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

Stefan Lamp† Mario Samano‡ Silvana Tiedemann§

July 2, 2025

Abstract

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

JEL codes: D44, L51, Q42, Q48

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

*We thank N. Astier, R. Camboni, E. Cantillon, A. Crawford, N. Fabra, D. Herrera-Araujo, P. Holmberg, H. Kim, M. Liebensteiner, M. Reynaert, S. Reynolds, E. Richert, M. Saethre, F. Salanie, P. Schmidt-Dengler, M. Wrede, and participants at the Bergen Competition Policy Conference, EAERE, IFN Stockholm Conference, Mannheim Energy Conference, RIDGE Workshop on Environmental Economics, Southern Economic Association Conference, Toulouse Energy and Climate Conference, Friedrich-Alexander-Universität, PUC-Chile, TSE, UC3M, University of Chile (DII), University of Padova, and the members of the Center for Sustainability at the Hertie School for their insightful comments and discussion. S. Lamp acknowledges support from ANR under grant ANR-17-EURE-0010 (Investissements d'Avenir program). S. Tiedemann gratefully acknowledges financial support from the German Federal Ministry of Education and Research through the ARIADNE Project (FKZ 03SFK5K0). M. Samano acknowledges financial support from the Social Sciences and Humanities Research Council of Canada grant 435-2023-0268.

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

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

§Hertie School Berlin and Neon Neue Energieökonomik. Email: `tiedemann@neon.energy`

1 Introduction

Renewable energy (RE) investment is seen as a key component in achieving 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 replaced largely by market-based support mechanisms such as RE auctions. In 2019, more than 100 countries have held such auctions (IRENA, 2019). Despite their widespread adoption—and in some jurisdictions, such as the European Union (EU), their mandatory use—the role of auction design as well as the determinants of the market participants' bidding behavior have not been empirically studied to the same extent. Understanding how auction design influence bidding behavior is essential for regulators seeking to design procurement schemes that minimize rents, encourage entry, and ensure efficient capacity allocation—ultimately easing the fiscal burden of achieving climate targets.

In this paper, we study the role of auction design—particularly pricing rules—for RE capacity when the outcome of the auction determines the level of the guaranteed electricity in-feed price (i.e., production subsidy) over the projects' lifetime. The role of auction design has been a central question in studies of government procurement for construction (e.g., Bajari and Ye, 2003; Krasnokutskaya and Seim, 2011) and spectrum allocation for telecommunications (e.g., Cramton, 2013; Fox and Bajari, 2013), among other industries. In the context of multi-unit auctions, revenue equivalence generally does not hold (Ausubel et al., 2014), making the impact of the pricing rule on auction outcomes an empirical question (e.g., Kang and Puller, 2008; Hortaçsu and McAdams, 2010). This seems particularly relevant in the context of RE procurement, given the long investment horizon of 20+ years, and little to no empirical guidance exists for policy makers.

The objective of RE auctions is to identify the most cost-effective suppliers of renewable generation capacity and to determine the level of the per-unit output subsidy once the plant is built. The auctioneer, in this case, the government, announces the desired volume of capacity

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

in advance, creating a perfectly inelastic demand curve. The auction rules allow participants to submit multiple quantity-price pairs (bids) in the same auction round, and several bids can be awarded—a multi-unit auction. 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 per bidder are determined by the intersection of this curve with the government demand curve. Importantly, this intersection also determines the level of the bidder-specific subsidy, which can be either based on a non-discriminatory pricing rule (*uniform auction*) or implemented as a discriminatory auction (*pay-as-bid*). This subsidy is received in the future and is contingent on the level of the market electricity price, which is not known at the time of the auction. The subsidy scheme is known as a one-sided contract-for-differences (CfD).

Our main research question is to understand to what extent the one-sided CfD subsidy scheme −under the uniform or pay-as-bid pricing rule− has implications for total procurement costs, costs efficiency, and the levels of market power exercised by the participants. Depending on the underlying cost of each quantity segment (RE project), the price-cost gap will be different in each auction format because the market clearing price may not be the same. Moreover, we analyze the relationship between a large set of observable and non-observable bid characteristics and the price submitted under both auction formats. This analysis quantifies some of the regulatory concerns about the size of the government demand and the location of sites.

Our contributions are twofold. First, we develop a framework to analyze auction formats in multi-unit auctions where the equilibrium price determines future subsidy payments through a one-sided CfD. Second, this paper contributes to the long-standing discussion regarding the relative performance of pay-as-bid and uniform-price multi-unit auctions by taking advantage of a policy change and the fact that we can observe both auction formats in the same market to estimate the empirical model and to make comparisons.

To achieve these goals, we make use of unique bid-level data from German RE auctions held between 2015 and 2019, with a focus on solar photovoltaic (solar) technology. Germany is a particularly interesting case to study as the country experimented with both uniform pricing (UP) and pay-as-bid (PAB) pricing rules in an initial pilot phase and then opted for a PAB format thereafter. In addition, all solar auctions were oversubscribed, making them well suited to analyze bidding behavior.[2] Our dataset includes bid quantities and prices of all bidders of winning and losing bids in each auction round. We also have information on the geographical location of each bid, enabling us to match bids with covariates such as solar irradiation and distance to the electricity network.

We build on the literature of multi-unit auctions (Hortaçsu and McAdams, 2010; Kastl, 2011) to obtain measures of bidders' costs taking into account the auction format and the specific context of RE subsidies, which rely on expectations about future market payoffs, a situation not previously considered in the literature. With a resampling technique used by the aforementioned authors, we simulate a large set of residual demand curves to determine market-clearing prices. By substituting those prices into a closed-form expression for the costs in this specific environment, we obtain estimates for the underlying cost of each bid. This allows us to compute measures of market power, conduct an analysis of factors that influence bidding behavior, and construct counterfactuals to study auction formats. We find that the density of the bidders' Lerner indices—a measure of market power—shifted to the right during the PAB rounds relative to the UP auction rounds.

We use linear regressions to identify the key factors associated with bidding behavior under the two auction formats, controlling for a rich set of fixed-effects and bid-specific control variables. We further allow the empirical estimates to depend on bidder types, proxied by size. We confirm that PAB auctions have higher markups, but that this effect is heterogeneous by bidder size. Large bidders show a smaller increase in markups in PAB relative to UP and small bidders. This also affects positively their probabilities of winning in PAB. Moreover, bid prices exhibit a robust and positive correlation with estimated costs, suggesting an average cost pass-through of about 0.7 and 0.8 €-cent/ kiloWatthour (kWh) for every one €-cent/kWh increase in costs.

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

Next, we use the structural model to study a series of counterfactuals, asking what would have happened to bidders' revenues and subsidy payments if the policymaker had conducted all auctions under a uniform pricing rule rather than PAB pricing. Since the theoretical literature does not provide a clear ranking on efficiency or revenue in multi-unit auctions with or without future cashflows, this is an empirical question (Ausubel et al., 2014). We take advantage of the fact that two auction rounds were implemented with uniform pricing rules in an initial pilot phase to estimate costs and average markups from this setting. For the counterfactual, we then assume that bidders under uniform pricing would have had similar markups throughout—markups obtained from UP estimates that depend on the bidder's size—or that they would bid their costs instead of the observed bids—truthful bidding—, which provides a competitive benchmark in which markups are zero by construction. In both cases, the auctioneer aggregates these bids to obtain the new supply curve, which determines a new market clearing price for each auction round. Our results indicate that under the two UP settings studied, quantity-weighted average markups would have been lower than under the PAB format in almost every auction round. None of these results is mechanical, since the marginal bid depends on the convexity of both the cost and bid curves at the intersection with the perfectly inelastic demand curve.

We proceed by calculating the subsidy payments under each auction format. Under UP, subsidies are determined by the market clearing price common to all bidders, while under PAB, they are determined by the bids themselves. We show that, depending on the shape of the aggregate bid and cost curves, either format may lead to a lower total amount of subsidy payments, necessitating further empirical investigation. Our analysis shows that total subsidies under both of our UP formats are lower than under PAB in almost all auction rounds. The only exceptions to this trend occur in rounds where the margins under uniform pricing are significantly larger or close to those under the PAB format. Detailed summary statistics of the differences in subsidies relative to the PAB setting show that the UP format would have lowered government's total procurement costs by an average difference of up to 1.26 € per kW of capacity over the lifetime of a solar installation. Over the 15 PAB auctions rounds analyzed, this would have led to a difference of about €2 million in subsidy payments. These results average over a variety of scenarios of the development of electricity prices into the future, which is needed to calculate the subsidy amounts.

To assess the efficiency of the PAB format in selecting low-cost bidders, we calculate the aggregate costs of the winning bids under PAB and the corresponding costs under truthful bidding—the perfectly competitive outcome—. This requires sorting the submissions by bid price in the first case and by marginal cost in the second. By construction, the costs under truthful bidding are the lowest possible costs. Comparison of aggregated costs reveals that there is an overall trend of PAB costs toward perfectly competitive costs, a feature that may help compensate for the relatively elevated procurement costs under this auction format.

Related Literature. We contribute to three main strands of the literature. First, we systematically quantify market power for the procurement of RE capacity in the context of multi-unit auctions and document the factors associated with bid prices and bidder costs. The analysis of multi-unit auctions has long been an active area of research, particularly comparing the efficiency of auction formats such as uniform vs. discriminatory pricing, the latter also referred to as pay-as-bid. While Vickrey (1961) proved that the revenue equivalence theorem holds in single-item auctions, Ausubel et al. (2014) showed that there is no clear ranking of sellers' revenues in multi-unit auctions. Instead, such a ranking is an empirical question that has been addressed mostly in the context of treasury auctions (Kang and Puller, 2008; Cassola et al., 2013; Elsinger et al., 2019) and to some extent in electricity generation markets.[3] The development of empirical methods to determine bidders' valuations or, in the case of procurement auctions, bidders' costs, has mostly been done in the field of government bond allocation (Hortaçsu and McAdams, 2010, 2018; Kastl, 2011). Some other applications

[3] There is also a strand of mostly theoretical literature that examines the electricity generation sector to compare the two auction formats. Federico and Rahman (2003) found that, under certain conditions, market power is higher in a UP auction than in a PAB auction. Holmberg (2009) uses a supply function approach to obtain comparisons. Fabra et al. (2011) builds on a duopoly model with investment and finds that PAB leads to lower prices than the UP auction while keeping capacity fixed. Holmberg and Wolak (2018) assume asymmetric information about production costs and find that buyers are better off under UP. Willems and Yueting (2023), show that PAB auctions are inefficient in the context of electricity generation because they incentivize a portfolio mix without sufficient base load capacity. In contrast to this literature, our paper examines procurement and therefore, capacity is not fixed.

of these techniques in electricity-related markets include Wolak (2003, 2007), Reguant (2014), and Kim (2022). The only application of these techniques to RE auctions that we know of are Ryan (2021) and Hara (2023). Ryan (2021) uses data from solar auctions in India to estimate a structural model, focusing on the role of counter-party risk in procurement. In comparison to his work, our paper aims to analyze the importance of auction design and the factors that influence bidding behavior in an environment with virtually no default risk. Hara (2023), on the other hand, studies risk aversion for large scale wind investors in Brazil that need to decide what share of production to offer to ensure at fixed prices. Compared to his setting, solar investors in Germany have a guaranteed (minimum) return, determined by the auction, that effectively works as a one-sided CfD and eliminates all downside risks. Our work focuses on the auction design and we show that even in this 'well-established' market, fundamentals evolve, and different types of bidders may respond heterogeneously to shifting policy paradigms.

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

Finally, we contribute to the literature on evaluating auction designs in the RE context. The question of how to best design auctions has been studied theoretically (Kreiss et al., 2017; Haufe and Ehrhart, 2018; Fabra and Montero, 2023) and empirically (Bayer et al., 2018; Matthäus, 2020; Anatolitis et al., 2022), yet the studies all complain about the lack of empirical evidence on the effectiveness of auctions in reducing support costs and efficiently selecting producers (see Del Río, Pablo and Kiefer, Christoph P., 2023, for a review), mostly due to the general unavailability of detailed bid-level auction data in this context, a limitation that this paper circumvents. In the absence of robust empirical studies, the literature on RE auctions refrains from making conclusive arguments about the performance of auctions, but rather argues that performance, both in terms of deployment and efficiency/cost, depends on the level of competition and the specific choice of eligibility criteria and bid bonds. In terms of market power and the impact of auctions on heterogenous bidders, the evidence is equally inconclusive. Grashof (2019) argues that auctions are likely to disadvantage smaller bidders, which would discourage policy acceptance and risk capacity expansion, yet 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. Our analysis highlights that factors such as the size of bidders are indeed strongly correlated with bidding behavior.[4]

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 accounting for future payments to recover bidders' costs and the regression analysis to decompose markups and other auction outcomes. Finally, Section 5 presents counterfactuals regarding the auction format and Section 6 concludes.

2 Institutional Background

In 2015, the German government introduced auctions for large-scale solar projects to steer capacity additions and to reduce subsidy payments.[5] 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 and other renewable technologies with the 2017 reform of the EEG in line with EU regulation.

The annual renewable energy capacity targets, defined by the EEG, are converted into a

[4]This paper also relates to other work studying the impact of RE investment and policy choices on electricity markets (e.g., Astier et al., 2023; Jarvis et al., 2022) and more generally relates to the literature assessing the social cost of inefficient procurement design (e.g., Eklöf, 2005).

[5]Furthermore, the government was aiming to overcome information asymmetries which, in the past, led to support levels that were considered as 'too high' creating unforeseen capacity additions in 2009 to 2012, or that were considered as 'too low' leading to fewer than expected installations in 2013 to 2015 (see also Online Appendix O.1).

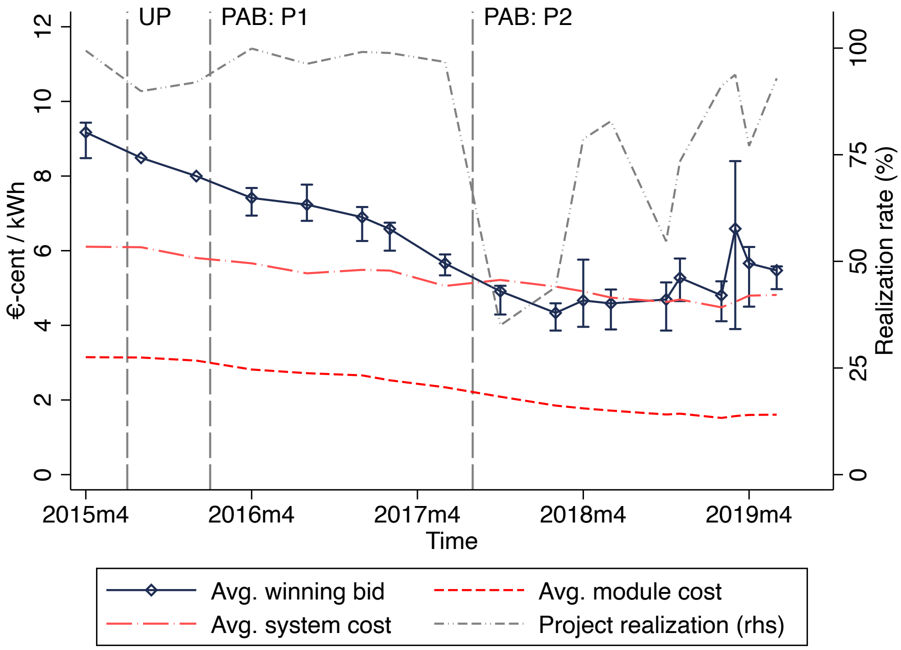
fixed auction volume and distributed over several rounds per year. As the pilot phase was considered successful, the government increased the annual volume demanded by making the auctions more frequent. Bidders with solar projects above 100 kilowatt (kW) (since 2017 restricted to $\geq$ 750 kW) and below 20 megawatt (MW) are invited to submit one quantity-price bid per project, but are not restricted on the number of projects (bids) they supply. All formally eligible bids are ranked according to their bid price and awarded until the cumulative volume exceeds the auction volume of the round. In general, the auction applies discriminatory pricing (pay-as-bid). Exemptions are the second and third auction rounds (both in 2015) in which awarded projects received the bid price of the last accepted bid (uniform pricing). The ex-post subsidy payments per unit of electricity produced depend not only on the bid price, but also on the realized market value of solar, as described below. Finally, German RE auctions are generally technology-specific, i.e., there is a specific auction for solar and another one for wind. Yet, several auction rounds from 2018 onwards have been run as joint auctions in which solar and wind were allowed to bid simultaneously.[6] The auctions are implemented by the Federal Network Agency, which however does not have significant power to alter the auction rules despite adjusting the ceiling prices in line with the provisions in the law (Tiedemann et al., 2019).

Figure 1 shows the average price of winning bids together with cost indicators for large, ground-mounted solar installations, as well as the ex-post project realization rate.[7] An initial observation is that the average price of winning bids decreased in the first three years after the introduction of the auctions in 2015. However, prices have stagnated since then. Interestingly, in the second half of 2017, the average winning bid price converted to the average system cost. We use this observation to distinguish between two periods during the PAB auction rounds implemented from 2016 to 2019. In Period 1, average winning prices have been decreasing,

[6]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.

[7]*Avg. module cost* represents the average cost of solar modules, and is based on monthly observations from PV Exchange. *Avg. system cost* includes additional hardware and installation costs and is based on quarterly survey data from the German Solar Industry Association. Both cost indicators refer to installations in the following 12 months. Project realization rate refer to the share of winning projects that are constructed within the legal limit of 24 months.

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



Notes: Average quantity-weighted winning bids in €-cent / kilowatt-hour (kWh) together with min/max accepted winning bids in pay-as-bid (PAB) auctions. The second and third auction rounds were implemented with uniform pricing (UP) rules and a single market clearing price is reported. Average solar module costs and system costs for ground-mounted installations (€ / kW), based on estimates from the industry, are converted to €-cent / kWh using average capacity factors and assuming a lifetime of 25 years with an annual discount rate of 5%.

but were above the average system costs and project realization rates were practically 100%. In Period 2, average winning prices have been flat and were close to (and in some auction rounds even below) the average system costs. This suggests that profit margins must have decreased in Period 2 relative to Period 1. This observation is also consistent with the ex-post project realization rates of winning bids, which show a large drop during the first auctions in Period 2, and a recovery in later rounds. Appendix Table A.1 lists the detailed auction dates, volume, and the price ceilings per auction round. Online Appendix O.1 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. In addition, bidders must provide evidence of having advanced in the project planning process and submit a bid bond.[8] The bid bond depends on the volume of the bid and the project planning status: bids in the initial planning phase must pay (or show proof of bank security over) 50 € / kW, bids for projects that are further advanced need to pay only 25 € / kW.[9] The main purpose of the bid bond is to discourage spontaneous bidders in the auction. Successful bids have 24 months to realize the projects, otherwise the total security is withheld. Furthermore projects that are commissioned later than 18 months after the auction date get a bid price deduction of 0.3 €-cent/kWh. Note that projects are location and bidder specific. Won projects can therefore not be resold on a secondary market and if a project changes its location a penalty of 0.3 €-cent/kWh applies.

Subsidy payments. The subsidy is a direct payment for every unit of electricity produced. The EEG guarantees that the transmission system operator provides a monthly payment to the investor for a period of 20 years after the project has been connected to the grid. The EEG defines the payment as the bid price reduced by the monthly average of hourly revenue on the wholesale electricity market by all solar plants in Germany, i.e., the monthly market value or average *capture price of solar*.[10] In the literature on RE support schemes this subsidy design is called a *sliding market premium* (e.g., Klobasa et al., 2013) or more recently *one-sided contract-for-difference (CfD)* (e.g., Beiter et al., 2021). Specifically, the subsidy is defined as

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

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

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

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

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

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

3 Data and Descriptive Statistics

Our data consist of all bids submitted to solar auctions in Germany held between the introduction of the German RE auctions in 2015 and June 2019, covering 18 auction rounds with a total of 1,791 bids.[11] We focus on solar installations only and exclude the 19 bids for wind projects in auctions where both technologies were admissible.[12] We exclude non-eligible bids which make up about 11% of the total number of observations. Our final dataset for all solar auctions consists of 1,573 individual bids. If not otherwise mentioned, we further exclude the first auction round (132 observations) from our analysis, as bidders did not have any knowledge about the potential number of competitors and no prior experience with the auction mechanism. Out of the remaining 1,441 individual bids, 235 belong to the two uniform auction rounds held in August and December 2015, and 1,206 observations belong to PAB auctions (April 2016 through June 2019). A common feature of multi-unit auctions is that bidders are not restricted to submit a single bid in the auction. The dataset reveals that there is a wide variety of bidding patterns across firms and across time periods.

Table 1 summarizes our data pooling all observations first and then by subsamples: the initial UP rounds and the two PAB periods, defined whether the average winning bid prices are above or below the average industry-wide system costs (see Figure 1). In addition to

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

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

Table 1: Summary statistics - German solar auctions

	All	UP	PAB	
			Period 1	Period 2
Bid-specific variables:				
Bid value (€-2019 c/kWh)	7.11	8.78	7.47	5.84
	(1.84)	(1.23)	(1.02)	(1.11)
Bid volume (MW)	5.57	4.48	5.25	6.27
	(5.76)	(2.99)	(3.25)	(7.44)
Avg. system cost (€-2019 c/kWh)	5.36	6.19	5.67	4.78
	(0.69)	(0.27)	(0.33)	(0.33)
Avg. module cost (€-2019 c/kWh)	2.32	3.22	2.72	1.69
	(0.69)	(0.13)	(0.23)	(0.21)
Solar irradiation (kWh/m^2)	1097.32	1095.30	1093.49	1099.26
	(44.21)	(42.30)	(39.85)	(46.42)
Distance to network (km)	20.28	20.29	21.47	19.84
	(11.31)	(11.95)	(11.37)	(10.96)
Land types (share):				
- Agriculture or grassland	0.20	0.00	0.17	0.31
	(0.40)	(0.00)	(0.38)	(0.46)
- Non-conventional buildings	0.10	0.00	0.10	0.15
	(0.30)	(0.00)	(0.29)	(0.36)
- Government land	0.07	0.00	0.06	0.10
	(0.25)	(0.00)	(0.24)	(0.30)
- Adjacent to railway or road	0.31	0.44	0.28	0.27
	(0.46)	(0.50)	(0.45)	(0.44)
- Site with previous usage	0.32	0.56	0.39	0.16
	(0.47)	(0.50)	(0.49)	(0.37)
$\mathbb{1}$(large bidder, project size)	0.21	0.19	0.17	0.25
	(0.41)	(0.39)	(0.38)	(0.43)
Auction-specific variables:				
Share of eligible bids	0.90	0.89	0.88	0.92
	(0.06)	(0.01)	(0.04)	(0.06)
# bids per round	87.39	117.50	84.00	78.60
	(30.64)	(4.95)	(23.63)	(31.75)
# bidders per round	39.56	63.50	37.40	33.40
	(15.63)	(2.12)	(8.68)	(13.75)
# bidders awarded per round	16.17	21.50	12.60	17.10
	(10.43)	(6.36)	(1.52)	(13.61)
# projects awarded per round	34	38	29	35
	(23.8)	(7.1)	(6.6)	(31.0)
HHI	989.43	630.98	730.82	1226.67
	(442.60)	(13.47)	(150.81)	(465.89)
C1, bid volume per round (%)	23.07	18.44	19.33	26.39
	(7.69)	(0.09)	(3.60)	(8.84)
C3, bid volume per round (%)	43.27	35.31	36.56	48.94
	(10.25)	(1.80)	(4.82)	(10.36)
C5, bid volume per round (%)	54.67	44.86	47.93	61.23
	(11.35)	(3.56)	(5.81)	(10.76)
Observations	1,573	235	420	786
Number of auctions	18	2	5	10

Notes: Individual bids from German solar auctions held between April 2015 and June 2019. 'All' includes the first auction round (held in April 2015, PAB format), omitted from the main analysis. Uniform price (UP) refers to auction rounds 2 and 3, Pay-as-bid (PAB) Period 1 to auction rounds 4 to 8, and Period 2 to auction rounds 9 to 18. Average system and module costs based on aggregate solar cost indicators from the industry. We provide a detailed overview of the individual auction rounds in Appendix Table A.1.

the bid related variables (bid value, bid volume, land type, and location) and the average industry-wide system costs, we match project-specific information on solar irradiation and 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.[13] We elaborate on the data sources and construction of these covariates in Online Appendix O.2.

Table 1 shows that there were some differences between the initial UP rounds and the PAB rounds. Submitted bids in the former were only admissible if they were located adjacent to railway or roads or sites with previous usage and hence the average project size (bid volume) is slightly smaller. At the same time, more bidders have been active in the first auction rounds with a larger number of total bids submitted, leading to lower market concentration measures.[14] On the other hand, the summary statistics show that in the PAB rounds, Period 2 (when the average winning bid prices were rather flat) exhibits some noticeable differences relative to the rest of the PAB auctions. In particular, we find that the average project size (bid volume) was slightly larger in line with the fact that there were more bids allowed on agricultural land. We also find that during this period the share of large bidders was higher and that the market was more concentrated, as indicated by the HHI and C1-C5 indices. Note however that all periods can be considered as competitive.[15] Projects were otherwise similar in terms of average solar irradiation and distance to nearest high-voltage network node.

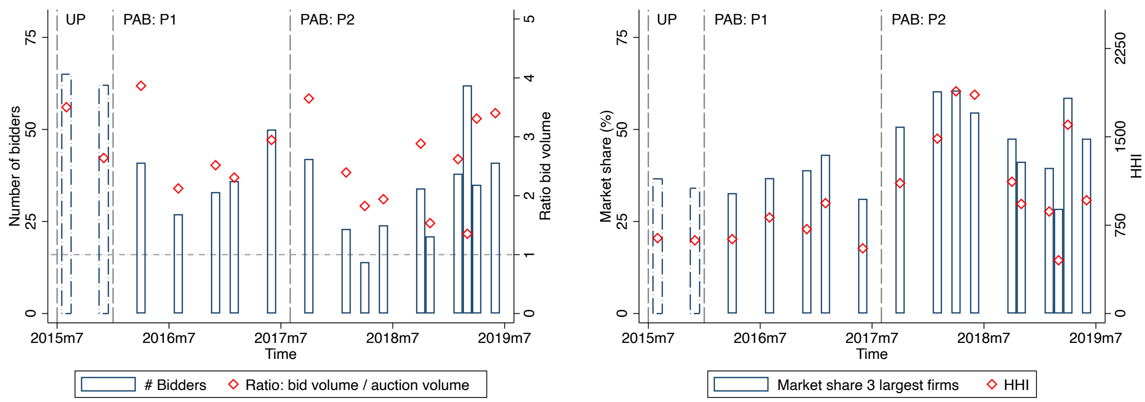
To get a better sense of how competition evolved over time, Figure 2 shows the number of bidders, the degree of over-subscription (defined as the ratio of total eligible bid volume to auction volume), as well as the HHI and C3 indices for individual auction rounds. While

[13] We define large bidders on the ex-post distribution of average project sizes by bidder, using the 90th percentile over all rounds. This classifies 22 out of 202 bidders as "large". The average number of bid steps (std. dev.) is 6.18 (5.29) for large bidders, and 2.29 (1.96) for small bidders, respectively. In the Online Appendix we perform a robustness check concerning the definition of large bidders.

[14] We report C1 to C5 as well as the Herfindahl-Hirschman Index (HHI). C5 is the sum of the submitted capacity shares of the five largest bidders by capacity size in a given round. Similarly for C1 (largest) and C3 (three largest). The HHI is defined as the sum of the squares of the submitted capacity shares in a given round.

[15] This finding resembles insights from the Sectoral Report of the German anti-trust authorities in 2019 (Wambach et al., 2019).

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. UP auction rounds represented in dash-dotted lines.

there is some variation in the number of bidders and the volume provided in each auction, all auction rounds have been over-subscribed.[16] Online Appendix Section O.2 discusses changes in bidder composition over time, highlighting that this was not of potential concern.

4 Empirical Strategy

In the following section, we first document the bidding behavior in uniform and PAB auction rounds relying on the detailed bid data and the policy change during the pilot phase 2015. We then adapt a model of multi-unit auctions to the context of RE procurement with a stream of future subsidy payments. We build on Hortaçsu and McAdams (2010) and Kastl (2011) who develop an empirical method to estimate valuations in multi-unit auctions based on Wilson (1979), taking into account the discreteness of bids as well as the fact that bidders have both private cost shocks and need to form common beliefs about the future electricity market. We use the model to recover costs that we employ to analyze observed bidding behavior. In Section 5, we then quantify the effect of the auction format on bidders' margins

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

and total subsidy payments using the estimated costs and markups.

4.1 Impact of Auction Payment Rules on Bid Prices

To get a first sense of the bidding behavior under the two pricing rules, we take advantage of the initial pilot phase in 2015 and 2016 in which the policy maker implemented the first auction round as PAB, but then announced two rounds with uniform pricing, before setting on PAB thereafter. This initial variation was precisely made to gain insights into the different payment rules.[17], and announced to participants before the start of the first round.[18]

For this first analysis, we take the change in payment rules as exogenous from the bidder's perspective and estimate the following regression with the project-level bid data.

$$b_{ik\tau} = \beta_0 + \beta_1 \mathbb{1}(\text{uniform pricing}) + \beta \mathbf{X}_{ik\tau} + \mu_i + \zeta_\tau + \varepsilon_{ik\tau}, \tag{2}$$

where $b_{ik\tau}$ refers to the price per kWh of project k submitted by bidder i in auction round τ, $\mathbb{1}$(uniform pricing) is an indicator function for rounds 2 and 3, which were implemented with uniform payment rules.[19] The regression controls for the following set of auction and bid specific variables: auction volume (linear and quadratic terms), average industry-wide solar PV system cost in next 12 months, distance to nearest high voltage network node, and average solar radiation in the project zip-code. We further include fixed effects for type of land, state, and year of the auction to account for common shocks that might affect the German solar industry beyond average system costs. In some specifications, we further include bidder fixed effects to identify differences in bidding behavior in the two auction formats within bidder.

We estimate Equation 2 pooling all 18 solar auction rounds (April 2015 to June 2019).[20]

[17] See evaluation report from December 2015 on the German pilot phase for solar PV (Tiedemann et al., 2015).

[18] The legal basis for the introduction of auctions for ground-mounted solar PV systems (FFAV) was published in the Federal Law Gazette I No. 5 of February 11, 2015 and entered into force on February 12, 2015 (http://www.bgbl.de/xaver/bgbl/start.xav?startbk=Bundesanzeiger_BGBl&jumpTo=bgbl115s0108.pdf). This document describes the detailed auction rules for the pilot phase, and was superseded by the 2017 reform of the Renewable Energy Act (EEG 2017).

[19] We use nominal bid values throughout, as the policy is expressed in nominal terms. The main results are not affected by choosing deflated prices instead.

[20] We include the first auction round in this regression to separately identify the year fixed effects from

Table 2: Auction format and bid prices

	(1)	(2)	(3)	(4)	(5)
𝟙(uniform pricing)	-1.501***	-1.396***	-1.220***	-1.313***	-1.165***
	(0.133)	(0.133)	(0.191)	(0.132)	(0.130)
𝟙(large bidder)	-0.277*	-0.308***	-0.052		
	(0.147)	(0.106)	(0.095)		
Auction volume (100 MW)	-1.150**	-1.028**	-2.286***	-0.660	-2.182
	(0.448)	(0.499)	(0.699)	(0.499)	(1.733)
Auction volume^2	0.164**	0.146*	0.385***	0.094	0.328
	(0.069)	(0.076)	(0.105)	(0.075)	(0.537)
Distance to network (100 km)	0.475*	0.439*	0.318	0.415	0.335
	(0.258)	(0.262)	(0.245)	(0.337)	(0.397)
Solar irradiation (MWh/m^2)	-1.915**	3.075*	1.271	2.893	3.674
	(0.871)	(1.660)	(1.869)	(2.273)	(2.747)
Avg. system cost (€/kWh)		0.679**	0.339	0.832**	0.748**
		(0.315)	(0.215)	(0.356)	(0.305)
N	1,573	1,573	598	1,573	583
Adjusted R^2	0.72	0.75	0.70	0.83	0.82
Mean DV	6.89	6.89	6.14	6.89	8.51
Land-type FE	No	Yes	Yes	Yes	Yes
State FE	No	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Bidder FE	No	No	No	Yes	Yes

Notes: DV: bid values. Sample: All 18 solar PV auction rounds held between April 2015 and June 2019. Regressions include a constant term. Column 3 limits the sample to winning bids, Columns 4 and 5 include bidder fixed effects, and Column 5 limits the sample further to auctions held in 2015-2016. Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The findings are presented in Table 2 and indicate that the average bids in uniform auctions have been about 1.2-1.5 €-cent/kWh lower compared to PAB rounds. These results are highly significant and stable across specifications, including, for example, aggregate cost measures, time, location, and bidder fixed effects and are unaffected by the choice of the estimation sample. We perform robustness checks, limiting the sample to winning bids only (Column 3) and restricting the sample to years 2015 and 2016 (Column 5). In the 2015-2016 sample (Column 5), the main effect for uniform pricing rule corresponds to a reduction of almost 14% in the average bid price when evaluated at the average price of 8.51 € / kWh. This is true even when controlling for bidder fixed effects.

Since bidding incentives differ between the uniform and PAB auction rounds, the average

the indicator variable for the uniform auction rounds (both UP rounds held in 2015).

difference may be due to the presence of low bid values in UP. However, we also observe differences in marginal bids, i.e., the highest bid price that cleared the auction in both formats. In R1 (PAB), the marginal price was 9.43 €-cents/kWh, resulting in a quantity-weighted average winning bid price of 9.17 €-cents/kWh. In the first uniform round (R2), however, the marginal price (and the clearing price of the auction) was 8.49 €-cents/kWh. This one-cent difference cannot be explained by an abrupt change in costs because the two auctions took place within four months, and the average system costs were almost unchanged during this period.

We further find evidence for heterogeneous bidding behavior in terms of bidder size, when considering all bids. Other control variables are in line with the expected sign, e.g., a larger distance to the nearest network node is typically related to a higher bid price, a more productive site (higher solar irradiation) with a lower price in Column (1). However, note that introducing state and other fixed effects can change this correlation pattern and generally render project-specific controls insignificant. Finally, the regression indicates that the average system cost is significant, with a coefficient of about 0.7–0.8. This means that a one-cent increase in cost leads to an approximate increase in the average bid value of about 0.7–0.8 cents. The average cost pass-through is lower and non-significant when focusing only on winning bids in column three.

Overall, these initial results indicate that firms bid lower prices under the uniform pricing rule than under the pay-as-bid rule. However, to understand bidding behavior under the two auction formats and to recover unobserved project-specific costs and markups, we need to turn to a structural model of bidding, which we discuss next.[21]

[21] Additionally, the exogeneity assumption of the policy change can be questioned, given that bidders were likely to have formed expectations regarding future pricing rules at the time of the UP auctions. The general policy recommendation in early July 2015, before the first UP implementation, leaned towards PAB for the future (see 'Executive Summary of Recommendations' on 'Designing renewable energy tenders for Germany', available online: https://www.bmwk.de/Redaktion/Migration/DE/Downloads/Publikationen/ausschreibungen-eeg-en.pdf?__blob=publicationFile&v=1, last accessed 5 June, 2025.

4.2 Bidding Model for Multi-unit Auctions with Contracts-for-Difference Payments

Model set-up. There are R auction rounds indexed by τ, where each auction consists of Q_τ divisible units (total solar capacity demanded by the government). In each individual auction round $\tau = 1, \dots, R$, there are N_τ bidders. As in Kastl (2011), we allow for bidder asymmetries by introducing G different groups of bidders, denoted by g, such that $N_\tau = \sum_{g=1}^{G} N_\tau^g$. Bidders are assumed to be symmetric conditional on belonging to group g. Otherwise, bidders are risk-neutral with independent private values (IPV). Similar to the context of treasury-bill auctions (e.g., Hortaçsu and Kastl, 2012; Elsinger et al., 2019), we claim that IPV is a good assumption in the context of RE auctions, as it can be argued that firms have idiosyncratic shocks to the project cost (e.g., land cost, financing, etc.).[22] However, as there is a common payoff uncertainty resulting from the evolution of the capture prices, we model this additional component as in Gupta and Lamba (2023). The main differences in our setting relative to the aforementioned literature is that firms face residual demand curves instead of residual supply curves and bidders maximize the expected net present value (NPV) over the lifetime of the projects.

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

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

that consists of a step function where each step k has for length the quantity offered $q_{i,k}$, for height the price offered $b_{i,k}$, and K_i is the number of steps of bidder i's submission.[23]

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

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

4.2.1 Payoff under pay-as-bid payment rule

The total expected NPV over the lifetime of the projects in the supply curve taking into account the subsidy scheme in each time period under PAB is

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

where

$$\pi_i = \sum_{k=1}^{K_i} \left[\sum_{t=13}^{T=252} \underbrace{\delta^t \left[\mathbb{1}(b_{i,k} > cp_t)(b_{i,k} - c_{i,k}) + \mathbb{1}(b_{i,k} \leq cp_t)(cp_t - c_{i,k}) \right]}_{\text{Discounted future profits}} \right] \mathbb{1}(q_{i,k} \leq q_i < q_{i,k+1}) \tag{3}$$

and $Q_i(\boldsymbol{y}^{-1}(\cdot;\boldsymbol{s}))$ is the total quantity awarded to bidder i as a function of the other bidders' supply curves and their private signals. Expectations are also drawn with respect to the capture price. Note that the total auction volume is pre-announced and therefore known to the bidders ex-ante. The discounted future profits term includes a monthly discount rate $\delta = 0.42\%$[24] and two possible revenues determined by the policy: either the subsidy is active because the capture price cp_t is too low or the producer receives cp_t, according to Equation 1. We include uncertainty about the common price component, cp_t, by considering the combination of discretized levels of growth paths and levels of volatility and then take the average over the equilibrium outcomes for each of those scenarios (Gupta and Lamba, 2023).[25]

To implement the model empirically, we need to make additional assumptions about the timing when the solar plant is built and starts to produce electricity as well as the evolution of the capture prices that are relevant for the ex-post auction payoffs. In line with the data, we assume that the solar plants are being built one year after the auction date, which means that

[24]This is equivalent to an annual discount rate of 5%. We justify the discount rate by a 3% social discount factor for public projects as it is commonly used in Europe and 2% capital depreciation. The capital depreciation takes into account solar panel deterioration, but also other factors such as maintenance and operation costs, insurance, and potential replacement investment for sub-components. We have also experimented with a higher annual discount rate of 10%, with similar results.

[25]In addition to the NPV setup presented here, Online Appendix Section O.3.1 develops a version of the multi-unit auction model without future payoffs and no common uncertainty, confirming our main findings.

they start producing at 13 months. Profits are guaranteed for 20 years, the policy horizon.[26] Moreover, we assume that the expectations concerning the evolution of the capture price (cp_t) are common to all bidders and evolve according to the following equation:

$$E[cp_t] = cp_0 \times \gamma_1 \phi_t \times \gamma_2 \sigma_t$$

where cp_0 refers to the price level of the capture price in the year where the investment took place, ϕ_t is a time trend (with both linear and quadratic terms), and σ_t is the expected volatility. The assumption about common beliefs for the future payoffs can be justified by the fact that project developers need to forecast the capture price at a monthly frequency for a 20-year period. This reinforces the common value aspect of these auctions. We make use of official policy documents and other publicly available industry forecasts to compute projected prices.[27] The introduction of different forecasts by different firms would require strong assumptions about each firm's information sets.

We calibrate the expected capture price in line with observed price levels and volatility at the time of investment and make some assumptions on expected price growth and increase in volatility over time based on wholesale market price predictions from government reports and policy documents. As further discussed in Online Appendix O.1.3, the capture price follows closely the wholesale electricity price. Yet, to account for uncertainty and for decoupling of the two in the future, given the increasing penetration of solar PV, we consider different price and volatility levels relative to the baseline scenario, over which we aggregate. We do so by pre-multiplying the expected growth trends with a factor $\gamma_i, i \in \{1, 2\}$. Further details can be found in Online Appendix O.1.3.

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

[27] Alternatively, one might consider futures markets, but these are only available for 2-3 years in the German wholesale electricity market. Market forecasts, on the other hand, are available from professional associations or for-profit businesses and are based on model predictions about future states of the electricity market, as well as long-term policy scenarios.

Recovering costs. We can group the terms inside the square brackets of the profits expression in Equation 3 by whether the subsidy is active or not,

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

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

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

where

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

and only $L_{1,k}$ and $L_{3,k}$ are functions of the time series of capture price forecasts and of the bid step.

To recover the cost $c_{i,k}$ we extend the perturbation argument in Kastl (2011, 2012) for optimal bidding to our empirical setting.[28] In particular, there is a set of necessary conditions

[28] In Online Appendix Section O.3.1 we also present a version of this model without considering future payoffs.

for each step k at which the estimated cost is continuous in q given by Equation 4 below. While the market clearing price $p_c(\boldsymbol{y}(\cdot;\boldsymbol{s}))$ is a function of all the submitted bid schedules and the signals, we omit these dependencies in what follows to improve readability, the optimality condition is:

$$\begin{aligned}\underbrace{\Pr(b_{i,k} < p_c < b_{i,k+1})}_{\equiv M_1}\pi_{i,k} &= \underbrace{\Pr(b_{i,k+1} \leq p_c)}_{\equiv M_2}(L_{1,k+1}(cp_t, b_{i,k+1})b_{i,k+1} - L_{1,k}(cp_t, b_{i,k})b_{i,k} \\ &+ L_{3,k+1}(cp_t, b_{i,k+1}) - L_{3,k}(cp_t, b_{i,k})), \end{aligned} \tag{4}$$

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

$$c_{i,k} = \frac{1}{L_2}\left[L_{1,k}b_{i,k} + L_{3,k} - \frac{M_2}{M_1}(L_{1,k+1}b_{i,k+1} - L_{1,k}b_{i,k} + L_{3,k+1} - L_{3,k})\right]. \tag{5}$$

Equation 4 describes the trade-off that a bidder is facing at each step k regarding potential gains and losses from offering a lower quantity $q_{i,k}$. The argument is as follows. Assume that the market clearing price $p_c(\boldsymbol{y}(\cdot;\boldsymbol{s}))$ occurs at a vertical segment of the individual supply curve. Then, by reducing the quantity by a small amount, bidder i losses $\pi_{i,k}$ times the small reduction in quantity and only if the price is indeed between the k-th and the $k+1$-th steps (given by $\Pr(b_{i,k} < p_c < b_{i,k+1})$). This shift of the supply curve to the left makes the step $b_{i,k+1}$ marginal and brings gains of $b_{i,k+1} - b_{i,k}$ in every time period where the subsidy is active, i.e., $b_{i,k+1} > cp_t$, as long as the new clearing price is at least $b_{i,k+1}$. This occurs with probability $\Pr(b_{i,k+1} \leq p_c)$. Those gains must be properly weighted by the functions $L_{1,k}$ and $L_{3,k}$ only, since L_2 is a constant. Note that in time periods where $b_{i,k+1} \leq cp_t$, the firm gets paid the capture price on all its inframarginal units regardless of the cost level. If losses and gains from bid shading are not equalized, then there exists a potential deviation in the bid schedule that leads to higher expected payoffs, so the bidding strategy cannot be optimal.

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

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

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

4.2.2 Payoff under uniform payment rule

Under the uniform pricing rules, the payoff function is different since it directly depends on the uniform market clearing price, i.e., the expression for π_i—the expression inside the integral—in Equation 3 is different,

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

where K_i is the total number of bid steps of firm i, and the contribution from a single step k is

$$\begin{aligned}\pi_{i,k} \quad &\equiv \quad \sum_{t|p_c > cp_t} \delta^t (p_c - c_{i,k}) + \sum_{t|p_c \leq cp_t} \delta^t (cp_t - c_{i,k}) \\ &= \quad p_c \sum_{t|p_c > cp_t} \delta^t - c_{i,k} \sum_{t=13}^{T=252} \delta^t + \sum_{t|p_c \leq cp_t} \delta^t cp_t \\ &= \quad L_1(cp_t, p_c) E(p_c | b_{i,k} < p_c < b_{i,k+1}) - L_2 c_{i,k} + L_3(cp_t, p_c)\end{aligned}$$

where

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

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

Assuming once again that the residual demand curve crosses between the steps k and $k+1$, if the bidder reduces her bid by one unit she loses $\pi_{i,k}$. Since by reducing the length of the k-th step the intersection of the vertical segment and the residual demand occurs at a higher point p'_c and this new price will affect all inframarginal units, the bidder gains $p'_c - p_c$ over each unit won properly scaled for the NPV. We write a minus sign on the right-hand side because price increases when quantity is reduced. Assume further that $L_3(cp_t, p'_c) - L_3(cp_t, p_c) = 0$ since at best the change in p_c does not affect which terms in the NPV sum are activated in L_3 and if there is a change in the number of terms that go inside this sum they are very small terms since $\delta^t < 0.01$ for $t \geq 50$. Then the optimality condition becomes

$$\underbrace{\Pr(b_{i,k} < p_c < b_{i,k+1})}_{\equiv M_1} \pi_{i,k} = -\underbrace{q_{i,k} L_1(cp_t, p_c) \frac{\partial E(p_c \mathbb{1}(b_{i,k} \leq p_c \leq b_{i,k+1}))}{\partial q_{i,k}}}_{\equiv M_2}. \tag{6}$$

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

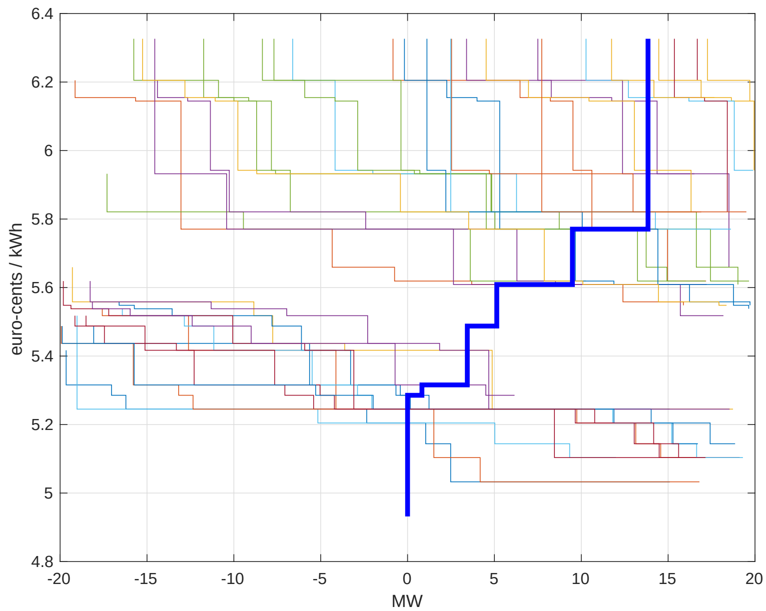
$$c_{i,k} = \frac{1}{L_2} \left[L_1(cp_t, p_c) E(p_c | b_{i,k} < p_c < b_{i,k+1}) + L_3(cp_t, p_c) + \frac{M_2}{M_1} \right]. \tag{7}$$

4.2.3 Estimation

To estimate market clearing prices and unobserved costs, we use a non-parametric estimator for resampling bids based on Hortaçsu and McAdams (2010) and Kastl (2011). We relax the symmetry assumption in the model by separating bidders into two groups $G = \{1, 2\}$, based on average project size, and assume symmetry only within each of the groups. We define a bidder as large if the average project size over the entire sample period is in the top ten percentile of the distribution of all bidders. This separation is correlated and statistically significant with bid values (see Columns 1 and 2 in Table 2). We also tried alternative definitions of size with similar results.[29]

[29] In particular, we define bidders as large in case they submit more than two bids on average over all auction rounds in which they participate. The results are presented in Online Appendix O.4.5.

Figure 3: Simulated residual demand curves and observed supply schedule



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

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.[30]

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.

[30]Unlike the literature that uses this algorithm for treasury auctions, we resample only from within the same round since rounds can be different one from another in several dimensions, e.g., number of competitors, the volume requested by the government, and by the expectations on future electricity prices. Online Appendix O.4.4 provides robustness for our results, pooling several rounds based on a four-dimensional kernel and confirms our main findings.

By repeating the above steps multiple times, we obtain a sample of market clearing prices, which can then be used to consistently estimate each bidder's winning probability using Equation 4 in PAB and Equation 6 in case of UP. At each step, we obtain several residual demand curves, each intersecting one of the observed supply curves, as shown in Figure 3. Each of those intersections gives a value for the price that can be used to evaluate the ratio in Equations 4 and 6, which in turn allows us to obtain the cost for each of the steps in the bid function. In a few cases, the recovered costs are negative or do not exist if the denominator is numerically very small.[31] 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.

4.2.4 Costs estimates

To build intuition, in Appendix Figure A.1 we show one example of an observed bid curve together with the estimated marginal costs. The two curves are monotonically increasing by construction and with a wide range of margins that tend to narrow down for high bid values. We interpret this as a sign that high cost projects are generally less profitable.

To measure the goodness-of-fit of the estimated costs from the model, we compare the median cost estimates to the median average system costs listed in Table 1. The model yields a median cost estimate of 5.33 €-cents/kWh, and the industry data suggests a comparable median average system cost of 5.05 €-cents/kWh.[32] This is a remarkable result, as no cost information was provided to the structural model. The estimated costs were recovered by inverting the optimality condition using only the observed bids as inputs.

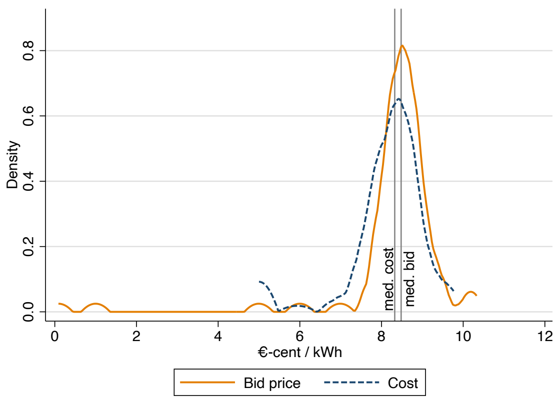
To compare estimated costs to observed bid values, we aggregate the individual bid and cost curves by bidder and period using quantity-weighted averages. The results are shown in Figure 4, where we plot the kernel densities for the observed bids and cost estimates in Panels

[31] 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.

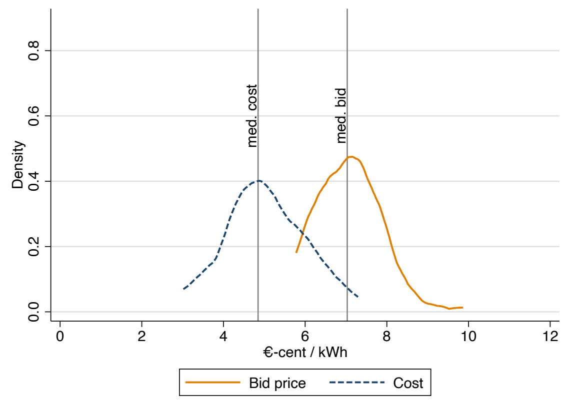
[32] This means that the median cost estimates are within 5% of the average industry-wide cost. Naturally, the model yields a larger dispersion of cost estimates than the aggregate data, with an inter-quartile range (P75 - P25) of 2.69 €-cents/kWh compared to 0.83 €-cents/kWh.

(a) to (c). Panel (d) from the same figure plots the density of the Lerner index, defined as the ratio of margins over bids, in each of the three periods.

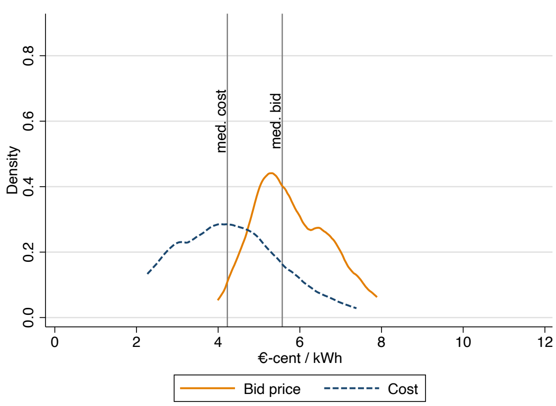
Figure 4: Estimated costs and observed bids densities



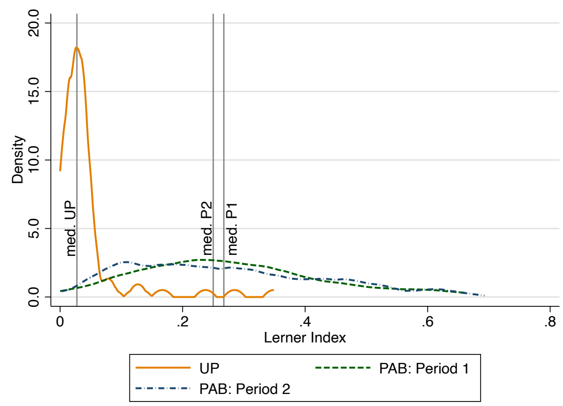
(a) UP: Auction rounds 2-3



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



(c) PAB, Period 2: Auction rounds 9-18



(d) Lerner Index, all three periods

Notes: Kernel densities of the costs obtained for uniform pricing rule (Equation 7 , Panel (a)) and PAB pricing (Equation 5, Panels (b) and (c)). Individual bids are aggregated by bidder and period using quantity-weighted averages. Panel (d) shows the average Lerner Index, defined as $\frac{b_i - c_i}{b_i}$, for each period separately.

The density of costs is shifted to the left relative to the density of the observed bids because of the existence of profit margins and that of market power. Interestingly, Panel (a) shows that the median bid and cost estimates are relatively close in uniform auction rounds

2 and 3, resulting in a low median markup (b_i/c_i) of 1.028. Yet, the gap widens considerably under PAB in Period 1 (auction rounds 4 to 8), where we find an median markup of 1.45 and Period 2 (rounds 9 to 18), with a markup of 1.31. This means that profit margins under PAB have been considerably larger than under UP, and that especially the period of decreasing prices (P1) had large average markups compared to the rest.[33] A different way to compare the estimates is to look at the Lerner Index as a measure of market power in Panel (d). In line with the markup results, we find that the auction format had an economically relevant impact on how bidders bid over costs. While the median Lerner Index under UP is 0.027, we find a value of 0.27 and 0.25 under PAB period 1 and period 2, respectively. This means that there was very low market power being exercised under uniform pricing while very similar levels of market power are present during the two PAB periods.

4.3 Analyzing Bidding Behavior

With the estimated costs and markups at hand, we next aim at analyzing bidding behavior under the two types of payment rules, as well as under the two different PAB periods. In line with the structural model, we focus on auction rounds 2-18 and omit the first auction round from this analysis. The main regression model resembles that of Equation 2 with the dependent variables being markups, defined as $\text{bid}_{i,k}/\text{cost}_{i,k}$, the probability of winning the auction $\Pr(\text{winning}_{i,k} = 1)$, and the bid value $\text{bid}_{i,k}$ directly. In the last two set of regressions, we include the estimated cost as an independent variable to test for auction efficiency and cost pass-through. As we do not include the first auction round held in 2015 (PAB), all estimates need to be interpreted with respect to the uniform auction rounds. As before, we include a rich set of market and bid-specific controls as well as land-type, location, time, 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 elec-

[33] To ensure that this difference is not driven by other time-varying factors, in Appendix Figure O.7, we plot the Lerner Index comparing the UP rounds 2 and 3 with adjacent PAB rounds 4 and 5 only and confirm a large and significant difference.

tricity network node, which is motivated by the market and regulatory concerns regarding the interconnection costs as a barrier of entry for renewable capacity.[34] We also consider solar irradiation and auction volume. At the *bid level*, we control for the land type and for whether the bidder is "large", according to the aforementioned definition of project size.

Markups. Table 3 shows the results of four different specifications where the dependent variable is the ratio of bids over the estimated marginal cost, the markups. While Section 4.2.4 provides a general overview of the cost and markup distribution, the regressions help to understand if this pattern holds when controlling for market factors and bid-specific variables. In line with the above discussion, we find that PAB periods 1 and 2 have led to higher average markups than UP. The differences are statistically significant and show a larger markup in P2, the period that is considered less competitive compared to UP and P1. We find no statistically different markups for large bidders under UP, but show that markups for large bidders under PAB are considerably smaller, especially in period 2. These results hold even when controlling for bidder fixed effects in Column (4). These results indicate that small project bidders, whose presence is an explicit objective of the auction design, secure a larger markup than larger bidders.

Probability of winning. To understand how the probability of winning differs between bidder types, Table 4 shows the results from a linear probability model with the main dependent variable being whether the bid was awarded or not. This regression also conditions on the estimated cost, as it allows us to analyze in how far the auction mechanisms selected the lowest cost bids. In line with the markup results, we find that there is no difference for large and small bidders in the probability of winning the auction under UP. Yet, the coefficient on the interaction of large bidder and the PAB format is positive and statistically significant in all specifications. This suggests that relative to UP rounds, large bidders are associated with a higher probability of winning the auction, although with lower markups

[34] See for instance Davis et al. (2023). We calculate the distance as the direct line from the centroid of the 5-digit zip code where the solar plant is located and the nearest high voltage network node (see Appendix Figure A.2).

Table 3: Markups

	(1)	(2)	(3)	(4)
$\mathbb{1}$(large bidder)	-0.038	-0.031	0.015	
	(0.024)	(0.027)	(0.034)	
$\mathbb{1}$(PAB P1)	0.296***	0.298***	0.345***	0.275***
	(0.041)	(0.041)	(0.084)	(0.086)
$\mathbb{1}$(PAB P2)	0.379***	0.378***	0.469***	0.468***
	(0.058)	(0.058)	(0.089)	(0.143)
$\mathbb{1}$(large bidder) $\times$ $\mathbb{1}$(PAB P1)	-0.242***	-0.247***	-0.274***	-0.205
	(0.078)	(0.077)	(0.075)	(0.127)
$\mathbb{1}$(large bidder) $\times$ $\mathbb{1}$(PAB P2)	-0.271***	-0.275***	-0.294***	-0.326**
	(0.073)	(0.071)	(0.066)	(0.132)
N	1,424	1,424	1,424	1,424
Adjusted R^2	0.12	0.12	0.14	0.38
Mean DV	1.27	1.27	1.27	1.27
Bid-specific controls	No	Yes	Yes	Yes
Land-type 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: Markups defined as $b_{i,k}/c_{i,k}$. All regressions include a constant term and control for auction volume. Bid-specific controls include distance to network and solar irradiation. Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

than small bidders as explained in the previous paragraph. Focusing on the coefficient related to the estimated cost, we find a negative and statistically significant coefficient across all different specifications, confirming the trade-off between a higher estimated cost and a lower probability of winning (Columns 2 - 4), indicating that the auction selects low-cost bids on average. When further distinguishing between PAB P1 and P2 in Column (5), we again find important heterogeneity across the periods, showing again the UP was better at selecting low cost bids. These results need to be, however, interpreted in line with the competitive environment of each auction period. As shown in Figure 2, the concentration measures have a higher variance in PAB Period 2 than in Period 1.

Heterogeneity of pass-through. Finally, in Table 5 we report regressions of the bid prices on the estimated costs. We expand on the previous model by including a triple interaction between the auction periods, bidder size, and estimated cost. This allows us to capture

Table 4: Probability of winning the auction

	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$(large bidder)	0.064	0.075	0.075		
	(0.070)	(0.069)	(0.068)		
$\mathbb{1}$(PAB P1)	-0.019	-0.193***	-0.140	-0.196	-1.501***
	(0.056)	(0.067)	(0.104)	(0.131)	(0.323)
$\mathbb{1}$(PAB P2)	-0.030	-0.273***	-0.365***	-0.443***	-1.462***
	(0.052)	(0.060)	(0.065)	(0.088)	(0.291)
$\mathbb{1}$(large bidder) × $\mathbb{1}$(PAB P1)	0.262**	0.312***	0.306***	0.331**	0.208*
	(0.106)	(0.114)	(0.115)	(0.129)	(0.118)
$\mathbb{1}$(large bidder) × $\mathbb{1}$(PAB P2)	0.168**	0.199***	0.144**	0.242***	0.173**
	(0.074)	(0.064)	(0.064)	(0.085)	(0.079)
Estimated cost		-0.069***	-0.067***	-0.066***	-0.196***
		(0.013)	(0.011)	(0.014)	(0.035)
Estimated cost × $\mathbb{1}$(PAB P1)					0.188***
					(0.042)
Estimated cost × $\mathbb{1}$(PAB P2)					0.132***
					(0.036)
N	1,441	1,424	1,424	1,424	1,424
Adjusted R^2	0.13	0.17	0.21	0.29	0.30
Mean DV	0.40	0.39	0.39	0.39	0.39
Bid-specific controls	No	Yes	Yes	Yes	Yes
Land-type FE	No	No	Yes	Yes	Yes
State FE	No	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes
Bidder FE	No	No	No	Yes	Yes

Notes: DV: bid awarded (binary). Linear probability model. All regressions include a constant term and control for auction volume. Bid-specific controls include distance to network and solar irradiation. Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

heterogeneous cost pass-through across auction formats and bidders' sizes. Focusing first on bid prices, in line with Table 2, we find that PAB led to higher conditional prices but that large bidders were bidding lower prices during this period. Second, focusing on the cost-pass through, we estimate an average pass-through rate of about 0.7 - 0.8 in UP rounds with no statistical differences for large bidders. In PAB, we generally find a lower pass-through of costs, or put differently, the cost is less informative for the observed bid values. While both interaction terms of Cost × PAB show a negative sign, the lower pass-through rate in PAB P1 relative to PAB P2 is in line with a less competitive market during this time period.[35]

[35] Although the relationship between competition and pass-through is not necessarily monotonic, most evidence suggests that more competitive markets are associated with higher pass-through rates. The underlying intuition is that, in competitive industries, markups are typically small, leaving firms with limited ability to

Table 5: Bid prices and cost pass-through

	(1)	(2)	(3)	(4)
$\mathbb{1}$(large bidder)	1.426	1.374	0.154	
	(1.714)	(1.728)	(2.004)	
$\mathbb{1}$(PAB P1)	3.482***	3.556***	4.944***	3.719***
	(0.954)	(0.969)	(0.780)	(1.088)
$\mathbb{1}$(PAB P2)	1.675*	1.761*	3.335***	1.889
	(0.932)	(0.951)	(0.807)	(1.159)
$\mathbb{1}$(large bidder) × $\mathbb{1}$(PAB P1)	-0.571	-0.470	0.833	-2.204
	(2.937)	(2.879)	(2.797)	(2.652)
$\mathbb{1}$(large bidder) × $\mathbb{1}$(PAB P2)	-3.703**	-3.705**	-2.021	-3.204
	(1.753)	(1.748)	(2.070)	(3.179)
Estimated cost	0.715***	0.720***	0.800***	0.671***
	(0.110)	(0.112)	(0.091)	(0.139)
Cost × $\mathbb{1}$(large bidder)	-0.189	-0.188	-0.043	-0.208
	(0.210)	(0.211)	(0.240)	(0.373)
Cost × $\mathbb{1}$(PAB P1)	-0.555***	-0.568***	-0.734***	-0.609***
	(0.116)	(0.118)	(0.099)	(0.136)
Cost × $\mathbb{1}$(PAB P2)	-0.353***	-0.366***	-0.534***	-0.348**
	(0.124)	(0.126)	(0.106)	(0.151)
Cost × $\mathbb{1}$(large bidder) × $\mathbb{1}$(PAB P1)	-0.004	-0.017	-0.160	0.277
	(0.399)	(0.390)	(0.369)	(0.316)
Cost × $\mathbb{1}$(large bidder) × $\mathbb{1}$(PAB P2)	0.536**	0.538**	0.319	0.434
	(0.225)	(0.224)	(0.274)	(0.410)
N	1,424	1,424	1,424	1,424
Adjusted R^2	0.74	0.74	0.81	0.86
Mean DV	6.57	6.57	6.57	6.57
Bid-specific controls	No	Yes	Yes	Yes
Land-type 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. All regressions include a constant term and control for auction volume. Bid-specific controls include distance to network and solar irradiation. Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Looking at the triple interaction term, we find no statistically significant differences between large and small bidders in PAB P1. Yet, without conditioning on land-type, state, and year fixed effects, we see differences in the pass-through rates for large bidders during PAB P2, indicating that these bidders might have been able to pass on a higher fraction of their cost during this period. This would be consistent with the idea that large bidders exercise market power in PAB P2. Yet, making the projects more comparable by adding additional fixed effects, the differences for large and small project bidders vanish.

4.4 Robustness

We perform several robustness checks for the reduced form regression results to show that the main data patterns hold independently whether we omit all zero margin bids (Online Appendix O.4.2), if we assume all bidders symmetric and we do not assign them into groups (Online Appendix O.4.3), if we pool several rounds based on a four-dimensional kernel for estimation (Online Appendix O.4.4), or whether we use the alternative definition of large bidders, based on the number of submitted projects (Online Appendix O.4.5) rather than project size. Our main estimates remain largely similar across all those different specifications and our main specifications.

The potential pooling of auction rounds merits additional discussion. As auction fundamentals may be changing over time, our main estimation algorithm treats each auction round independently. Yet, this may induce a bias in the estimates, as the non-parametric estimators are best performing for large samples. The literature thus typically pools multiple auction rounds for the empirical implementation, based on observable auction characteristics. To check the robustness of our results, we therefore follow a similar approach and define a four-dimensional kernel based on the number of bidders, the auction identifier, auction volume, and the pricing rule. We allow for any adjacent rounds to be merged, in case these are

absorb cost shocks. In contrast, in less competitive markets, firms are more likely to balance the reduction in markup against the potential decline in demand caused by higher final prices, resulting in incomplete pass-through.

not 'too different' and re-estimate the model based on this larger set of bid curves.[36] One additional advantage of treating each auction round independently for estimation means that unobserved auction heterogeneity should be less of a problem for our empirical application.

Finally, to examine the assumption of independent private signals, we run a regression of the bid prices on publicly available information regarding the auction outcomes of the previous rounds, as well as market and bid-specific factors that are known to the bidders (Appendix Table A.3). We then implement a test on the correlations of residuals between pairs of bidders participating in the same auction rounds. This test follows directly Bajari and Ye (2003).[37] 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 absolute z-scores of 0.82 and a corresponding average p-values of 0.49, showing that there is no indication that the pairwise residuals are systematically correlated. This test can be also interpreted as no evidence for coordinated behavior of the bidders.[38]

5 Counterfactual Analysis

We use the structural model to study a set of counterfactuals. We focus on three main outcomes: market power, procurement costs, and efficiency. In all those cases we ask the question, how do the outcomes from a pay-as-bid auction compare to those from a uniform auction? Given the lack of theoretical guidance to rank these formats in multi-unit auctions, our estimates allow us to provide an empirical answer in the present context. This question is also motivated by the actions of the regulator, who in early rounds experimented with a non-discriminatory auction format. We compute subsidies under each auction format and discuss

[36] In practice this procedure pools both UP rounds, and merges PAB rounds with adjacent rounds (auction identifier $\pm$ 1) if these are not too different in terms of number of bidders or total auction volume.

[37] We condition on pairs of bidders that have at least 4 interactions. Bid prices are quantity weighted. This leaves us with a total of 55 bidders and 481 observations.

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

the effects of the policy parameter that defines the subsidy payments itself: the capture price.

5.1 Auction Format and Market Power

To test for the impact of the auction format, in a first approximation, we set the bids equal to the estimated costs as the bidders' strategies to simulate a uniform auction format and call this the *truthful bidding* benchmark. This is equivalent to the truthful bidding case in treasury auctions (see, e.g., Hortaçsu and McAdams, 2010; Elsinger et al., 2019). This circumvents modeling the strategies of each player and simplifies finding the equilibrium.[39] In this auction format, we build the supply curve directly from the estimated costs, intersect it with the inelastic demand curve given by the requested volume in a given auction, and find in this way the uniform market clearing price. While the literature has highlighted that firms have incentives to bid above marginal costs also in the uniform auction format, e.g., due to a restricted number of bid steps (Hortaçsu et al., 2018), truthful bidding can be considered as a useful benchmark in which zero markups are assumed.

In addition, we make use of the bids from the uniform auction rounds to estimate a linear regression of markups on firm characteristics. We focus our attention on the binary variable related to firm size as defined in the previous section.[40] The results are shown in Appendix Table A.2 and highlight that small bidders have an average markup of 5.8% and large bidders of 1.6% in the unconditional regression in Column 1. We consider the case in which those markups are applied to the recovered costs from the discriminatory rounds, depending on bidder size. Therefore, the assumption is that the level of market power exercised in the two early rounds with uniform pricing is the same in this counterfactual across all subsequent rounds. Although the truthful bidding case, which is widely used in the literature, represents the extreme case of no market power, our heterogeneous markup counterfactual is a more realistic scenario based on our own estimates from actual interactions in a uniform price

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

[40]This choice is mostly due to data convenience, as we do not observe firm characteristics in our original data and can only recover additional information on legal status and type of firm for a subset of bidders. The proposed methodology can be, however, extended to incorporate additional firm characteristics.

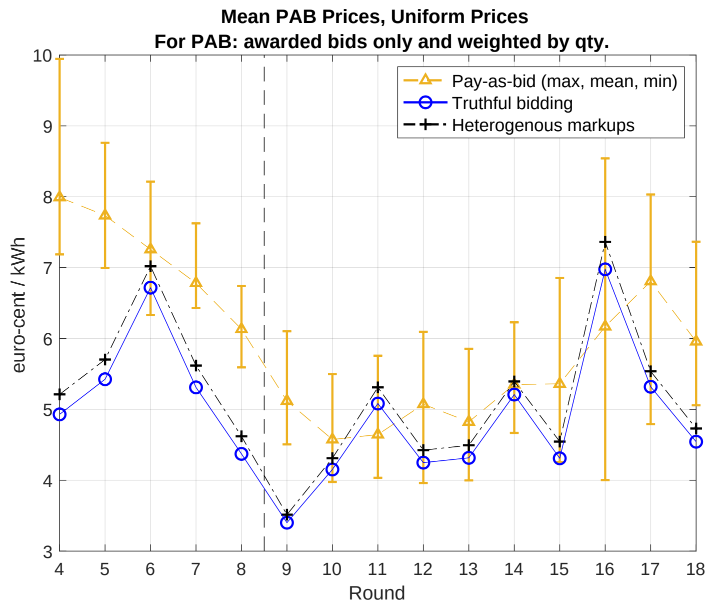
setting in the same market and conditional on an observable characteristic, bidder's size.

Figure 5 shows the clearing prices for the two versions of the uniform price auctions together with the PAB prices. For the truthful bidding case we construct the perfectly competitive supply curves directly using the estimated costs ranked from lowest to highest. For the heterogeneous markups case we use the truthful bidding supply curve and multiply it by the corresponding markup factor depending on whether the bidder is large or small. The PAB line is obtained through simulation using the estimated marginal costs, therefore, it is close to but not identical to the line shown in Figure 1, in addition each round point is equally spaced in the x-axis and we start at round 4. Altogether, this makes a fair comparison across counterfactuals and not between counterfactual outcomes and data.

The main difference between the outcomes from the three auction formats is that market clearing prices are lower under truthful bidding and the heterogeneous markups clearing prices are most of the time in between the PAB and the truthful bidding cases. The main exceptions are rounds 11, 14, and 16, which require further discussion. As highlighted in Section 3, rounds 11, 14, and 17 were implemented as joint wind and solar auctions. While in round 17, no wind bids were present, the total supply in rounds 11 and 14 was affected by wind bids, even these bids were not awarded. The presence of wind bids might have, however, affected the bidding strategies of solar investors. Round 16, on the other hand, had a target volume that exceeded any other round's by more than double the volume, see Table A.1, and thus might have led to higher market clearing prices. These are the only rounds in which we find counterfactual clearing prices close to and above the observed PAB prices.

We compute the markups for each of the winning bids under each format (p_c/c_i in the cases of uniform pricing and b_i/c_i in the PAB case) using the estimated costs. Figure 6 shows the quantity-weighted means of those markups by round. Although it is entirely possible that setting the bids equal to the costs selects the most competitive equilibrium, obtaining lower market power in the uniform price auction is not a mechanical feature of the model since under PAB bidders still face a trade-off between bidding low to get selected and bidding high to maximize their payoff. The truthful bidding setting gives a lower bound on government

Figure 5: Pay-as-bid versus truthful bidding

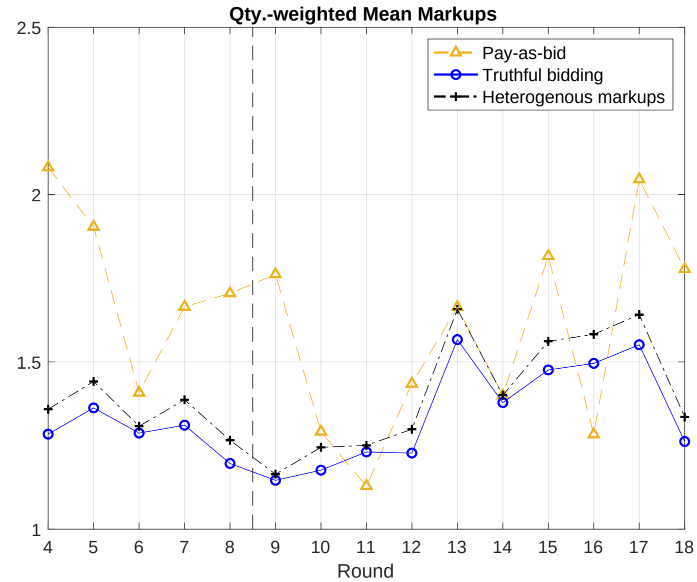


Notes: Truthful bidding is a counterfactual where each firm submits bids that are equal to its estimated costs. In the heterogeneous markups case we multiply by a markup of 1.07 for small bidders and by 1.02 for large bidders to their respective cost curves. The PAB line also shows min/max bands. The PAB line is obtained through simulation using the estimated marginal costs, therefore, it is not identical to the line shown in Figure 1. Note that it is possible that the clearing price under uniform pricing 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.

expenditure within the class of uniform price auctions, whereas the heterogeneous markup case gives a more realistic outcome based on the two early uniform price auctions.[41] Our main finding is that in this market, a uniform price auction would have given place to a lower exercise of market power as was already suggested in Figure 4 Panel (d) where the density of the Lerner index shifted to the right for PAB rounds relative to the UP rounds. The overall average quantity-weighted markups for PAB, truthful bidding, and heterogenous markups are, respectively, 1.62, 1.33, and 1.39. When not considering rounds 11, 14, and 16, we find that the average quantity-weighted markups are, in the same order as above, 1.71, 1.32, and 1.39. The particularities of those three rounds only seem to matter on the aggregate for PAB but not for uniform pricing.

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

Figure 6: Markups under different auction formats



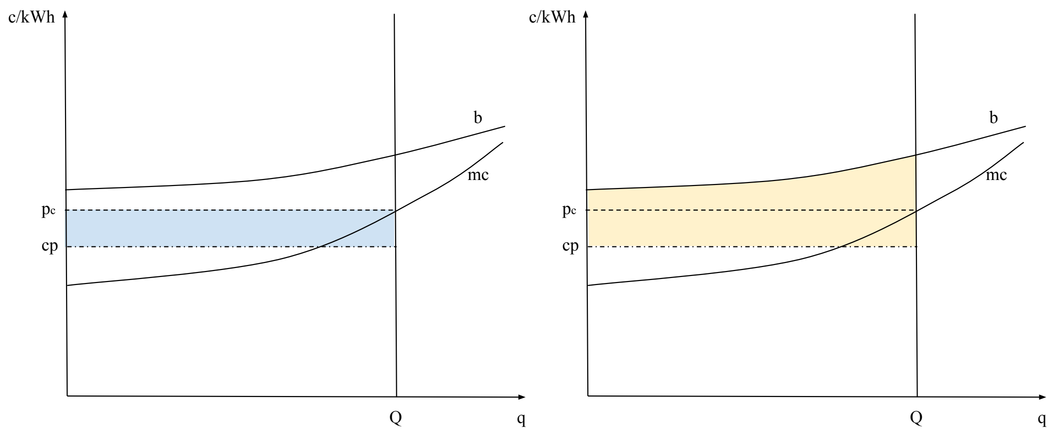
Notes: Truthful bidding is a counterfactual where each firm submits bids that are equal to their estimated costs. Heterogeneous markups applies a different markup to each bidder depending on their size (see main text for details). PAB refers to the observed bids. For each round and for each auction format, markups of winning bids only and graph shows quantity-weighted means.

5.2 Total Procurement Costs

An important outcome of procurement auctions is how much the allocation costs the government. Recall that the auctions are used to determine which developers get the right to build solar sites and the amount of the subsidy they will receive over the entire project horizon as a function of the capture price. Developers privately incur the construction costs of the solar sites, not the government. Therefore, the procurement costs in these auctions are the total subsidy payments over 20 years aggregated over all the awarded solar sites. The size of the subsidy depends on the auction format since the market clearing price and the gap between the cost curve and the bid curve do so as well. To evaluate this, we compute the quantity-weighted sliding premia at each time period under uniform pricing,

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

Figure 7: Subsidy under uniform pricing is lower than under pay-as-bid



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

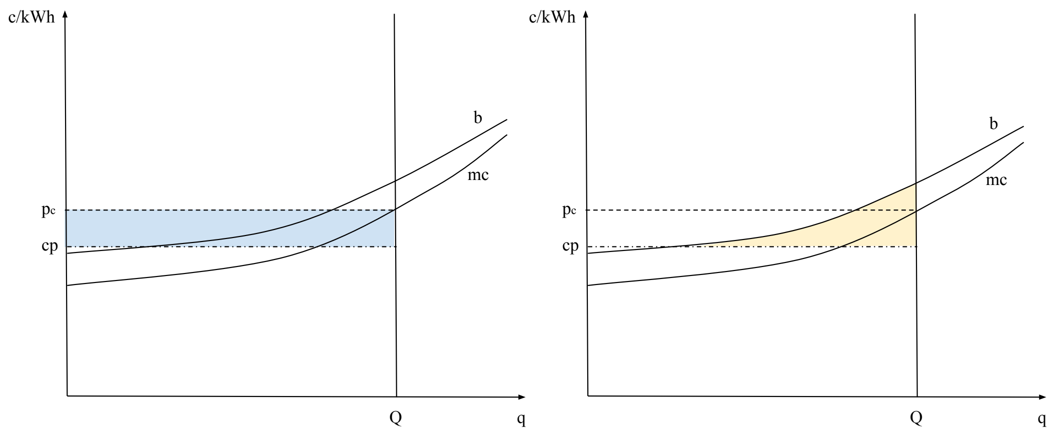
and the quantity-weighted sliding premia under the PAB format in each time period,

$$S_{PAB_t} = \sum_i \frac{q_i}{Q} \theta \max\{b_i - cp_t, 0\},$$

where Q is the total awarded volume, q_i is each of the winning project's capacities, and θ represents the time duration of the output, in other words, the length of the time interval t and is assumed equal to 1 hour. Note that an implication of this is that we assume a capacity factor of 100% and therefore, these subsidy calculations represent the upper bound on the subsidy amounts. Q and the capacity sizes of the projects are also constant over time, but the outcome of the max operator is time-dependent. Together, the units of S_{PAB_t} are € per kW of installed capacity.

The relationship between the subsidies is an empirical question. Figure 7 shows an ex-

Figure 8: Subsidy under pay-as-bid is lower than under uniform pricing



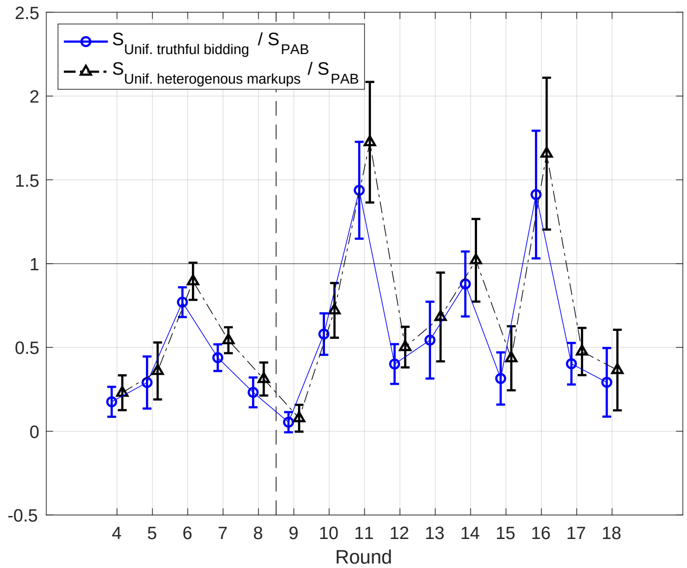
Notes: This is the same as Figure 7 except that the aggregate bid curve b is much closer to the estimated costs curve mc. The subsidy under uniform pricing (blue rectangle, left panel) is greater than under PAB (yellow area, right panel) in this case.

ample of a bidding curve and its corresponding cost curve where the subsidy under uniform price is lower than the subsidy under PAB.[42] However, it is not difficult to find configurations where the opposite is true. Figure 8 shows one of these possibilities, which repeats the same configuration as in Figure 7 except that the bidding curve is closer to the cost curve than before. Therefore, the subsidy under uniform pricing does not change but the one for PAB does, and in fact it shrinks relative to the previous configuration.

Since the two types of subsidy cannot be ranked in size in general, we study the ratio S_U/S_{PAB} of the two subsidies for each auction round averaging over the scenarios defined in the previous section for the monthly evolution of the capture price time series, where S_U is the discounted sum of the per-period subsidy S_{U_t} and similarly for S_{PAB}. Note that the parameter θ cancels out when taking the ratio of the two subsidies amounts and the implicit assumption on the capacity factor is eliminated. We bootstrap the supply curve 200 times within each scenario, which allows us to construct confidence intervals. Figure 9 presents the results for truthful bidding and heterogeneous markups. In most rounds, subsidies under

[42]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 9: Subsidies under pay-as-bid and truthful bidding



Notes: Each line represents the ratio of the subsidies under truthful bidding and PAB S_U/S_{PAB} at each auction round, where S_U is the discounted sum of the quantity-weighted per-period subsidies $S_{U_t} = \sum_i \frac{q_i}{Q}\theta \max\{p_c - cp_t, 0\}$, p_c is the market clearing price under uniform pricing, q_i are the quantities awarded, Q is the total volume awarded, θ is the duration of the output, S_{PAB} is the discounted sum of the per-period subsidies $S_{PAB_t} = \sum_i \frac{q_i}{Q}\theta \max\{b_i - cp_t, 0\}$, and cp_t is the capture price. The confidence intervals were obtained by bootstrapping the supply curve 200 times at each round and at each scenario.

uniform pricing are clearly lower than under PAB. Rounds 11, 14, and 16 are the exception, these are precisely the rounds where markups under uniform pricing are larger than under PAB (see Figure 6), as discussed above. The heterogeneous markup case increases the value of this ratio but not as a parallel shift since it is a multiplicative markup on the cost curve that depends on the size of the bidder.

Table 6 expands on these results by showing statistics of the difference in subsidies in net present value and €-cent / kW of capacity installed units relative to the PAB format. From both panels, we observe that the quantity-weighted mean over all rounds indicates that PAB was more costly in terms of subsidies than the two uniform price formats studied here. However, there is considerable variation across the two time periods consistent with Figure 9. In the beginning of the policy, PAB was extremely costly, but as we transition into Period 2 this same format appears to be less expensive than before. As mentioned earlier,

Table 6: Differences in Subsidies

Δ subsidies (truthful bidding - PAB) (€-cent per kW of capacity installed)			
	All rounds	Period 1	Period 2
Mean	-93.27	-125.71	-56.2
S.E.	53.93	57.57	49.77
25th perc.	-122.1	-144.19	-96.86
Median	-85.02	-118.3	-46.98
75th perc.	-54.25	-95.87	-6.69

Δ subsidies (heterogeneous markups - PAB) (€-cent per kW of capacity installed)			
	All rounds	Period 1	Period 2
Mean	-73.89	-105.87	-37.35
S.E.	51.86	63.17	49.43
25th perc.	-102.72	-124.34	-78.02
Median	-65.64	-98.45	-28.13
75th perc.	-34.87	-76.02	12.15

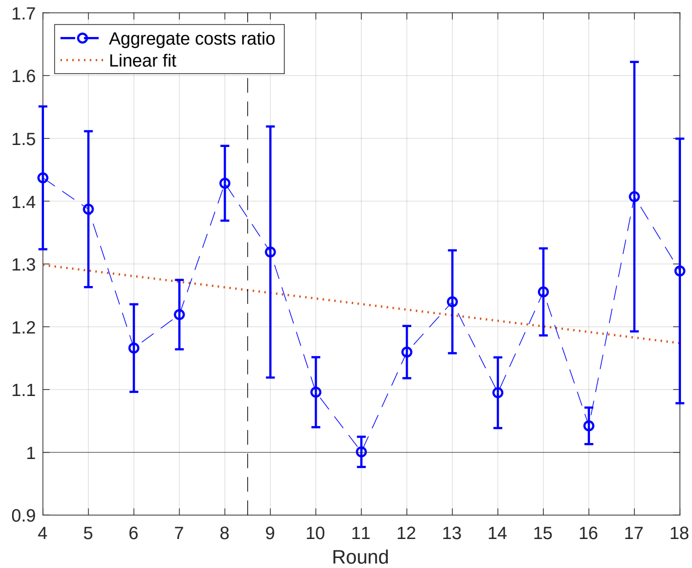
Notes: Each of the panels shows statistics for the difference in subsidies in net present value per unit of capacity installed between truthful bidding and PAB and between the heterogeneous markup outcomes and PAB, respectively. Columns Period 1 and Period 2 report the results conditional on each of those rounds periods. The standard errors are calculated by bootstrapping with 200 iterations and all statistics are quantity-weighted and averaged over the different scenarios of capture prices.

the large change in this difference in Period 2 is related to lower margins and a large increase in demand. The lower panel reports the same differences but in the heterogeneous markup case. The disadvantage of PAB gets attenuated in Period 2.

To put these results in context, we provide a back-of-the-envelope calculation of the total difference in subsidy payments. Using the mean difference in subsidies of 1.26 € / kW in Period 1 in the truthful bidding case, the average project capacity of 5.3 MW, and the average number of winning projects of 29 in Period 1 (Table 1), the overall savings if truthful bidding could have been implemented instead of PAB over the five auction rounds in Period 1 would have been €0.96 million (or equivalently €0.19 million per auction round). Similarly, using the difference in subsidies in Period 2 of 0.56 € / kW, such savings would have accounted for €1.03 million over the lifetime of the installations. This difference is purely driven by the choice of the pricing rule.

5.3 Costs Efficiency

Figure 10: Aggregate marginal costs by pay-as-bid and truthful bidding



Notes: For each round, the dots indicate the mean of the ratio of aggregate costs under PAB and the aggregate costs under truthful bidding. The bars represent ± 1 S.D. using 200 bootstrapping samples averaged over the scenarios for forecast prices.

The policy's objective is not only to award subsidies to developers, but to choose those developers that have the lowest costs. To assess the success of the policy in this regard, we compare the aggregate costs of the winning projects under PAB with the aggregate costs of the truthful bidding allocation. More precisely, we compute the integral of the marginal cost curve up to the clearing price under PAB and divide it by the integral of the marginal cost curve up to the clearing price under the perfectly competitive counterfactual.[43] We report the ratio of those aggregate costs in Figure 10. By construction, any allocation other than the perfectly competitive outcome will have higher costs, therefore, we use such outcome as the benchmark of efficiency. Over time, the ratio exhibits a slight trend towards the benchmark,

[43] Alternatively, we could benchmark against the outcomes of a multi-unit Vickrey auction (e.g., generalized second-price auction or Vickrey–Clarke–Groves auction). However, we prefer the simpler benchmark presented in the main text since the multi-unit Vickrey auction is a mechanism rarely used in practice and because it is not straightforward to define the payments since the units of the good are not equal in our case, each project is of a different size. In this auction format, a bidder who wins n units pays the sum of the n-th highest non-awarded bids other than her own. Since bids in our case represent projects of different sizes, this would require to assume that all projects are fully homogeneous.

followed by a stabilization period where most values are approximately 10% to 25% above it. Coincidentally, the three rounds with the largest standard deviations (9, 17, and 18) also had the highest average awarded volume per project (see Tables 1 and A.1.). The final two rounds featured an unusually low number of awarded projects; however, these projects were, on average, very large. Consequently, these rounds displayed a distinct type of winning bid compared to others. Overall, PAB allocations are less costly over time relative to the truthful bidding allocation. This observation is largely consistent with the findings of the linear probability model in Table 4. Using Column 5 of that table, the probability of winning is 0.8% lower if costs increase by 1 €-cent/kW in Period 1, but the same probability is 6.4% in Period 2. Thus, an eight-fold change in the likelihood of not being selected in the last part of the sample if costs increase.

6 Conclusion

This paper outlines key findings regarding auctions distributing payments to solar power electricity producers in Germany in the form of subsidies that depend on the evolution of electricity prices in the future. Recognizing the limitations of a reduced-form approach, we employ a structural multi-unit auction model to recover bidders' unobservable costs under both discriminatory and non-discriminatory pricing rules. These cost estimates serve as the basis for measuring market power and conducting counterfactual analyses to assess the effects of alternative auction formats.

Our results suggest that non-discriminatory pricing rules can substantially reduce subsidy expenditures, while also highlighting a broader trend toward increased cost efficiency in RE auctions over time. These findings underscore the importance of auction design in shaping both market outcomes and fiscal implications. Despite the widespread adoption or RE auctions, the impact of auction design and the factors shaping participants' bidding behavior remain relatively understudied. Yet understanding how auction design influences bidding is crucial for regulators aiming to develop procurement schemes that minimize rents, encourage entry, and ensure efficient capacity allocation.

This paper offers a structural approach to addressing these questions in the context of German RE auctions. Our analysis is based on the assumption of independent auction rounds and risk-neutral bidders—simplifying assumptions that yield a tractable model. Future work could build on this framework by relaxing these assumptions. As the energy transition advances, the choice of auction mechanisms to allocate capacity and structure incentives becomes central to both economic efficiency and public finance. More broadly, the challenge of procuring goods and allocating subsidies in multi-unit, multi-technology environments is not unique to energy and holds relevance across a wide array of public procurement contexts.

References

Anatolitis, Vasilios, Alina Azanbayev, and Ann-Katrin Fleck, "How to design efficient renewable energy auctions? Empirical insights from Europe," *Energy Policy*, July 2022, *166*, 112982.

Astier, Nicolas, Ram Rajagopal, and Frank A Wolak, "Can distributed intermittent renewable generation reduce future grid investments? Evidence from France," *Journal of the European Economic Association*, 2023, *21* (1), 367–412.

Ausubel, Lawrence M, Peter Cramton, Marek Pycia, Marzena Rostek, and Marek Weretka, "Demand reduction and inefficiency in multi-unit auctions," *The Review of Economic Studies*, 2014, *81* (4), 1366–1400.

Bajari, Patrick and Lixin Ye, "Deciding between competition and collusion," *Review of Economics and Statistics*, 2003, *85* (4), 971–989.

Bayer, Benjamin, Dominik Schäuble, and Michele Ferrari, "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*, November 2018, *95*, 305–327.

Beiter, Philipp, Lena Kitzing, Paul Spitsen, Miriam Noonan, Volker Berkhout, and Yuka Kikuchi, "Toward global comparability in renewable energy procurement," *Joule*, 2021, *5* (6), 1485–1500.

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

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

Cramton, Peter, "Spectrum auction design," *Review of Industrial Organization*, 2013, *42*, 161–190.

Davis, Lucas W, Catherine Hausman, and Nancy L Rose, "Transmission Impossible? Prospects for Decarbonizing the US Grid," Technical Report, National Bureau of Economic Research 2023.

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

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

Egerer, Jonas, "Open source electricity model for Germany (ELMOD-DE)," Technical Report, DIW Data Documentation 2016.

Eklöf, Matias, "Assessing social costs of inefficient procurement design," *Journal of the European Economic Association*, 2005, *3* (4), 826–850.

Elsinger, Helmut, Philipp Schmidt-Dengler, and Christine Zulehner, "Competition in treasury auctions," *American Economic Journal: Microeconomics*, 2019, *11* (1), 157–84.

Fabra, Natalia and Juan-Pablo Montero, "Technology-neutral versus technology-specific procurement," *The Economic Journal*, 2023, *133* (650), 669–705.

_ , Nils-Henrik M von der Fehr, and María-Ángeles de Frutos, "Market design and investment incentives," *The Economic Journal*, 2011, *121* (557), 1340–1360.

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

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

Grashof, Katherina, "Are auctions likely to deter community wind projects? And would this be problematic?," *Energy Policy*, February 2019, *125*, 20–32.

Gupta, Seher and Rohit Lamba, "Treasury auctions during a crisis," *Available at SSRN 4251675*, 2023.

Hara, Konan, "Encouraging Renewable Investment: Risk Sharing Using Auctions," Technical Report, Working paper 2023.

Haufe, Marie-Christin and Karl-Martin Ehrhart, "Auctions for renewable energy support – Suitability, design, and first lessons learned," *Energy Policy*, October 2018, *121*, 217–224.

Holmberg, Pär, "Supply function equilibria of pay-as-bid auctions," *Journal of Regulatory Economics*, 2009, *36*, 154–177.

_ **and Frank A Wolak**, "Comparing auction designs where suppliers have uncertain costs and uncertain pivotal status," *The RAND Journal of Economics*, 2018, *49* (4), 995–1027.

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

_ **and** _ , "Empirical work on auctions of multiple objects," *Journal of Economic Literature*, 2018, *56* (1), 157–84.

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

_ **,** _ **, and Allen Zhang**, "Bid shading and bidder surplus in the us treasury auction system," *American Economic Review*, 2018, *108* (1), 147–169.

IRENA, "Renewable Energy Auctions: Status and Trends beyond Price," Technical Report 2019.

Jarvis, Stephen, Olivier Deschenes, and Akshaya Jha, "The private and external costs of Germany's nuclear phase-out," *Journal of the European Economic Association*, 2022, *20* (3), 1311–1346.

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

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

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

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

Klessmann, Corinna, Silvana Tiedemann, Fabian Wigand, Tobias Kelm, Jenny Winkler, Mario Ragwitz, Marie-Christin Haufe, and Karl-Martin Ehrhart, "Ausschreibungen für PV-Freiflächenanlagen: Auswertung der ersten zwei Runden: im Auftrag des BMWi," Berlin 2015.

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

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

Kreiss, Jan, Karl-Martin Ehrhart, and Marie-Christin Haufe, "Appropriate design of auctions for renewable energy support – Prequalifications and penalties," *Energy Policy*, 2017, *101*, 512–520.

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

Liñeiro, Taimyra Batz and Felix Müsgens, "Evaluating the German PV auction program: The secrets of individual bids revealed," *Energy Policy*, December 2021, *159*, 112618.

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

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

Ryan, Nicholas, "Holding Up Green Energy," Technical Report, National Bureau of Economic Research 2021.

Schlesinger, Michael, Peter Hofer, Andreas Kemmler, Almut Kirchner, Sylvie Koziel, Andrea Ley, A Piégsa, F Seefeldt, S Straßburg, K Weinert et al., "Entwicklung der Energiemärkte–Energiereferenzprognose," *Projekt Nr. 57/12. Studie im Auftrag des Bundesministeriums für Wirtschaft und Technologie. Basel/Köln/Osnabrück: ewi/gws/prognos*, 2014.

Tiedemann, Silvana, C Klessmann, F Wigand, and S Förster, "Auctions for Renewable Energy Systems in Germany: Pilot scheme for ground-mounted PV," *Report of the EU-funded AURES II project D*, 2015, *4*.

_ , Marian Bons, Thobias Sach, Martin Jakob, Corinna Klessmann, Vasilios Anatolitis, Anna Billerbeck, Jenny Winkler, Holger Höfling, Tobias Kelm, Jochen Metzger, Henning Jachmann, Luise Bangert, Christoph Maurer, Bernd Tersteegen, Lion Hirth, Juliane Reimann, Karl-Martin Ehrhart, and Ann-Katrin Hanke, "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 2019.

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

Wambach, Achim, Dagmar Kollmann, Jürgen Kühling, Thomas Nöcker, and Angelika Westerwelle, "Wettbewerb mit neuer Energie. Sektorgutachten der Monopolkommission gemäß § 62 EnWG," Technical Report, Sektorgutachten Energie 2019.

Willems, Bert and Yu Yueting, "Bidding and Investment in Wholesale Electricity Markets: Discriminatory versus Uniform-Price Auctions," 2023.

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

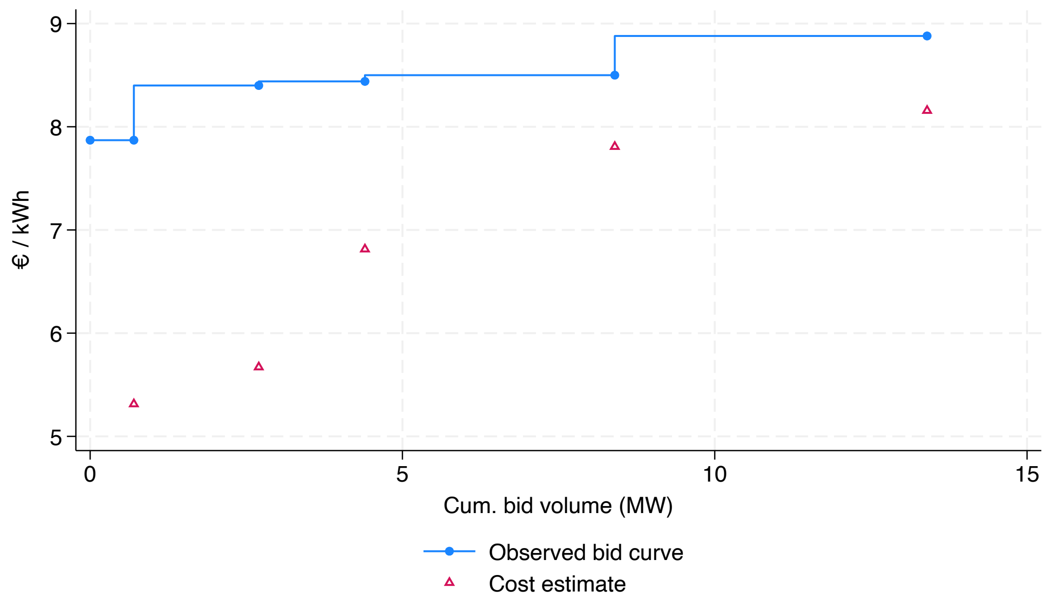
Wolak, Frank A, "Measuring unilateral market power in wholesale electricity markets: The California market, 1998–2000," *American Economic Review*, 2003, *93* (2), 425–430.

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

Appendix

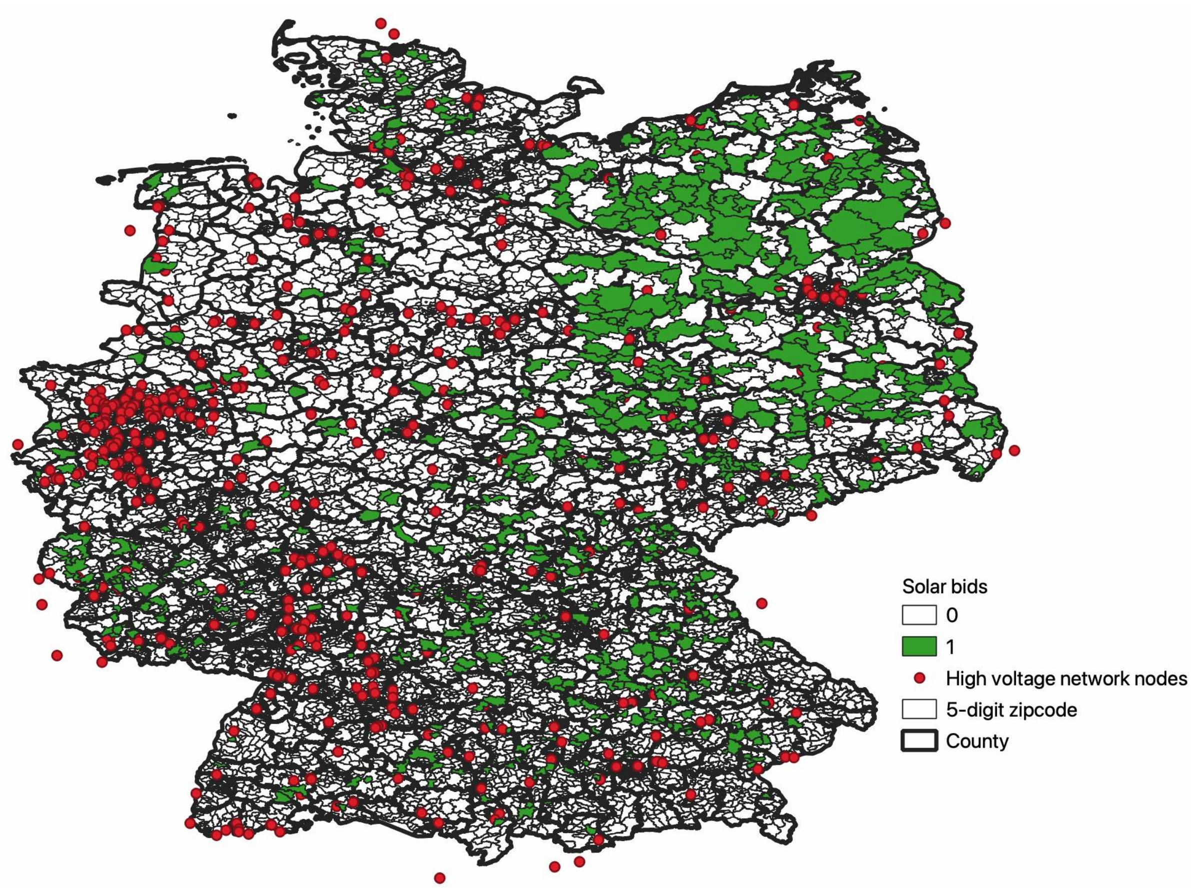
A Additional Figures and Tables

Figure A.1: Bid curve and cost estimates



Notes: Example of bid curve and cost estimates for one bidder under PAB pricing. We omit the bidder indicator as well as the round number in order to comply with the anonymization of the data. In this case, there are five different quantity-price pairs (bids) submitted by this bidder.

Figure A.2: Solar bids and network nodes



Notes: Map of Germany indicating the zip codes for which a bid has been submitted in at least one auction round and the access points (nodes) to the high voltage electricity network. Average zip code size differ by state.

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

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

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

Table A.2: Heterogeneous markups by size

	(1)	(2)	(3)
$\mathbb{1}$(large bidder)	-0.042*	-0.039*	-0.029
	(0.021)	(0.022)	(0.019)
Avg. system cost (€/kWh)			-0.150**
			(0.073)
Constant	1.058***	1.171***	2.014***
	(0.016)	(0.101)	(0.467)
N	233	233	233
Adjusted R^2	0.02	0.06	0.11
Mean DV	1.05	1.05	1.05
Land-type FE	No	Yes	Yes
State FE	No	Yes	Yes

Notes: DV: Markups. Sample limited to UP rounds 2 and 3. Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3: Bid values and past auction outcomes

	(1)	(2)	(3)
# bids, prev. auction	-0.002	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Med. winning bid, prev. auction	0.526***	0.476***	0.466***
	(0.104)	(0.112)	(0.111)
Max. winning bid, prev. auction	0.326***	0.315***	0.319***
	(0.090)	(0.089)	(0.088)
Avg. system cost, prev. auction	-0.433***	-0.404***	-0.390***
	(0.145)	(0.145)	(0.143)
Distance to network (100 km)	0.383*	0.360*	0.358
	(0.210)	(0.195)	(0.218)
Solar irradiation (MWh/m^2)	-1.542*	-0.181	-0.166
	(0.829)	(0.838)	(1.082)
Auction volume (100 MW)	-1.459***	-1.533***	-1.525***
	(0.333)	(0.360)	(0.343)
Auction volume^2	0.252***	0.261***	0.260***
	(0.052)	(0.056)	(0.053)
$\mathbb{1}$(large bidder)	-0.238	-0.254*	-0.246**
	(0.163)	(0.135)	(0.117)
Capture price (last three years)	0.731**	0.670**	0.676**
	(0.339)	(0.320)	(0.322)
Land-type: Building		0.408***	0.423**
		(0.149)	(0.184)
Other		0.491***	0.526***
		(0.100)	(0.131)
Adjacent road or railway		0.564***	0.558***
		(0.088)	(0.086)
Site, prev. usage		0.497***	0.509***
		(0.076)	(0.106)
N	1,424	1,424	1,424
Adjusted R^2	0.690	0.707	0.710
Mean DV	6.571	6.571	6.571
State FE	No	No	Yes

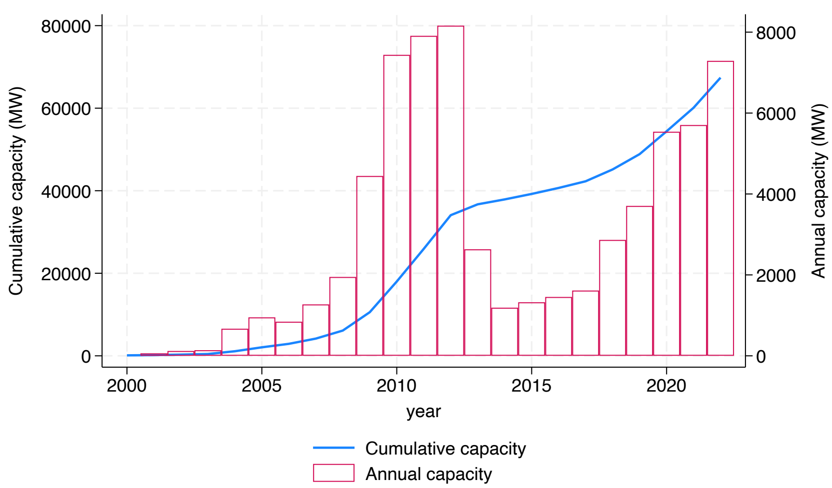
Notes: DV: bid values. Regressions include a constant term. Land-type: all estimates with respect to agricultural land (omitted category). Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Online Appendix

O.1 Additional Institutional Details

O.1.1 The German solar market around the introduction of the auctions

Figure O.1: Evolution of the Germany Solar Market



Source: Federal Ministry of Economics and Climate Action, Working Group Renewable Energy Statistic (AGEE-Stat)

The market for large scale solar in Germany was rather unstable in the years prior to the introduction of the auction mechanism in 2015. First, module prices had declined more rapidly than anticipated by the policy maker, leading to an unexpected surge in capacity (and related subsidy payments) and windfall profits to investors in the years 2009-2012 (see Appendix Figure O.1). The government responded to these developments by reducing the governmental set subsidy (feed-in tariff, FIT) and reducing supply (excluding the possibility to construct solar on agricultural land, and introducing a maximum size of 10 MW of capacity per plant, EEG 2012). Furthermore, the government introduced a dynamic reduction of FITs as a function of the total added solar capacity. However, module prices stagnated in the following years mainly due to the import tariffs on Chinese modules imposed by the European Union, leading to low uptake. While the annual total installed capacity for ground-mounted solar exceeded 3 gigawatt (GW) in 2012 (representing 40% of total new solar capacity), it declined dramatically to around 1.2 GW in 2013 and further to about 0.6 GW in 2014 (Tiedemann et al., 2019; Klessmann et al., 2015). Given this uncertainty in the market environment and the difficulty to set the 'correct' FIT rates, the government began to consider auctions for large solar and wind installations, with the objective to lower the total subsidy cost, while providing sufficient incentives for RE investment.

O.1.2 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.1.3 Data and prediction of the capture prices

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

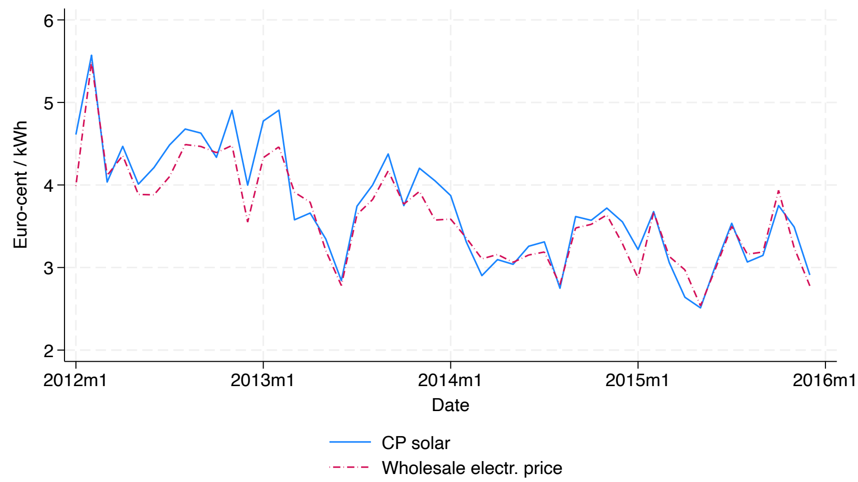
At the moment of the auction participation, we assume that the investors have information on past capture prices and wholesale electricity market prices for the years leading up to the auction. This information is publicly available on the website of the German Network Transmission Operators (https://www.netztransparenz.de/).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

To account for these elements, we use information from policy reports that are publicly available and that make long-term price forecasts about the level and volatility of wholesale electricity prices.[44] Note that the wholesale electricity prices and the capture price are highly correlated. In the period prior to the first auction round included in our sample, January 2012 - December 2015, the two monthly time series show a correlation coefficient of $\rho = 0.96$ (see Figure O.2). This, however, does not mean that in future periods the same correlation patterns remains, mainly due to the "cannibalization effect" of solar PV, and the fact that the production from new solar capacity is highly correlated with the production of the existing solar stock. We thus want to allow for the possibility that the capture rate, the ratio between the capture price and the wholesale electricity price, does change over time. In particular, we take the wholesale electricity prices as upper bound, and account with lower growth rates and volatility measures for the fact that solar PV might be less valued in future periods, as it mostly produces during the day, when prices are depressed due to the large and increasing installed capacity of renewables.

The main driving forces for the long-term price evolution of wholesale electricity prices in Germany are discussed in a White Paper published by the German government in 2017

[44] In particular, Schlesinger et al. (2014) and vbw / Prognos Strompreisprognose 2023 (accessible here: https://www.vbw-bayern.de/Redaktion/Frei-zugaengliche-Medien/Abteilungen-GS/Wirtschaftspolitik/2023/Downloads/vbw_Strompreisprognose_Juli-2023-3.pdf).

Figure O.2: Monthly capture price and wholesale electricity price in Germany, 2012-2015



Source: Monthly capture prices for solar PV and wholesale electricity prices available from https://www.netztransparenz.de/

'Electricity 2030: long-term trends - tasks for the coming years'.[45] The most relevant factors include i) increased electricity demand (stemming mostly from electrification in industry and transportation), ii) decreased electricity supply (nuclear and coal phase out), and iii) increase in RE capacity (according to RE targets set by the government). While i) and ii) have an increasing impact on prices, iii) will lead to lower price levels, but likely will result in higher price volatility as renewable output of plants is highly correlated.

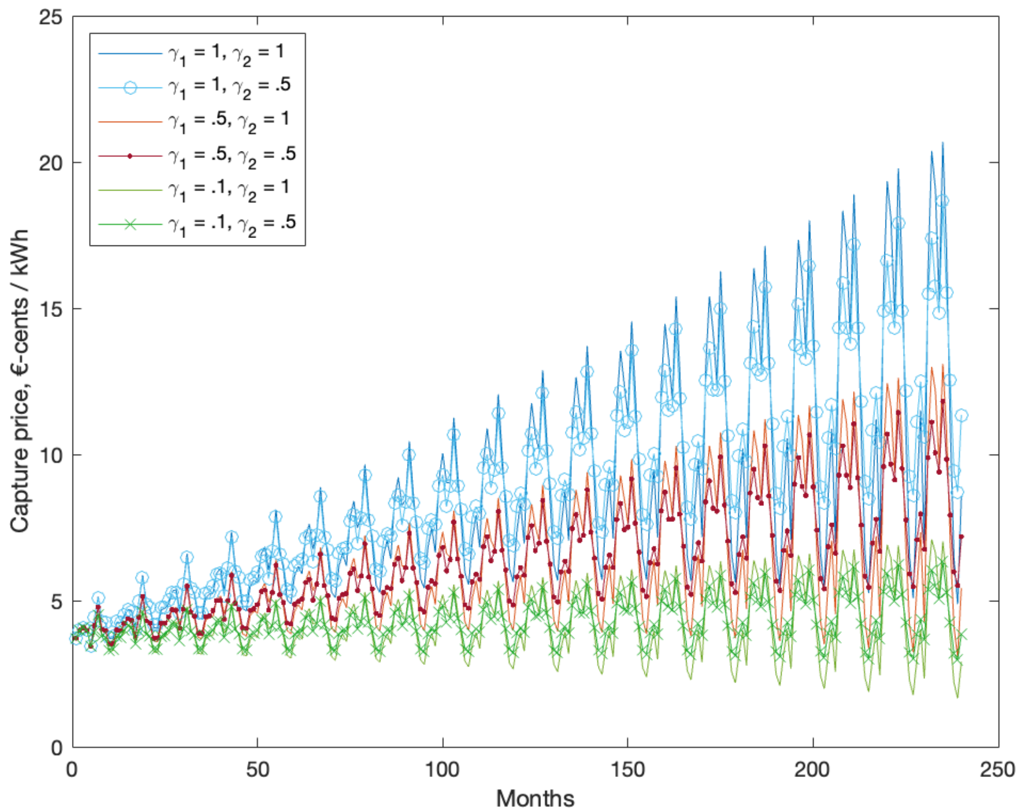
To capture the long-term price trend, we use the baseline scenario for nominal price evolution in Schlesinger et al. (2014) and interpolate linearly between reported years.[46] To account for the increase in volatility, we use the final volatility estimates in vbw / Prognos Strompreisprognose (2023) for the year 2035 and perform linear interpolation at the monthly level with respect to the baseline volatility measures.

We parameterize the time series of capture prices to simulate the evolution over 240 months (20 years), starting at month 13 after each auction date. Figure O.3 shows the main scenario for the wholesale electricity price ($\gamma_1 = \gamma_2 = 1$), as well as alternative scenarios with a lower growth rate and a lower volatility for the capture price of solar PV. These scenarios are drawn exemplary for auction round 4, held in April 2016. For reference, the

[45] https://www.bmwk.de/Redaktion/EN/Publikationen/electricity-2030-concluding-paper.html
[46] We use nominal prices as the bid price in the policy is not indexed to inflation.

quantity-weighted average bid price of winning bids was 7.14 €-cents/kWh in this auction round.

Figure O.3: Simulation of capture price paths for 240 months (20 years), auction round 4: April 2016



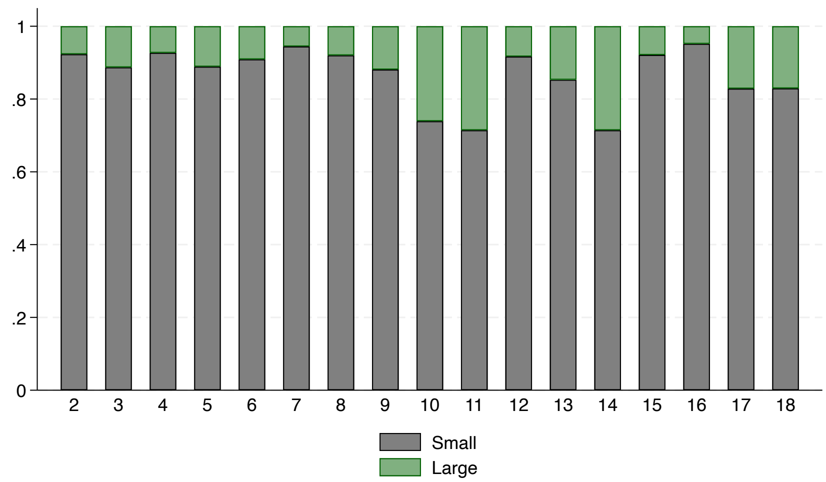
Notes: See text for details.

To account for uncertainty in the capture price time series and lower capture rates in the future, we simulate a total of six scenarios, multiplying the baseline growth rate by the following factors [1, 0.5, 0.1], and the volatility measure by [1, 0.5].

O.2 Data Background

Auction data. While the bid data are anonymized, individual bidders (and projects) can be tracked over time given a unique identification number. We use public information from the list of auction winners (published by the Federal Network Agency[47]) to obtain additional information on the type of bidders, whenever they have won at least one project. For these calculations we treat each auction round - bidder as a unique observation. Out of the 648 unique auction-bidder pairs, we can identify approximately 80% in terms of legal status (private vs. public company) and type of firm (investor focused, solar park, or utility). Most observations in the data are private companies that qualify as "small" bidders (Figure O.4).

Figure O.4: Share of large vs. small bidders by auction round in estimation sample



Source: Main estimation sample. Bid data, 2015-2019.

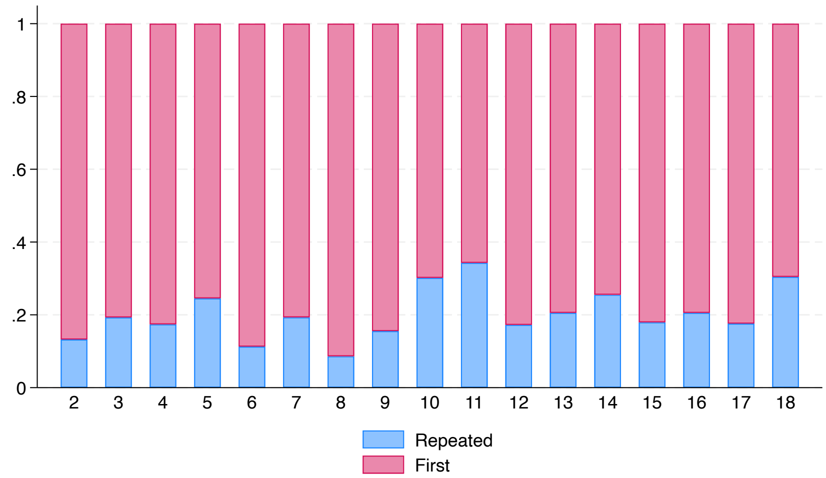
Another concern is that bidders who participated in an auction round and lost may reapply with the same project at a later stage. Yet, using the unique project identifiers, we find that only 19% of all bids show up more than once in the data. 81% of project bids are first-time bids, so the assumption of independence across rounds does not seem too restrictive (see also Figure O.5 for a breakdown by round).

Irradiation data. We control for the available sunshine at the location of the solar installation, the irradiation amount. 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 from 2010 to 2016 at the county level provided by the German Weather Service.[48]

[47] `https://www.bundesnetzagentur.de/DE/Fachthemen/ElektrizitaetundGas/Ausschreibungen/Solaranlagen1/BeendeteAusschreibungen/start.html`, last accessed: 5 June 2025.

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

Figure O.5: Share of repeated bids by auction round



Source: Main estimation sample. Bid data, 2015-2019.

Solar cost indicators. We also use two aggregate solar cost indicators, the module price index in Euros per kilowatt (€/kW) provided by PVxchange and a system price index provided by the German Solar Association (BSW). Both indicators measure average cost factors for typical installations of large ground-mounted solar in Europe and Germany. From 2014 until the end of 2020 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 solar system costs, which decreased from roughly 1,000 €/kW in 2015 to 750 €/kW in 2019. To calculate the module cost and system cost measures and to account for price expectations at the time of the auction, we take the average expected costs in the next 12 months. For the analysis, we further convert the installation capacity (in €/kW) to €/kWh, we assume a lifetime of 25 years and an annual discount factor of 5%. We calculate the annual production based on observed capacity factors for realized bids at the solar installation level, whenever these are available, and use interpolated (average) capacity factors otherwise.

Interconnection costs to the electricity grid. To proxy for the interconnection costs, we calculate the distance between the solar installation and the electricity grid as a direct line from the centroid of the 5-digit zip code in which the solar installation is located and the nearest high voltage network node (see Appendix Figure A.2).[49] The data on the German

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

high-voltage network are obtained from Egerer (2016).

O.3 Alternative Model Specifications

O.3.1 Multi-unit auction model without future payoffs

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

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

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

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

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

where p_c is the market clearing price.[50]

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

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

step k of the firm's supply curve,

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

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

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

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

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

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

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

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

Solving for the costs gives

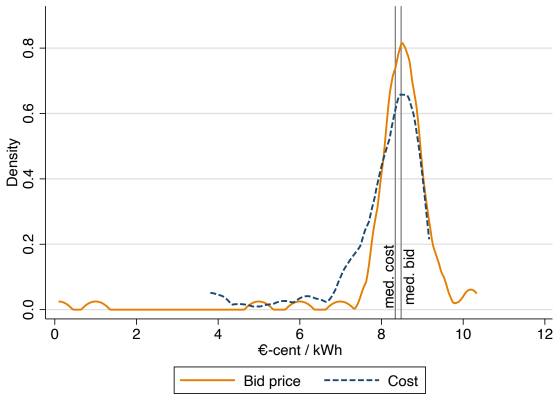
$$c_{i,k} = E(p_c | b_{i,k} < p_c < b_{i,k+1}) + \frac{M_2}{M_1},$$

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

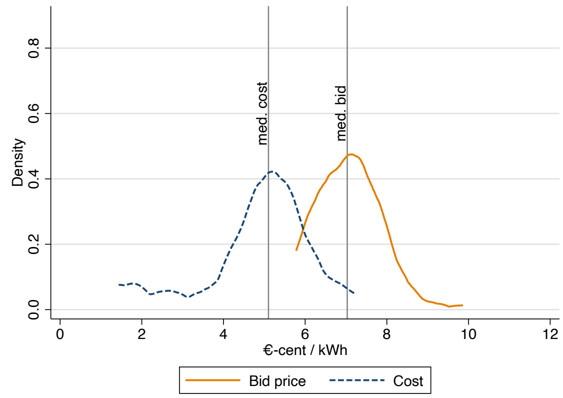
We show the estimated costs, margins, and Lerner index densities using this model with no future payoffs in Figure O.6. The main difference with respect to the full model is that the Lerner index densities for the PAB rounds are less flat and for the UP rounds more mass for higher values, making it evident that the two models lead to different estimates of market power.

The correlations between markups, the probability of winning, and bid prices with indicators of bidder's size and time period using this static model are reported in Tables O.1 - O.3. Without taking into account future payoffs, the markups for P1 and P2 have a larger difference between them than in the main model with future payoffs. Another difference is that in the static model there is no statistically significant correlation of passthrough when conditioning on size and time period, whereas in the full model there is evidence of a significant effect on the triple interaction.

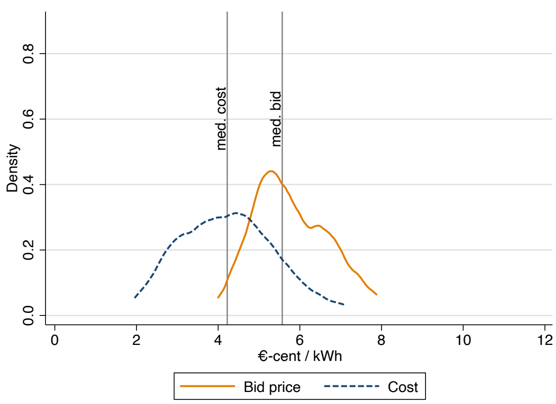
Figure O.6: Estimated costs and observed bids densities: no future payoffs



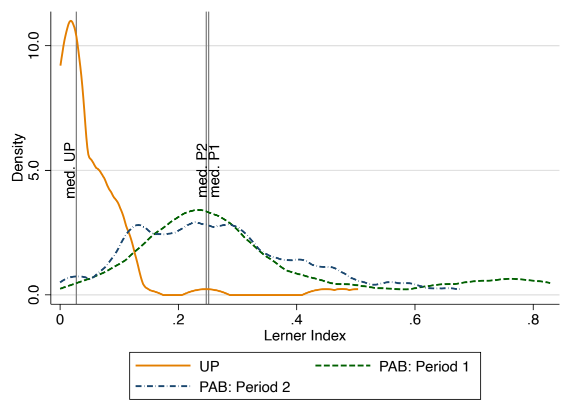
(a) UP: Auction rounds 2-3



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



(c) PAB, Period 2: Auction rounds 9-18



(d) Lerner Index, all three periods

Notes: Kernel densities of the costs obtained from a model that only considers 'static' auction payoffs and from the observed bids for uniform pricing rule in Panel (a) and PAB pricing in Panels (b) and (c). Individual bids are aggregated by bidder and period using quantity-weighted averages. Panel (d) shows the average Lerner Index, defined as $\frac{b_i - c_i}{b_i}$, for each period separately.

Table O.1: Markups, no future payoffs

	(1)	(2)	(3)	(4)
$\mathbb{1}$(large bidder)	-0.065*	-0.044	0.013	
	(0.037)	(0.041)	(0.056)	
$\mathbb{1}$(PAB P1)	0.568***	0.574***	0.742***	0.636***
	(0.077)	(0.079)	(0.145)	(0.167)
$\mathbb{1}$(PAB P2)	0.413***	0.411***	0.570***	0.534***
	(0.074)	(0.073)	(0.113)	(0.167)
$\mathbb{1}$(large bidder) × $\mathbb{1}$(PAB P1)	-0.528***	-0.539***	-0.586***	-0.584***
	(0.098)	(0.098)	(0.098)	(0.163)
$\mathbb{1}$(large bidder) × $\mathbb{1}$(PAB P2)	-0.270**	-0.278***	-0.293***	-0.368**
	(0.108)	(0.104)	(0.110)	(0.180)
N	1,424	1,424	1,424	1,424
Adjusted R^2	0.10	0.10	0.11	0.21
Mean DV	1.37	1.37	1.37	1.37
Bid-specific controls	No	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: Markups defined as $b_{i,k}/c_{i,k}$. Costs obtained from a model that only considers 'static' auction payoffs. All regressions include a constant term and control for auction volume. Bid-specific controls include distance to network and solar irradiation. Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table O.2: Probability of winning the auction, no future payoffs

	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$(large bidder)	0.064	0.070	0.073		
	(0.070)	(0.070)	(0.071)		
$\mathbb{1}$(PAB P1)	-0.019	-0.138**	-0.107	-0.156	-1.433***
	(0.056)	(0.065)	(0.105)	(0.129)	(0.200)
$\mathbb{1}$(PAB P2)	-0.030	-0.187***	-0.294***	-0.357***	-1.310***
	(0.052)	(0.058)	(0.065)	(0.088)	(0.260)
$\mathbb{1}$(large bidder) × $\mathbb{1}$(PAB P1)	0.262**	0.305***	0.299***	0.333***	0.178*
	(0.106)	(0.110)	(0.112)	(0.120)	(0.106)
$\mathbb{1}$(large bidder) ×$\mathbb{1}$(PAB P2)	0.168**	0.193***	0.133*	0.236***	0.160*
	(0.074)	(0.069)	(0.069)	(0.084)	(0.082)
Estimated cost		-0.044***	-0.042***	-0.037***	-0.170***
		(0.011)	(0.009)	(0.011)	(0.030)
Cost × $\mathbb{1}$(PAB P1)					0.190***
					(0.028)
Cost × $\mathbb{1}$(PAB P2)					0.121***
					(0.030)
N	1,441	1,424	1,424	1,424	1,424
Adjusted R^2	0.13	0.15	0.19	0.28	0.30
Mean DV	0.40	0.39	0.39	0.39	0.39
Bid-specific controls	No	Yes	Yes	Yes	Yes
Land-type FE	No	No	Yes	Yes	Yes
State FE	No	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes
Bidder FE	No	No	No	Yes	Yes

Notes: DV: bid awarded (binary). Linear probability model. Costs obtained from a model that only considers 'static' auction payoffs. All regressions include a constant term and control for auction volume. Bid-specific controls include distance to network and solar irradiation. Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table O.3: Bid prices and cost pass-through, no future payoffs

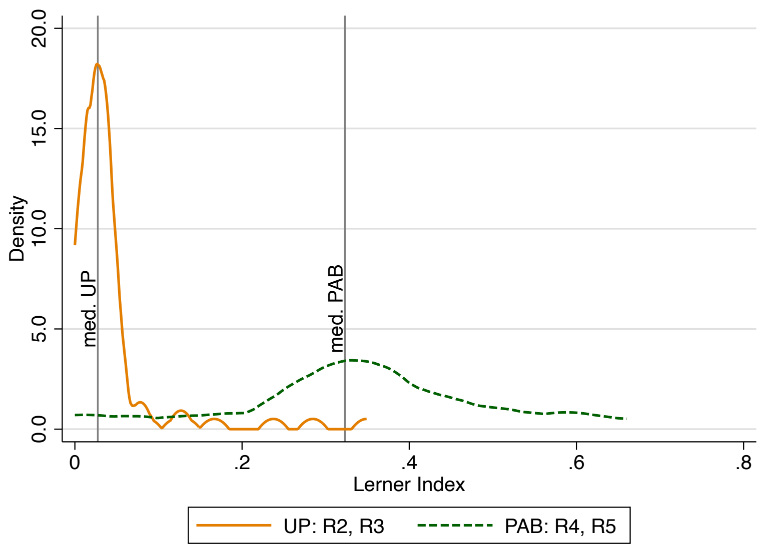
	(1)	(2)	(3)	(4)
$\mathbb{1}$(large bidder)	0.086	-0.091	-2.558	
	(1.654)	(1.670)	(1.801)	
$\mathbb{1}$(PAB P1)	2.914**	2.969**	4.027***	2.385
	(1.159)	(1.168)	(1.199)	(1.449)
$\mathbb{1}$(PAB P2)	0.957	1.023	2.351*	0.622
	(1.191)	(1.198)	(1.232)	(1.524)
$\mathbb{1}$(large bidder) × $\mathbb{1}$(PAB P1)	0.027	0.278	2.975	-0.397
	(2.577)	(2.536)	(2.524)	(2.211)
$\mathbb{1}$(large bidder) × $\mathbb{1}$(PAB P2)	-2.044	-1.886	1.060	-0.430
	(1.900)	(1.871)	(1.819)	(2.213)
Estimated cost	0.597***	0.600***	0.654***	0.472***
	(0.137)	(0.138)	(0.142)	(0.181)
Cost × $\mathbb{1}$(large bidder)	-0.027	-0.011	0.286	0.110
	(0.207)	(0.207)	(0.221)	(0.280)
Cost × $\mathbb{1}$(PAB P1)	-0.510***	-0.520***	-0.630***	-0.442**
	(0.139)	(0.140)	(0.146)	(0.180)
Cost × $\mathbb{1}$(PAB P2)	-0.289*	-0.299*	-0.425***	-0.213
	(0.154)	(0.153)	(0.151)	(0.189)
$\mathbb{1}$(large bidder) × $\mathbb{1}$(PAB P1) × cost	-0.045	-0.076	-0.396	0.081
	(0.344)	(0.337)	(0.331)	(0.276)
$\mathbb{1}$(large bidder) × $\mathbb{1}$(PAB P2) × cost	0.314	0.295	-0.080	0.089
	(0.250)	(0.245)	(0.233)	(0.277)
N	1,424	1,424	1,424	1,424
Adjusted R^2	0.70	0.70	0.78	0.84
Mean DV	6.57	6.57	6.57	6.57
Bid-specific controls	No	Yes	Yes	Yes
Land-type 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. Costs obtained from a model that only considers 'static' auction payoffs. All regressions include a constant term and control for auction volume. Bid-specific controls include distance to network and solar irradiation. Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

O.4 Robustness Checks

O.4.1 Main model estimates, Rounds 2 to 5

Figure O.7: Lerner Index: UP versus PAB pricing (auction rounds 2 - 5)



Notes: Lerner index defined as $\frac{b_i - c_i}{b_i}$. For each bidder and period, we subtract the average cost from the average bid (quantity-weighted) and divide by the average bid. The plot shows the resulting kernel density. Sample: auction rounds 2 to 5.

O.4.2 Main model regressions, omitting zero margins

Table O.4: Markups

	(1)	(2)	(3)	(4)
$\mathbb{1}$(large bidder)	0.024	0.046	0.106	
	(0.052)	(0.059)	(0.067)	
$\mathbb{1}$(PAB P1)	0.345***	0.354***	0.416***	0.375***
	(0.043)	(0.044)	(0.095)	(0.104)
$\mathbb{1}$(PAB P2)	0.443***	0.446***	0.506***	0.505***
	(0.063)	(0.062)	(0.100)	(0.170)
$\mathbb{1}$(large bidder)$\times$ $\mathbb{1}$(PAB P1)	-0.039	-0.056	-0.086	0.133
	(0.153)	(0.158)	(0.171)	(0.289)
$\mathbb{1}$(large bidder) $\times$ $\mathbb{1}$(PAB P2)	-0.300***	-0.313***	-0.336***	-0.105
	(0.098)	(0.100)	(0.106)	(0.248)
N	974	974	974	974
Adjusted R^2	0.12	0.12	0.14	0.35
Mean DV	1.40	1.40	1.40	1.40
Bid-specific controls	No	Yes	Yes	Yes
Land-type 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: Markups defined as $b_{i,k}/c_{i,k}$. All regressions include a constant term and control for auction volume. Bid-specific controls include distance to network and solar irradiation. All observations with zero imputed margin, i.e., $b_{i,k} = c_{i,k}$, have been removed from the estimation sample. Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table O.5: Probability of winning the auction

	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$(large bidder)	-0.088	-0.153*	-0.158*		
	(0.157)	(0.090)	(0.091)		
$\mathbb{1}$(PAB P1)	-0.100	-0.381***	-0.354***	-0.463***	-2.266***
	(0.066)	(0.070)	(0.113)	(0.167)	(0.348)
$\mathbb{1}$(PAB P2)	-0.095*	-0.465***	-0.516***	-0.570***	-2.152***
	(0.055)	(0.059)	(0.066)	(0.109)	(0.304)
$\mathbb{1}$(large bidder) × $\mathbb{1}$(PAB P1)	0.084	0.106	0.086	0.238	0.036
	(0.201)	(0.144)	(0.142)	(0.208)	(0.242)
$\mathbb{1}$(large bidder) × $\mathbb{1}$(PAB P2)	0.245	0.345***	0.268***	0.187	-0.009
	(0.163)	(0.102)	(0.100)	(0.207)	(0.229)
Estimated cost		-0.100***	-0.097***	-0.092***	-0.294***
		(0.011)	(0.012)	(0.013)	(0.034)
Cost × $\mathbb{1}$(PAB P1)					0.252***
					(0.043)
Cost × $\mathbb{1}$(PAB P2)					0.208***
					(0.041)
N	991	974	974	974	974
Adjusted R^2	0.11	0.22	0.25	0.38	0.41
Mean DV	0.28	0.26	0.26	0.26	0.26
Bid-specific controls	No	Yes	Yes	Yes	Yes
Land-type FE	No	No	Yes	Yes	Yes
State FE	No	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes
Bidder FE	No	No	No	Yes	Yes

Notes: DV: bid awarded (binary). Linear probability model. All regressions include a constant term and control for auction volume. Bid-specific controls include distance to network and solar irradiation. All observations with zero imputed margin, i.e., $b_{i,k} = c_{i,k}$, have been removed from the estimation sample. Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

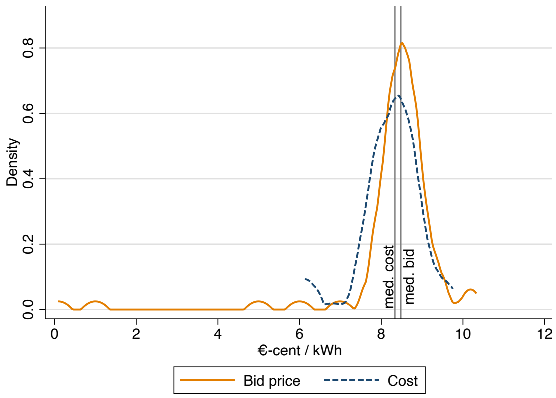
Table O.6: Bid prices and cost pass-through

	(1)	(2)	(3)	(4)
$\mathbb{1}$(large bidder)	-1.721*	-1.546	-1.526	
	(0.993)	(0.967)	(1.296)	
$\mathbb{1}$(PAB P1)	0.322	0.369	2.439***	2.173***
	(0.487)	(0.485)	(0.521)	(0.637)
$\mathbb{1}$(PAB P2)	-1.357***	-1.300***	0.878	0.330
	(0.430)	(0.439)	(0.544)	(0.776)
$\mathbb{1}$(large bidder) × $\mathbb{1}$(PAB P1)	3.552	3.434	3.782	-5.609**
	(2.769)	(2.729)	(2.898)	(2.216)
$\mathbb{1}$(large bidder) × $\mathbb{1}$(PAB P2)	0.047	-0.189	0.160	-6.729***
	(1.012)	(0.991)	(1.309)	(1.389)
Estimated cost	0.347***	0.350***	0.496***	0.459***
	(0.051)	(0.052)	(0.056)	(0.059)
Cost × $\mathbb{1}$(large bidder)	0.252*	0.231*	0.209	-0.694***
	(0.133)	(0.130)	(0.166)	(0.172)
Cost × $\mathbb{1}$(PAB P1)	-0.153**	-0.162**	-0.390***	-0.378***
	(0.070)	(0.070)	(0.077)	(0.078)
Cost × $\mathbb{1}$(PAB P2)	0.049	0.039	-0.211***	-0.146
	(0.069)	(0.069)	(0.078)	(0.109)
$\mathbb{1}$(large bidder) × $\mathbb{1}$(PAB P1) × cost	-0.578	-0.568	-0.626	0.623*
	(0.432)	(0.426)	(0.443)	(0.333)
$\mathbb{1}$(large bidder) × $\mathbb{1}$(PAB P2) × cost	-0.003	0.023	-0.023	0.870***
	(0.143)	(0.141)	(0.174)	(0.192)
N	974	974	974	974
Adjusted R^2	0.76	0.76	0.83	0.89
Mean DV	6.76	6.76	6.76	6.76
Bid-specific controls	No	Yes	Yes	Yes
Land-type FE	No	No	Yes	Yes
State FE	No	No	Yes	Yes
Year FE	No	No	Yes	Yes
Bidder FE	No	No	No	Yes

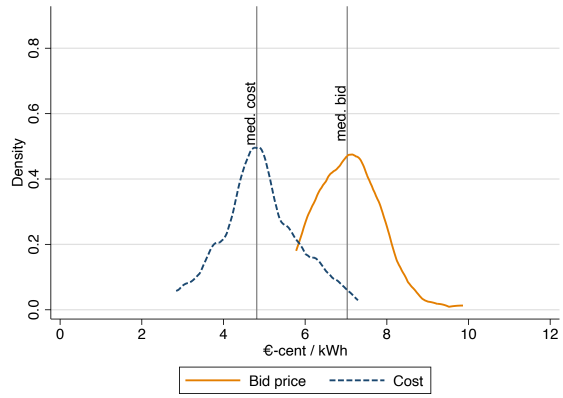
Notes: DV: Bid values. All regressions include a constant term and control for auction volume. Bid-specific controls include distance to network and solar irradiation. All observations with zero imputed margin, i.e., $b_{i,k} = c_{i,k}$, have been removed from the estimation sample. Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

O.4.3 Model estimates with symmetric bidders

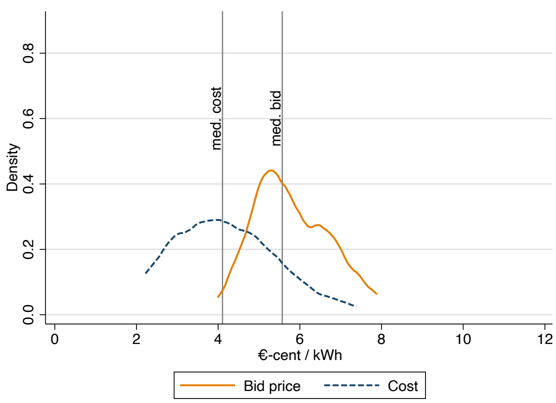
Figure O.8: Estimated costs and observed bids densities: symmetric bidders



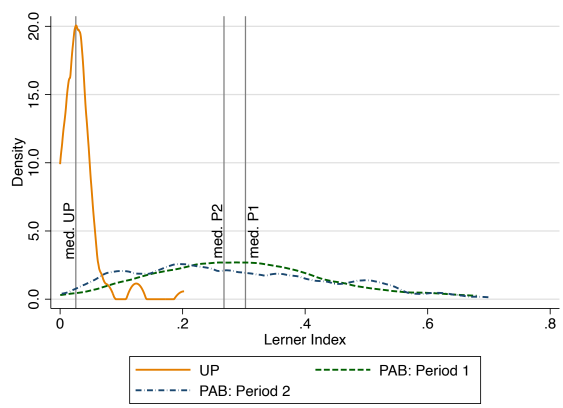
(a) UP: Auction rounds 2-3



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



(c) PAB, Period 2: Auction rounds 9-18

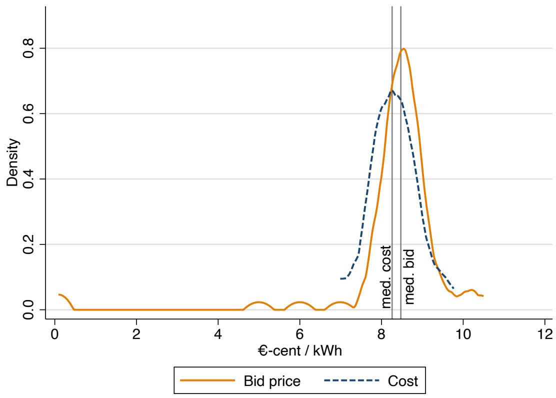


(d) Lerner Index, all three periods

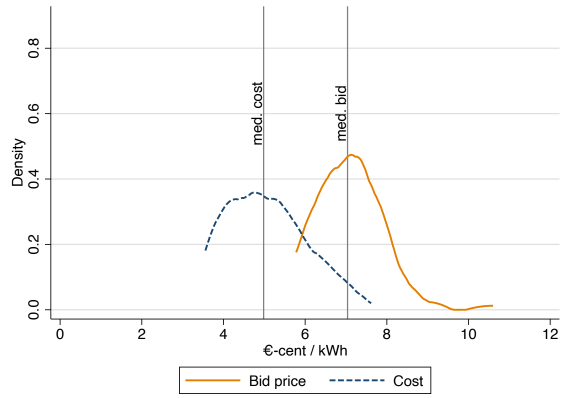
Notes: Kernel densities of the costs obtained for uniform pricing rule (Equation 7 , Panel (a)) and PAB pricing (Equation 5, Panels (b) and (c)). Model does not consider bidder heterogeneity by size. Individual bids are aggregated by bidder and period using quantity-weighted averages. Panel (d) shows the average Lerner Index, defined as $\frac{b_i - c_i}{b_i}$, for each period separately.

O.4.4 Model estimates, pooling several rounds for estimation

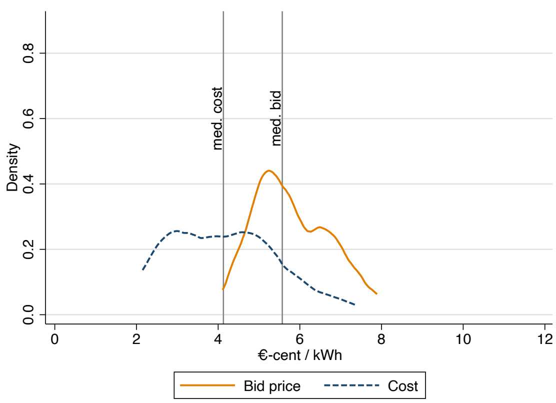
Figure O.9: Estimated costs and observed bids densities: symmetric bidders



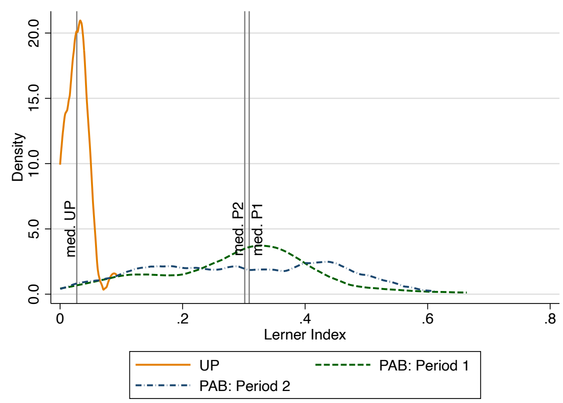
(a) UP: Auction rounds 2-3



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



(c) PAB, Period 2: Auction rounds 9-18



(d) Lerner Index, all three periods

Notes: Kernel densities of the costs obtained for uniform pricing rule (Equation 7 , Panel (a)) and PAB pricing (Equation 5, Panels (b) and (c)). Rounds are pooled for estimation based on four-dimensional kernel, incl. number of bidders, auction id, auction volume, and pricing rule, so that each auction is at most pooled with one round before and one round after. Individual bids are aggregated by bidder and period using quantity-weighted averages. Panel (d) shows the average Lerner Index, defined as $\frac{b_i - c_i}{b_i}$, for each period separately.

O.4.5 Robustness: 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 25 bidders (out of 202 unique bidders) as 'large', which, however correspond to about 64% of all bids. The omitted category are 'small bidders' with fewer project bids.

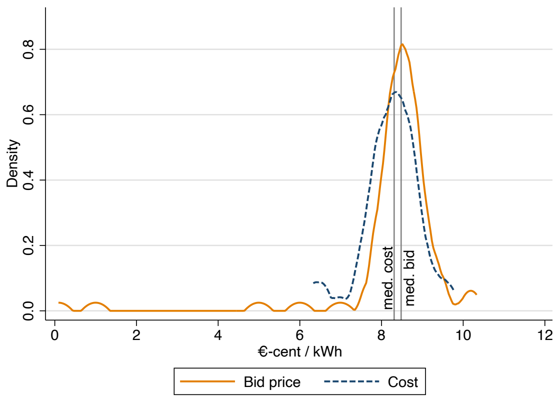
To obtain the regression tables, we first run the model with the alternative group definition, and in a second step, estimate the linear regressions. Size of individual coefficients and direction of estimates are similar to the main regressions, yet, the alternative group definition leads to lower statistical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

Table O.7: Markups, alternative definition of 'large' bidder

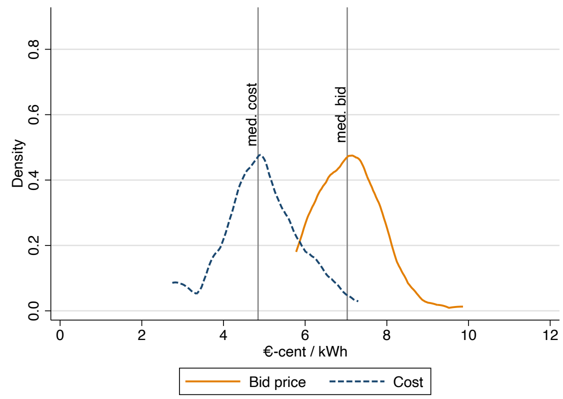
	(1)	(2)	(3)	(4)
$\mathbb{1}$(large bidder)	0.009	0.017	0.007	
	(0.014)	(0.015)	(0.021)	
$\mathbb{1}$(PAB P1)	0.537***	0.538***	0.609***	0.630***
	(0.048)	(0.048)	(0.094)	(0.129)
$\mathbb{1}$(PAB P2)	0.566***	0.567***	0.700***	0.683***
	(0.048)	(0.048)	(0.080)	(0.123)
$\mathbb{1}$(large bidder) $\times$ $\mathbb{1}$(PAB P1)	-0.287***	-0.288***	-0.284***	-0.399***
	(0.081)	(0.080)	(0.086)	(0.137)
$\mathbb{1}$(large bidder) $\times$ $\mathbb{1}$(PAB P2)	-0.331***	-0.335***	-0.336***	-0.339**
	(0.074)	(0.073)	(0.076)	(0.146)
N	1,424	1,424	1,424	1,424
Adjusted R^2	0.19	0.19	0.22	0.37
Mean DV	1.29	1.29	1.29	1.29
Bid-specific controls	No	Yes	Yes	Yes
Land-type 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: Markups defined as $b_{i,k}/c_{i,k}$. All regressions include a constant term and control for auction volume. Bid-specific controls include distance to network and solar irradiation. Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

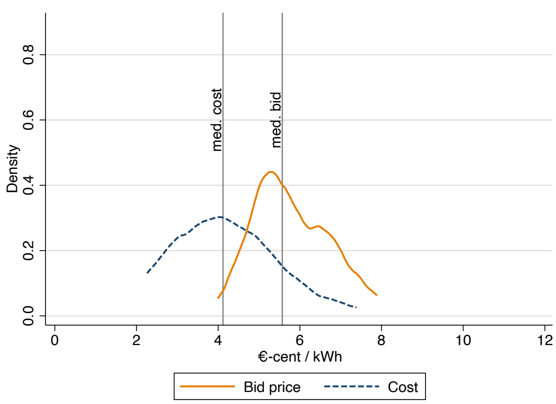
Figure O.10: Estimated costs and observed bids densities: alternative definition of 'large' bidders



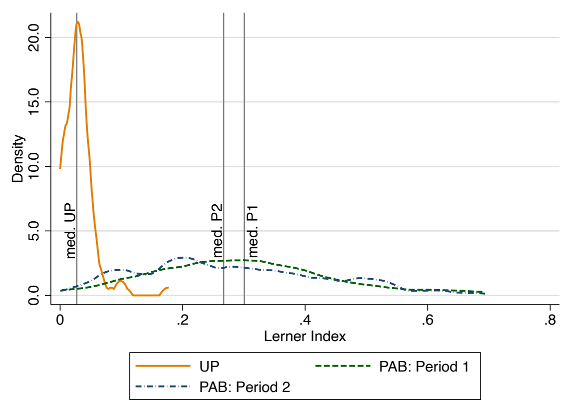
(a) UP: Auction rounds 2-3



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



(c) PAB, Period 2: Auction rounds 9-18



(d) Lerner Index, all three periods

Notes: Kernel densities of the costs obtained for uniform pricing rule (Equation 7 , Panel (a)) and PAB pricing (Equation 5, Panels (b) and (c)). Estimates are based on an alternative definition of 'large' bidders, based on the average number of submitted projects per auction. Individual bids are aggregated by bidder and period using quantity-weighted averages. Panel (d) shows the average Lerner Index, defined as $\frac{b_i - c_i}{b_i}$, for each period separately.

Table O.8: Probability of winning the auction, alternative definition of 'large' bidder

	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}$(large bidder)	0.156**	0.161**	0.167**		
	(0.074)	(0.069)	(0.069)		
$\mathbb{1}$(PAB P1)	0.019	-0.157**	-0.154*	-0.146	-1.638***
	(0.058)	(0.069)	(0.090)	(0.118)	(0.545)
$\mathbb{1}$(PAB P2)	0.084	-0.140*	-0.286***	-0.312***	-1.696***
	(0.056)	(0.071)	(0.071)	(0.110)	(0.530)
$\mathbb{1}$(large bidder) $\times$ $\mathbb{1}$(PAB P1)	-0.021	0.025	0.018	0.033	0.051
	(0.116)	(0.119)	(0.111)	(0.152)	(0.128)
$\mathbb{1}$(large bidder) $\times$ $\mathbb{1}$(PAB P2)	-0.123	-0.076	-0.099	-0.076	-0.033
	(0.092)	(0.092)	(0.082)	(0.137)	(0.133)
Estimated cost		-0.054***	-0.055***	-0.060***	-0.220***
		(0.011)	(0.012)	(0.013)	(0.061)
Cost $\times$ $\mathbb{1}$(PAB P1)					0.194***
					(0.064)
Cost $\times$ $\mathbb{1}$(PAB P2)					0.171***
					(0.061)
N	1,441	1,424	1,424	1,424	1424
Adjusted R^2	0.10	0.12	0.18	0.28	0.29
Mean DV	0.40	0.39	0.39	0.39	0.39
Bid-specific controls	No	Yes	Yes	Yes	Yes
Land-type FE	No	No	Yes	Yes	Yes
State FE	No	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes
Bidder FE	No	No	No	Yes	Yes

Notes: DV: bid awarded (binary). Linear probability model. All regressions include a constant term and control for auction volume. Bid-specific controls include distance to network and solar irradiation. Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table O.9: Bid prices and cost pass-through, alternative definition of 'large' bidder

	(1)	(2)	(3)	(4)
$\mathbb{1}$(large bidder)	1.961	2.013	1.873	
	(1.330)	(1.351)	(1.144)	
$\mathbb{1}$(PAB P1)	6.159***	6.202***	7.521***	6.140***
	(0.425)	(0.422)	(0.331)	(1.008)
$\mathbb{1}$(PAB P2)	3.381***	3.432***	5.053***	3.687***
	(0.443)	(0.443)	(0.353)	(1.015)
$\mathbb{1}$(large bidder) $\times$ $\mathbb{1}$(PAB P1)	-2.697**	-2.763**	-2.753**	-1.574
	(1.334)	(1.358)	(1.173)	(1.461)
$\mathbb{1}$(large bidder) $\times$ $\mathbb{1}$(PAB P2)	-2.747*	-2.798*	-2.565**	-1.110
	(1.429)	(1.448)	(1.205)	(1.471)
Estimated cost	0.929***	0.933***	0.998***	0.872***
	(0.043)	(0.042)	(0.020)	(0.112)
Cost $\times$ $\mathbb{1}$(large bidder)	-0.240	-0.249	-0.233*	-0.068
	(0.161)	(0.164)	(0.139)	(0.176)
Cost $\times$ $\mathbb{1}$(PAB P1)	-0.933***	-0.940***	-1.096***	-0.924***
	(0.059)	(0.059)	(0.047)	(0.126)
Cost $\times$ $\mathbb{1}$(PAB P2)	-0.499***	-0.508***	-0.704***	-0.527***
	(0.067)	(0.067)	(0.055)	(0.127)
$\mathbb{1}$(large bidder) $\times$ $\mathbb{1}$(PAB P1) $\times$ cost	0.374**	0.384**	0.396***	0.235
	(0.164)	(0.168)	(0.145)	(0.179)
$\mathbb{1}$(large bidder) $\times$ $\mathbb{1}$(PAB P2) $\times$ cost	0.314*	0.323*	0.324**	0.123
	(0.182)	(0.184)	(0.152)	(0.185)
N	1,424	1,424	1,424	1,424
Adjusted R^2	0.75	0.75	0.82	0.86
Mean DV	6.57	6.57	6.57	6.57
Bid-specific controls	No	Yes	Yes	Yes
Land-type 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. All regressions include a constant term and control for auction volume. Bid-specific controls include distance to network and solar irradiation. Standard errors clustered at the bidder level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.