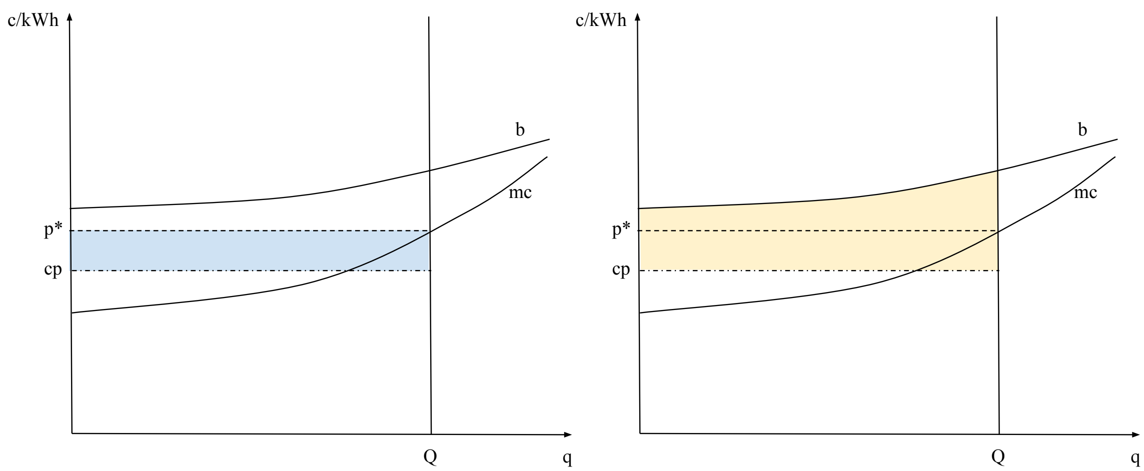
$$S_{PAB} = \sum_i q_i \max\{b_i - cp, 0\}.$$

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 pay-as-bid.[32] 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 pay-as-bid does, and in fact it shrinks relative to the previous configuration.

Since the two subsidy types cannot be ranked in size in general, we compute the ratio S_U/S_{PAB} between the two subsidies for each auction round and with three different levels of a constant capture price (2, 3.75, and 5 cents / KWh). Our middle value represents the prevailing capture price during the sample period of our data. Figure 12 presents the results. The subsidies under truthful bidding are never larger than the subsidies under pay-as-bid in all rounds except in rounds 14 and 16, which are precisely the two only rounds where margins under truthful bidding are larger than under pay-as-bid (see Figure 9). As the capture price increases, S_U/S_{PAB} decreases in almost all rounds because a higher capture price erodes the safety net provided by the policy more in a high-margins environment (pay-as-bid) than in a low-margins environment (truthful bidding). This relationship tends to reverse once again in the rounds where the exercise of market power is reversed across the two format auctions.

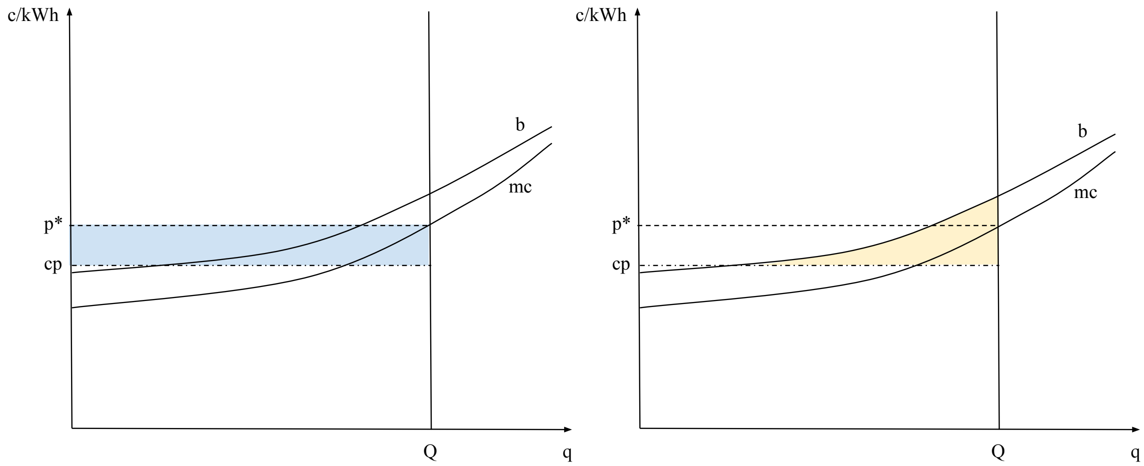
[32] In order to simplify the exposition of this argument, we use smooth functions instead of step functions but the same reasoning applies to both.

Figure 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 pay-as-bid. p^* is the market clearing price assuming uniform pricing can be approximated by the valuations curve v (truthful bidding), cp is the capture price. The uniform price subsidy is defined as $S_U = \sum_i q_i \max\{p^* - cp, 0\}$ over all the quantities up to Q (government's demand). The yellow area on the right panel represents the subsidy under pay-as-bid 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. It is clear that the blue rectangle is smaller than the yellow area.

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

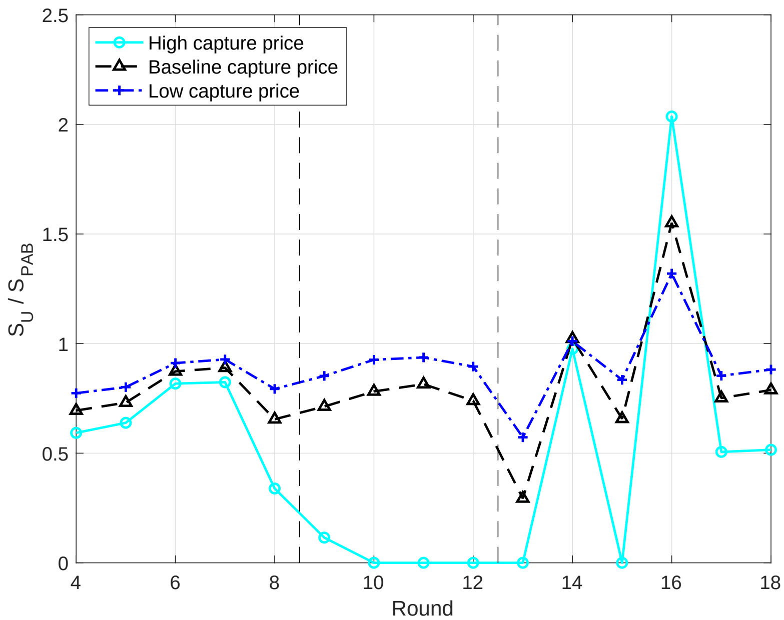


Notes: This is the same as Figure 10 except that the aggregate bid curve b is much closer to the valuations curve v. It is clear that the subsidy under uniform pricing (blue rectangle, left panel) is greater than under pay-as-bid (yellow area, right panel).

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's 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 pay-as-bid case is the one that corresponds to the ordering given by the curve of estimated costs. In other words, we do not compute a new set of strategies, but rather we simply 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 0.1248, while under pay-as-bid a value of 0.1301. In each case, the reported value is the simple average over the

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



Notes: Each line represents the ratio of the subsidy per kWh under truthful bidding and pay-as-bid S_U/S_{PAB} at each auction round, where $S_U = \sum_i q_i \max\{p^* - cp, 0\}$, p^* is the market clearing price under uniform pricing, q_i are the quantities awarded, $S_{PAB} = \sum_i q_i \max\{b_i - cp, 0\}$, and cp is a constant level of the capture price. As the capture price increases, subsidy under truthful bidding decreases and overall, the subsidy under truthful bidding is lower than under pay-as-bid.

per-round elasticities. This means that a 1% increase in government demand is associated to an increase of 0.12% of the clearing price under truthful bidding and a 0.13% under pay-as-bid. Given that all rounds were over-subscribed, 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 an alternative auction format. 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.

7 Funding and Conflict of interest

Silvana Tiedemann gratefully acknowledges financial support from the German Federal Ministry of Education and Research through the ARIADNE Project (FKZ 03SFK5K0). Stefan Lamp acknowledges support from ANR under grant ANR-17-EURE-0010 (Investissements d'Avenir program).

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. and Cramton, P. (2002). Demand reduction and inefficiency in multi-unit auctions.

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.

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.

Haufe, M.-C. and Ehrhart, K.-M. (2018). Auctions for renewable energy support – Suitability, design, and first lessons learned. *Energy Policy*, 121:217–224.

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.

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.

Kiefer, C. P. and del Río, P. (2024). Analysing the impact of renewable energy auctions on market concentration. *Renewable Energy*, 221:119664.

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.

Kreiss, J., Ehrhart, K.-M., and Haufe, M.-C. (2017). Appropriate design of auctions for renewable energy support – Prequalifications and penalties. *Energy Policy*, 101:512–520.

Kruger, W., Nygaard, I., and Kitzing, L. (2021). Counteracting market concentration in renewable energy auctions: Lessons learned from South Africa. *Energy Policy*, 148:111995.

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.

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.

Voss, A. and Madlener, R. (2017). Auction schemes, bidding strategies and the cost-optimal level of promoting renewable electricity in germany. *The Energy Journal*, 38(1 suppl):229–264.

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.

A 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.[33]

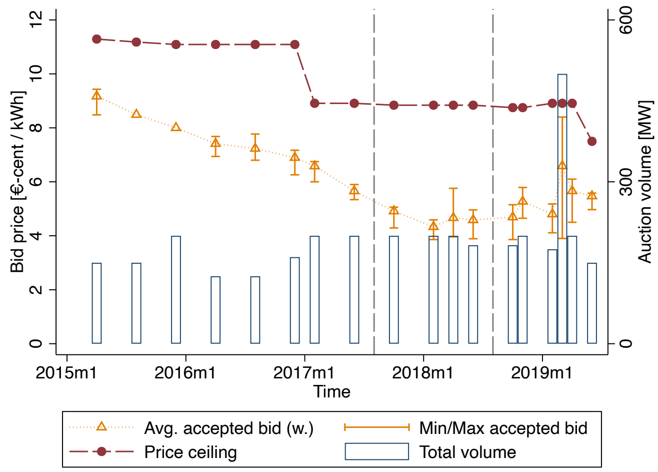
Solar cost indicators. We also use two cost indicators, the module price index in EUR per kilowatt (EUR/kW) provided directly by PVxchange and a system price index provided directly by the German Solar Association (BSW). Both indicators measure average cost factors for typical installations of ground 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 cost measure in the next 12 months. To convert the installation capacity (EUR / kW measures) into EUR / kWh, we assume a lifetime of 25 years and an annual discount factor of 10%. Moreover, we use observed capacity factors (based on annual production) for realized bids at the solar installation level.

Interconnection cost to electricity network. To proxy for the interconnection cost, 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 B.3).

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

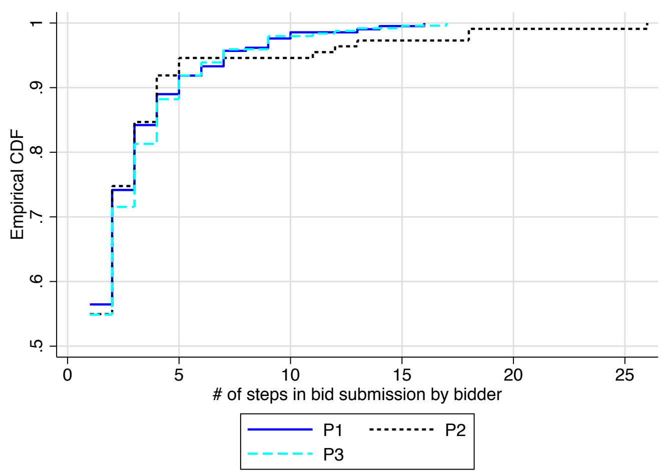
B Additional Figures and Tables

Figure B.1: Solar auctions in Germany: 2015-2019



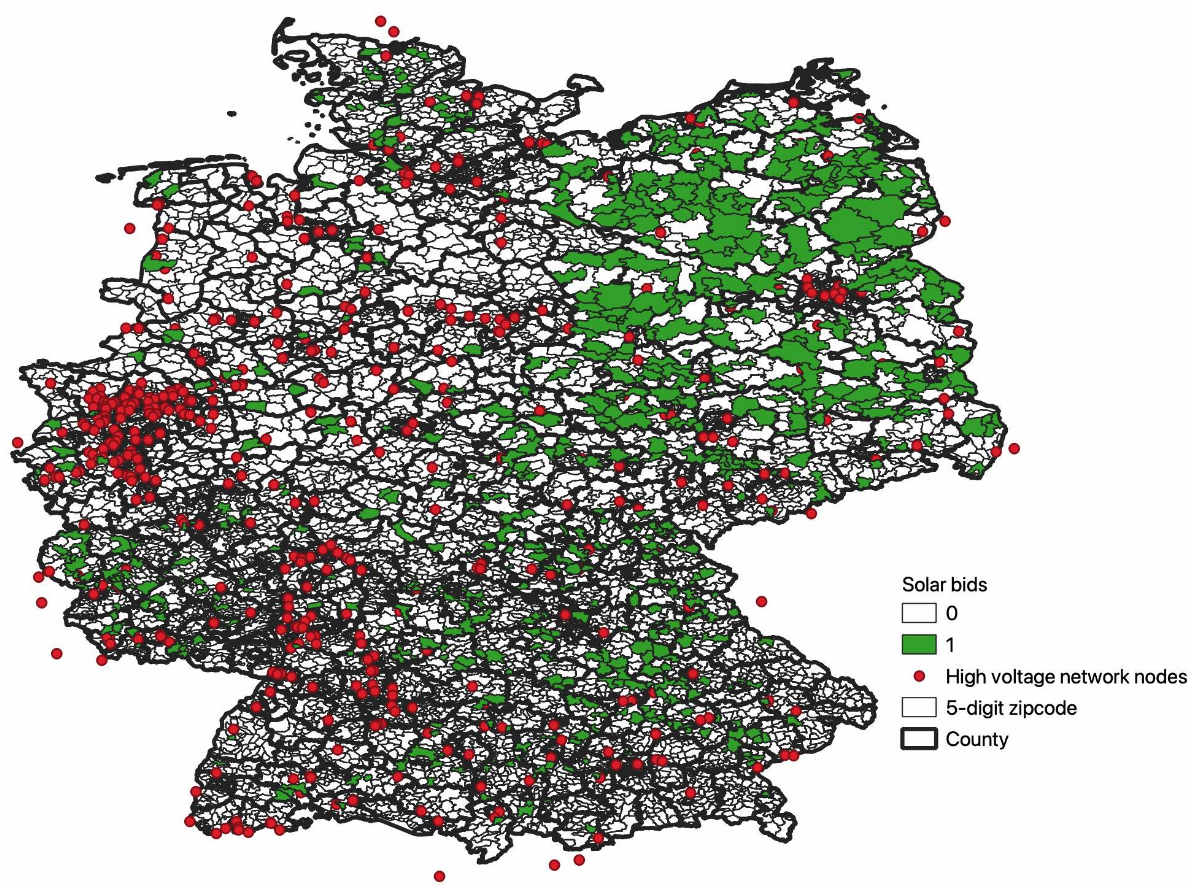
Notes: Total volume is equal to the government demand in each auction round. The price ceiling is the maximum allowed bid price. Average quantity-weighted bid prices (€-cent / kWh) of winning bids with their minimum and maximum. The second and third auction round in 2015 were uniform price auctions and therefore, only a single market clearing price is reported.

Figure B.2: Number of "steps" in submitted bid curves



Notes: For each period of our sample, we count the proportion of bidding curves relative to the total number of bidding curves for each number of steps. Slightly more than 50% of the bidding curves contain only one step but in a handful of cases the curves contain up to 25 steps.

Figure B.3: Solar bids and network nodes



Notes: Map of Germany indicating the zipcodes for which a bid has been submitted in at least one auction round and the access points (nodes) to the high voltage electricity network.

Table B.1: DV: Bid values

	(1)	(2)	(3)	(4)
Large bidder (size, p90)	-0.600***	-0.680***	-0.427***	
	(0.189)	(0.194)	(0.120)	
System costs	11.634***	11.478***	3.905**	4.990**
	(1.325)	(1.244)	(1.958)	(1.937)
Auction volume > 200MW	0.686***	0.685***	-0.047	0.001
	(0.202)	(0.196)	(0.160)	(0.173)
Distance to network		0.574	0.536*	0.425
		(0.348)	(0.293)	(0.391)
Solar irradiation		-4.204***	-0.504	-0.837
		(1.065)	(1.170)	(1.154)
N	1143	1143	1143	1143
Adjusted R2	0.28	0.30	0.64	0.73
Mean DV	6.45	6.45	6.45	6.45
Constant	Yes	Yes	Yes	Yes
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. Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.2: DV: Bid values

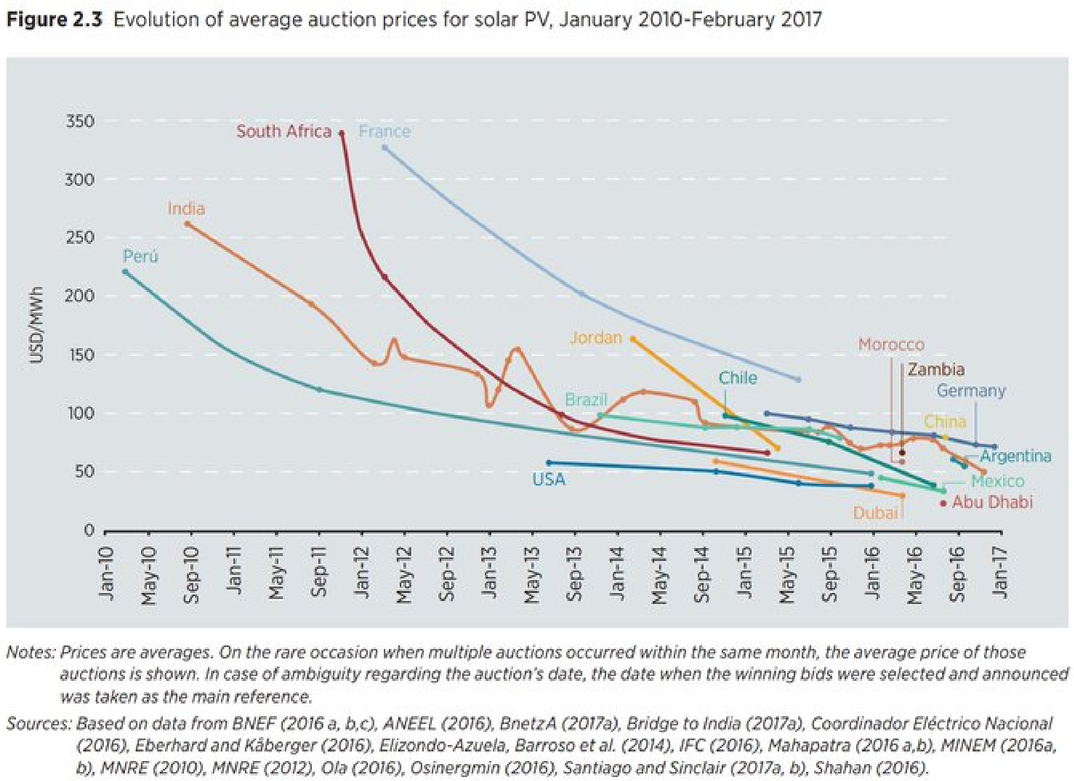
	(1)	(2)	(3)	(4)
Estimated cost (cost)	0.236***	0.220***	0.109***	0.094***
	(0.028)	(0.033)	(0.023)	(0.022)
Distance to network	0.441	0.250	0.407	0.321
	(0.298)	(0.344)	(0.268)	(0.302)
Large bidder (size, p90)	-2.628***		-0.807***	
	(0.539)		(0.260)	
Auction volume > 200MW	0.394**	0.293	-1.881***	-1.970***
	(0.159)	(0.188)	(0.183)	(0.209)
Large bidder × cost	0.349***	0.408***	0.074	0.113*
	(0.079)	(0.085)	(0.064)	(0.067)
System costs	8.015***	7.986***		
	(1.231)	(1.841)		
N	1143	1143	1143	1143
Adjusted R2	0.52	0.63	0.74	0.83
Mean DV	6.45	6.45	6.45	6.45
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. Columns 1 and 2 include average system costs to control for decreasing cost trends. Columns 3 and 4 include auction round FEs. Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Online Appendix

O.1 Additional Figure

Figure O.1: Evolution of solar prices in auctions worldwide



Notes: Taken from IRENA 2017.

O.2 Additional Institutional Details

O.2.1 The German solar market before 2015

The market for utility 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 (89-90 Tiedemann et al., 2019; Klessmann et al., 2015, 22). 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.2.2 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.

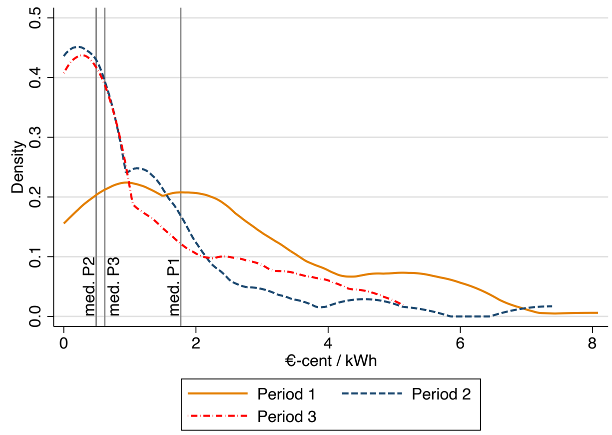
Third, the second auction of 2019 was significantly larger than the other auction rounds. This change in auction volume (demand) was unexpected and is related to an amendment to the EEG Act increasing the annual volume to 1,800 MW (from about 500 MW in the preceding years), which is more than threefold 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 2). 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 Additional Robustness Checks

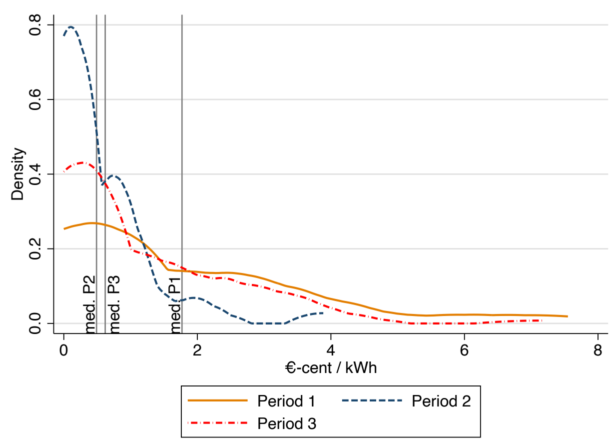
O.3.1 Robustness check: Model estimates with symmetric bidders

Figure O.2: 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.3: Margins with symmetric bidders, pooling 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 in case the auctions are not too different, e.g., round 16 with more than double the auction volume is treated individually also in this setting.

O.3.2 Robustness check: Regressions with non-imputed costs

Table O.1: DV: Bid values

	(1)	(2)	(3)	(4)	(5)
Estimated cost (cost)	0.326***	0.152***	0.168***	0.154***	0.158***
	(0.041)	(0.023)	(0.025)	(0.024)	(0.029)
Distance to network			0.590**	0.586**	0.529*
			(0.280)	(0.279)	(0.277)
Large bidder (size, p90)			-0.645***	-1.576***	
			(0.186)	(0.353)	
Auction volume > 200MW			-0.012	-0.005	-0.087
			(0.166)	(0.168)	(0.231)
Large bidder × cost				0.166***	0.251***
				(0.052)	(0.043)
N	811	811	811	811	811
Adjusted R2	0.23	0.67	0.71	0.72	0.80
Mean DV	6.68	6.68	6.68	6.68	6.68
Constant	Yes	Yes	Yes	Yes	Yes
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.2: DV: Bid awarded (yes/no)

	(1)	(2)	(3)	(4)	(5)
Bid price (deflated)	-0.171***				
	(0.027)				
Estimated cost (cost)		0.006	-0.015*	-0.016*	-0.021**
		(0.014)	(0.008)	(0.008)	(0.009)
Auction volume > 200MW			0.830***	0.822***	0.844***
			(0.048)	(0.047)	(0.069)
Large bidder (size, p90)			0.342***	0.341***	
			(0.100)	(0.100)	
Solar irradiation				-0.612	-0.167
				(0.620)	(0.613)
Distance to network				-0.078	-0.142
				(0.120)	(0.144)
System costs				-1.337	-1.843**
				(0.894)	(0.819)
N	811	811	811	811	811
Adjusted R2	0.13	0.04	0.31	0.31	0.38
Mean DV	0.32	0.32	0.32	0.32	0.32
Constant	Yes	Yes	Yes	Yes	Yes
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.3: DV: Bid values

	(1)	(2)	(3)	(4)
Estimated cost (cost)	0.184***	0.101***	0.098***	0.083***
	(0.032)	(0.025)	(0.026)	(0.027)
Period=2	-1.491***	-0.724***	-0.734***	-1.176***
	(0.240)	(0.185)	(0.184)	(0.224)
Period=3	-1.505***	-0.992***	-1.008***	-1.449***
	(0.313)	(0.210)	(0.201)	(0.275)
Period=2 × cost	-0.128***	-0.023	-0.013	0.065**
	(0.048)	(0.037)	(0.044)	(0.030)
Period=3 × cost	0.117**	0.159***	0.144***	0.164***
	(0.049)	(0.035)	(0.037)	(0.043)
Auction volume > 200MW		-0.065	-0.040	-0.109
		(0.167)	(0.168)	(0.220)
Large bidder (size, p90)		-0.536***	-0.193	
		(0.181)	(0.217)	
Large bidder × cost			-0.032	0.151*
			(0.039)	(0.086)
Period=2 × Large bidder			-2.583***	-1.496***
			(0.357)	(0.475)
Period=3 × Large bidder			-1.208	-0.210
			(0.798)	(1.354)
Period=2 × Large bidder × cost			0.462***	0.304***
			(0.081)	(0.076)
Period=3 × Large bidder × cost			0.201*	0.058
			(0.104)	(0.184)
N	811	811	811	811
Adjusted R2	0.54	0.75	0.75	0.83
Mean DV	6.68	6.68	6.68	6.68
Constant	Yes	Yes	Yes	Yes
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.3.3 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 43 bidders (out of 160) as 'large', which roughly represent 74% of all bids. This alternative measure has a sample correlation with our baseline measure of 0.739.

To obtain the regression tables, we first run the model with the alternative group definition, and in a second step, estimate the linear regressions.

Table O.4: DV: Bid values

	(1)	(2)	(3)	(4)	(5)
Estimated cost (cost)	0.312***	0.113***	0.114***	0.014	0.010
	(0.043)	(0.022)	(0.022)	(0.027)	(0.035)
Distance to network			0.612**	0.642**	0.501
			(0.294)	(0.291)	(0.333)
Large bidder (> 2 bids/round)			-0.045	-0.796***	
			(0.112)	(0.216)	
Auction volume > 200MW			-0.130	-0.160	-0.213
			(0.154)	(0.149)	(0.151)
Large bidder × cost				0.143***	0.150***
				(0.037)	(0.044)
N	1153	1153	1153	1153	1153
Adjusted R2	0.19	0.64	0.64	0.65	0.74
Mean DV	6.44	6.44	6.44	6.44	6.44
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: bidding values. Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

	(1)	(2)	(3)	(4)	(5)
Bid price (deflated)	-0.217***				
	(0.017)				
Estimated cost (cost)		0.029***	0.021**	0.021**	0.019**
		(0.010)	(0.009)	(0.009)	(0.009)
Auction volume > 200MW			0.620***	0.611***	0.642***
			(0.055)	(0.055)	(0.062)
Large bidder (> 2 bids/round)			0.063	0.063	
			(0.059)	(0.057)	
Solar irradiation				-0.058	-0.337
				(0.650)	(0.483)
Distance to network				-0.116	-0.084
				(0.108)	(0.104)
System costs				-1.341*	-2.102**
				(0.791)	(1.023)
N	1153	1153	1153	1153	1153
Adjusted R2	0.17	0.05	0.17	0.17	0.27
Mean DV	0.40	0.40	0.40	0.40	0.40
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: DV: Bid values

	(1)	(2)	(3)	(4)
Estimated cost (cost)	0.143***	0.042*	0.010	-0.021
	(0.027)	(0.024)	(0.030)	(0.027)
Period=2	-1.585***	-0.571**	-0.438	-0.773***
	(0.257)	(0.240)	(0.303)	(0.236)
Period=3	-1.941***	-1.438***	-1.004***	-1.559***
	(0.325)	(0.279)	(0.366)	(0.507)
Period=2 × cost	-0.119**	-0.089*	-0.139**	-0.057
	(0.048)	(0.047)	(0.063)	(0.050)
Period=3 × cost	0.143**	0.191***	0.057	0.155
	(0.055)	(0.048)	(0.067)	(0.096)
Auction volume > 200MW		-0.172	-0.206	-0.268*
		(0.149)	(0.149)	(0.149)
Large bidder (> 2 bids/round)		-0.031	-0.515**	
		(0.095)	(0.201)	
Large bidder × cost			0.058	0.089**
			(0.043)	(0.037)
Period=2 × Large bidder			-0.252	-0.048
			(0.368)	(0.345)
Period=3 × Large bidder			-0.483	-0.113
			(0.477)	(0.621)
Period=2 × Large bidder × cost			0.085	0.040
			(0.080)	(0.068)
Period=3 × Large bidder × cost			0.157*	0.055
			(0.084)	(0.109)
N	1153	1153	1153	1153
Adjusted R2	0.51	0.69	0.69	0.78
Mean DV	6.44	6.44	6.44	6.44
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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$