Solar Market Frictions:
The Role of Platforms and Policies

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Abstract

This paper estimates a structural model of the solar photovoltaic (PV) installation market using detailed data from an online platform. The model incorporates households' solar installation choices and sellers' strategic bidding. Counterfactual simulations evaluate how equilibrium outcomes respond to changes in market structure and government subsidies, yielding two main results: (1) an increase from one to five bids through the platform reduces gross installation prices by $4,000 (15.5%), and (2) the U.S. Solar Investment Tax Credit increases total surplus on the platform by $1.35 per dollar of subsidy expenditure by mitigating market power and reducing pollution externalities.

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Solar photovoltaics (PV) allow homeowners to generate zero-emissions electricity by bolting panels to their rooftops. Consequently, policymakers have offered numerous incentives to encourage household investment in solar PV and reduce electricity sector emissions. Nonetheless, adoption remains sparse, with fewer than 4% of U.S. single-family homes having installed a solar system by 2020 (Barbose et al., 2021).

Like many contracting services, solar installations are customized and priced case by case. Hence, buyers in these markets must bear substantial hassle costs to contact potential sellers. These frictions have implications for market power—when collecting price quotes is costly for buyers, any seller asked to give a quote can expect to be bidding against few or no other sellers, increasing that seller's optimal markup. The social cost of market power may be magnified in markets with positive externalities such as renewable energy, energy efficiency, and communications technologies.

Online platforms can alleviate market frictions by linking buyers to sellers. Platforms compile information about a buyer's characteristics and pass the data to a broad set of sellers who can then submit bids via the platform. Thus, platforms can provide buyers access to more price quotes than they would otherwise obtain offline. In this way, platforms may increase the number of transactions completed and improve market efficiency by connecting buyers to better-matched sellers or reducing prices by increasing competition.

In this paper, I estimate a structural model of the rooftop solar market that incorporates households' solar installation choices and sellers strategically bidding on projects through an online platform. First, I use the estimates to quantify markups embedded in solar installation bids submitted through the platform. Second, I measure the platform's effect on consumers' solar adoption choices and welfare. Third, I evaluate counterfactuals. In one series of counterfactuals, I measure the impact of changing the number of installation bids each household obtains on equilibrium prices, economic surplus, solar installations, and environmental externalities. In the next set of counterfactuals, I assess the welfare impacts of the most extensive U.S. solar subsidy program, the Investment Tax Credit (ITC), for buyers and sellers on the platform.

Understanding how market structure influences solar installation prices is essential for addressing both affordability concerns and low adoption rates in the solar industry. Despite falling prices, the average solar installation still exceeded $20,000 in 2020. Figure 1 shows that hardware material costs account for less than 30% of the total price of a U.S. residential solar installation. The balance of system cost, or "soft cost," includes installation labor, permitting, inspection, interconnection costs, and installers' markups. High soft costs suggest that market power may be restricting residential solar investments (O'Shaughnessy et al., 2019). Evidence supports the presence of market power within the solar installation market. For instance, Pless and van Benthem (2019) show that solar subsidy pass-through rates imply market power. Similarly, Borenstein (2017) and Gillingham et al. (2016) show that households with high electricity rates and higher expected incomes pay more for solar installations, indicating price discrimination. Many U.S. markets now have numerous installers, suggesting that high hassle costs enable imperfectly competitive pricing. Therefore, platforms could reduce installation prices by increasing competition among installers.

Imperfect competition can also impact the efficiency of government subsidy programs by determining the share of subsidies passed through to end-consumer prices (Weyl and Fabinger, 2013). If monopolistic sellers respond to subsidies by increasing gross prices, subsidies may only generate small increases in solar installations and associated environmental benefits. On the other hand, subsidies may increase welfare by addressing unpriced environmental externalities and market power. Thus, an empirical analysis is needed to evaluate the welfare effects of solar subsidies.

To investigate counterfactual market outcomes and welfare in the solar PV market, I develop a three-stage model. First, a solar installation project is announced, and potential sellers learn about its characteristics, deciding whether to bid based on expected marginal profits. In the second stage, sellers learn their marginal cost and submit bids. The optimal bid depends on the installer's cost, the household's price elasticity, and expected competition. In the final stage, the household chooses one of the bidding sellers or the outside option.

The allocation mechanism is a multi-attribute auction (i.e., a beauty contest auction) where buyers consider factors other than prices, such as installers' ratings and experience. I estimate the model using methods from Krasnokutskaya et al. (2020) and Yoganarasimhan (2015) and a novel dataset of residential solar auctions from a major online platform. Unlike most solar PV data, I observe non-winning bids and bids to households choosing the outside option, allowing precise estimates of elasticities and markups.

I augment the platform data with detailed household-level demographic information, including average monthly electricity expenditure, home market value, and demographic variables like age, race, and educational attainment. While these data are highly detailed, a limitation is that the platform sample may not fully represent the population of potential solar buyers. Nonetheless, I demonstrate that the observable characteristics of platform shoppers closely resemble those of other solar adopters in the broader market. Notably, the sample exhibits significant variation in home values, allowing me to measure differences in seller participation and pricing across households of differing wealth. Therefore, the data allow for an assessment of which households benefit most from using the platform.

Findings I find that 45% of gross installation prices are due to markups over marginal cost, higher than previous estimates in the literature (e.g., Bollinger and Gillingham, 2019). Noteably, these markups exclude installers' overhead and marketing costs. Based on Fu et al. (2016), I calculate that installers' average net profit margins in 2016 were 24.8%

Leveraging a full-information assumption,[1] I find that buyers derive substantial consumer surplus gains from using the online platform. However, these consumer surplus gains differ across markets and household demographics. Wealthier households benefit more, as higher-valued homes attract more bids and purchase larger solar systems.

The first set of counterfactuals shows that increasing the number of bids per household significantly impacts consumer welfare and market outcomes. Varying the number of bids per project, I find that an increase from one to five bids lowers gross prices by 15.5%, about $4,000 per installation, and boosts consumer surplus and solar purchases. This result highlights the potential benefits of reducing search frictions in negotiated price markets.

The second set of counterfactuals measures the impact of eliminating the Solar Investment Tax Credit (ITC) on prices, economic surplus, and pollution externalities. The ITC enables

[1]Estimating consumer surplus gains from the platform requires an assumption that buyers are fully informed about the outside option, which includes off-platform installers' prices and characteristics.

solar buyers to deduct 30% of the gross installation price from federal taxes. Removing the ITC increases net bid prices by at least 20% and reduces bids per project by over 7%. Each subsidy dollar increases total surplus on the platform by at least \$1.35, including \$0.55 in consumer surplus, \$0.69 in producer surplus, \$0.11 in environmental benefits.[2] This highlights a surprising potential benefit of solar subsidies—under imperfect competition, subsidies can improve welfare by enabling more transactions where the buyer's willingness to pay exceeds the seller's marginal cost. However, the results should be interpreted cautiously because they do not capture all of the welfare impacts of the ITC, such as the impact on off-platform sellers and buyers.

The results have several policy implications. The model estimates and counterfactuals suggest that installer markups are substantial and that increasing competition through online platforms can reduce prices. Yet, as of 2016, only 3% of solar buyers used an online platform (O'Shaughnessy and Margolis, 2018). Some policymakers, such as the state of Connecticut, have begun advertising platforms to potential solar adopters.[3] Similar approaches in other industries, like healthcare,[4] suggest that policymakers could develop or advertise platforms to reduce solar PV prices and boost adoption.

The second set of counterfactuals is relevant to renewable energy policy. In recent years, policymakers have removed or considered removing several existing subsidy policies, such as the ITC. I find that removing the ITC substantially reduces the economic surplus among users of the online platform and modestly reduces associated environmental benefits. These results, therefore, suggest that renewable energy subsidies can—in some cases—help correct market power distortions in addition to reducing pollution externalities.

The results also provide insights into the economics of two-sided platforms more broadly. Many other industries have shifted transactions online in the past decade. In markets characterized by high hassle costs—-such as home mortgages or customized services—platforms can deliver substantial price reductions and consumer welfare gains. However, the empirical

[2]Producer surplus includes gross profits and bid preparation costs. I rely on exit survey data to estimate incremental adoption and pollution damages avoided by the ITC.

[3]See the Connecticut Greenbank's website gosolarct.com operated under CT Legislature's Public Act 11-80.

[4]The Affordable Care Act established health insurance marketplaces to reduce premiums.

results also show that the magnitude of these welfare gains can differ substantially across consumers when sellers can discriminate on both the extensive margin (selection into bidding) and the intensive margin (bid prices). More specifically, the findings indicate that price-sensitive consumers may benefit relatively less from platforms because they attract fewer bids.

Related Literature This paper builds on multiple literatures. First, it relates to the growing literature on the economics of the residential solar market. Several papers estimate the adoption response to price or subsidy changes. For instance, Hughes and Podolefsky (2015), Pless and van Benthem (2019), and Gillingham and Tsvetanov (2019) use quasi-experimental approaches to estimate the elasticity of demand and quantify the adoption response to subsidy programs. Feger et al. (2022), De Groote and Verboven (2019), and Langer and Lemoine (2022) develop dynamic discrete choice models focusing on the binary decision of when to adopt in order to evaluate subsidy policies.[5] I build on this work by modeling buyers' choice of installer and competition among installers.[6]

Supply-side behavior and incentives are crucial in determining equilibrium prices and technology adoption. Most previous literature has yet to model the supply side of the solar PV market. To fill this gap, I develop a model accounting for: (1) imperfect competition due to imperfectly informed consumers, (2) seller selection into bidding, (3) strategic pricing based on household characteristics, and (4) sellers' imperfect information about their competition. This model allows me to account for supply and demand responses to counterfactuals, such as subsidy policy changes. One notable paper that estimates a supply-side model of the solar PV installation market is Bollinger and Gillingham (2019), who estimate a dynamic supply model to decompose static markups from dynamic pricing incentives driven by learning-by-doing. O'Shaughnessy and Margolis (2018) compare installation prices paid by solar consumers who used an online platform and those who did not, finding platform users pay lower prices. I build on O'Shaughnessy and Margolis (2018) by developing a structural approach to measure markups, assess platform effects on consumer welfare, and investigate counterfactuals.

This paper also pertains to literature on competition in search markets, platforms, interme-

[5]An exception is Bollinger and Gillingham (2019) who estimate a dynamic model including installer choice.

[6]Gerarden (2023) formulates a model of competition in the upstream solar panel manufacturing market.

diaries, and the internet. Seminal work by Baye and Morgan (2001) theoretically investigated intermediaries in online markets. Recent empirical studies examine the effect of intermediaries or technology increasing price transparency in industries like life insurance (Brown and Goolsbee, 2002), waste management (Salz, 2022), health care (Brown, 2019), and retail gasoline (Luco, 2019). Many studies assess the impact of online platforms on prices and aggregate consumer welfare, but few examine which consumers benefit most in negotiated price markets. I provide a novel distributional analysis of consumer welfare gains, accounting for endogenous seller bidding participation and pricing.

The remainder of the paper proceeds as follows: the next section details the online platform and provides descriptive statistics. Section 3 develops a model of buyer and seller behavior in the solar PV market, and Section 4 discusses the methods used to estimate the model. Section 5 presents the welfare and counterfactual results, and Section 6 concludes.

2 Background and Data

Shopping for a rooftop solar system is time-intensive, often requiring buyers to call installers and schedule site visits. These hassle costs can enable sellers to increase markups. A 2017 National Renewable Energy Laboratory survey found over 80% of solar shoppers contacted two or fewer installers before deciding (Sigrin et al., 2017). Recently, online platforms have emerged as an alternative to direct buyer-seller interactions.

For example, the U.S.-based platform EnergySage Inc. connects potential solar customers with a network of installers. EnergySage allows households to conduct multi-attribute auctions, where bidders submit proposals that include price and other characteristics like solar panel brand. The buyer selects the winning bidder based on these multi-dimensional bids. In multi-attribute auctions, buyers can choose based on any criteria and are not obligated to select the lowest price. These auctions are similar to scoring auctions, except that the choice rule is not announced to the bidders.

Each EnergySage auction has several stages. First, consumers create an account on the platform and provide details like the installation address and monthly electricity bill. Second, registered installers receive project notifications, including a Google Maps photo of the buyer's roof (see Appendix Figure A.1) and other details. Installers then submit quotes, which include system price, panel brand, inverter brand, and seller information like star ratings. Buyers can then select a quote or opt not to purchase any offers. Appendix Figure A.2 shows the purchaser's comparison tool on the platform.

Solar PV systems can be paid for with cash, loans, or leases. On EnergySage, 97% of buyers choose to buy with cash or a loan, likely due to the platform's net present value calculations, which favor purchases over leases. This trend reflects a broader market shift away from leases. According to Barbose et al. (2021), the market share for leased systems grew from 2007 to 2012 but fell to 35% by 2020, with further declines expected due to the rise of residential loan products.

2.1 Data and Descriptive Statistics

This study's primary data set includes bid prices and consumer purchase choices for solar auctions on the EnergySage platform from 2014 to 2016 in Arizona, California, Colorado, Connecticut, Massachusetts, New York, and Texas. EnergySage collects information on each household's address, average monthly electricity bill, and whether the buyer obtained other off-platform quotes. The auction data is then merged with household-level demographic data from Acxiom's Infobase and ZIP code level solar environmental benefits estimates from Sexton et al. (2021).[7] See Appendix B for more details on data processing and sample construction.

Project Characteristics: Appendix Table A.1 provides descriptive statistics of the sample of 10,488 potential installation projects. Households in the sample vary in monthly electricity expenditure, search behavior, solar generation potential, and home valuation. The mean electric bill was \$187/month with a standard deviation of \$89/month, and about 17% of households reported having quotes from off-platform installers. The average project received 3.54 bids, with noticeable variation across projects—a quarter of projects obtained two or fewer bids, while 25% received five or more bids. Appendix Figure A.3 shows that the mean number of bids per project increased while bid prices fell during the sample period in most core-based

[7] This is a marketing database that compiles household-level data from various sources such as public records.

statistical areas (CBSAs). The figure also illustrates the substantial variation in bids per project and prices across CBSAs. Lastly, Appendix Table A.2 shows the composition of projects across states and time. The number of projects tripled each year, with over 40% in California, reflecting the state's large share of U.S. solar installations.[8]

Although the platform data is highly detailed, a limitation of the data is that platform users may not represent all solar shoppers, potentially affecting external validity. I use income data from Barbose et al. (2018) to compare platform users to solar adopters more broadly. Appendix Figure A.5 shows that the income distribution of platform users is similar to the broader population of solar adopters, though platform users are slightly lower-income. Despite this similarity, there could be other differences, so the reader should interpret my results with this caveat in mind.

An advantage of the data is that there is a large amount of demographic heterogeneity. Therefore, when estimating the demand model, I focus on estimating heterogeneity in preferences across households with different wealth and energy use behavior. Estimating these heterogeneous preferences allows me to assess which types of households benefit most from using the platform.

Characteristics of Solar Bids: Appendix Table A.3 provides details about the bids submitted. Bids differ in price per watt, system capacity, panel brand, and inverter type. Buyers often get quotes for different panel brands, with EnergySage providing ratings for each make. Premium panels, like those from LG Electronics, have higher efficiency and better warranties, making up 34% of bids. Premium Plus panels, like those from SunPower, are less common and more expensive, comprising less than 4% of bids.

The inverter, converting DC to AC, is another key component. String inverters are the cheapest but can underperform in shade. Microinverters and power optimizers perform better in partial shade but are pricier, comprising 73% of bids.[9]

Seller quality also influences a buyer's choice, and EnergySage provides metrics like star ratings, experience, and reviews. Although sellers' names are anonymized, each installer is identified in the data by unique IDs. By the end of 2016, 60% of bids came from five-star-rated

[8] Appendix Figure A.4 maps the projects, showing concentration in larger metropolitan areas.

[9] Microinverters are identified by if the brand is Enphase Energy or SolarEdge Technologies.

installers, while 18% came from unrated installers. The average bid was from an installer with nearly 2,400 completed installations, but there is notable variation in experience.[10]

A notable limitation of the data is that sellers using the platform during the sample period were primarily small to mid-sized installers, and therefore, the supply-side estimate may not directly apply to larger national installers.

Panel B of Appendix Table A.3 compares winning and non-winning bids in the Los Angeles area for the first half of 2016. Winning bids had lower prices and were more likely from five-star-rated installers with premium panels and microinverters, indicating the importance of non-price factors.

To compare platform purchases to the broader market, I appended EnergySage data to the Lawrence Berkeley Lab's Tracking the Sun Database. Regressions with zip code and time fixed effects in Appendix Table A.4 reveal that platform prices are about 15% lower, and have similar system sizes to off-platform transactions. Additionally, the regressions show that platform transactions are slightly less likely to include SunPower modules (rated Premium Plus) but more likely to use LG panels (rated Premium) and microinverters. So, while there are some differences in the equipment used, there does not appear to be a systematic bias toward higher-quality equipment or larger systems on the platform.

Finally, a defining feature of this market is that sellers can adjust their participation and pricing strategies based on the observable characteristics of buyers. For instance, installers may choose to forego submitting bids to low-income households or to bid higher prices to households with higher electricity bills. Appendix Section C shows descriptive evidence of selective entry and price discrimination. These patterns motivate the structural model outlined in the next section

[10]Several installers do not report residential installation experience; I set these installer's experience levels equal to the median installation experience in the overall sample.

3 Model

Having discussed the data, I develop a structural model that incorporates heterogeneous buyer preferences and strategic participation and bidding by sellers. In the model, each buyer i seeks to procure installation services for a single indivisible project using a multi-attribute auction. Throughout the paper, I use i to refer to both a buyer and their respective project. Buyer i's project is distinguished by its project type $\mathbf{z}_i$, which is characterized by the geographic market where the project is located, the time period, and the characteristics of the household. For each project of type $\mathbf{z}_i$, there is a set $\mathcal{N}(\mathbf{z}_i)$ of potential sellers that choose whether or not to submit a bid for the project.

Each seller j is differentiated by their type, which is characterized by a vector $\mathbf{w}_j$. A seller's type could be distinguished by a relatively parsimonious measure such as a star-rating category, a relatively higher dimensional variable such as a unique installer ID (i.e., seller fixed effects), or a combination of variables.

Each seller's type is observable to both the buyer and the other potential sellers. If a seller chooses to participate in the auction for project i they then also select a price bid B_{ij}. Each seller is only permitted a single bid for each project. Sellers' bids are characterized by their price in addition to a vector of non-price characteristics $\mathbf{x}_{ij}$, such as panel quality and inverter type. In contrast to the seller's type $\mathbf{w}_j$, $\mathbf{x}_{ij}$ is allowed to vary across projects for a given seller.

3.1 Demand

The allocation rule in a multi-attribute auction comes from the buyer's choice problem. Let $\mathcal{J}_i \subset \mathcal{N}(\mathbf{z}_i)$ be the set of sellers that decide to participate in the auction for project i. Buyer i then chooses between the project bids ($j \in \mathcal{J}_i$) and an outside option ($j = 0$) to maximize their utility. The outside option includes the choice to forgo purchasing solar or purchasing from an off-platform installer. Buyer i's utility from selecting option j is given by:

$$\begin{aligned} u_{ij} = B_{ij}\alpha_i + \mathbf{x}_{ij}'\beta + \mathbf{w}_j'\gamma + \delta_i + \zeta_{ig} + (1-\lambda)\varepsilon_{ij} \\ \alpha_i = \mathbf{z}_i^{(1)\prime}\tilde{\alpha}, \quad \delta_i = \mathbf{z}_i^{(2)\prime}\tilde{\delta}. \end{aligned} \tag{1}$$

Here B_{ij} is the bid price for option j, and α_i is the price sensitivity of buyer i. Buyer price sensitivity, α_i, is a function of an m-dimensional vector household characteristics denoted $\mathbf{z}^{(1)} = \mathbf{z}_{1:m}$, such as the household's home market valuation. Utility is affected by $\mathbf{x}_{ij}$, the non-price characteristics of the bid, such as the panel brand quality, and the solar inverter type. Utility also depends on attributes of each seller that are fixed across bids, $\mathbf{w}_j$, such as installer fixed effects. The δ_i term is a demand shifter for buyer i that allows utility for all of the "inside options" to vary depending on a p-dimensional vector of household characteristics $\mathbf{z}^{(2)} = \mathbf{z}_{m+1:m+p}$ such as the geographic market and time-period. Notice that the variables determining the project type, $\mathbf{z}$, include both sets of household-level variables in $\mathbf{z}^{(1)}$ and $\mathbf{z}^{(2)}$. Choices are also influenced by ε_{ij}, an independent and identically distributed random term that is assumed to follow a type-one extreme value distribution; ζ_{ig} is also an idiosyncratic term but is assumed to be constant for each buyer across all options within a group g. ζ_{ig} follows the unique distribution distributed such that $\zeta_{ig} + (1 - \lambda)\varepsilon_{ij}$ is also an extreme value random variable. This utility specification leads to the nested logit model, which accommodates correlation in preferences within pre-specified groups. Here, one group is the outside option, and the other includes all platform bids ("the inside option"). Some households may visit the platform out of curiosity about solar prices, while others are committed to selecting an installation bid. The nested logit model can accommodate these unobserved differences in preferences. As λ approaches zero, there is no correlation in preferences for each inside option, reducing to the standard logit model. As λ approaches one, preferences for each "inside option" become perfectly correlated. The overall level of utility is not identified, so I normalize the utility of the outside option to zero plus an error term ($u_{i0} = 0 + \varepsilon_{i0}$).

In modeling the buyer's choice, I assume each buyer chooses the installation option that delivers the highest utility per unit of capacity. This assumption simplifies the demand model because I can model the buyer's decision as a simple discrete choice instead of a discrete-continuous choice.[11] Thus, B_{ij} in utility is the bid price in dollars per watt. Current public policies largely dictate each buyer's optimal system capacity. In particular, net-metering rules allow residential solar customers to sell electricity generated by their rooftop system to their

[11] I consider the robustness of the results to a discrete-continuous model specfaction in Appendix D.

utility at the retail electricity rate as long as the household's annual generation does not exceed their annual consumption. Any solar generation that exceeds the household's annual consumption is compensated far below the retail rate. As a result, the system capacity that will deliver the largest net present benefit to the buyer is the capacity that equates the expected annual solar generation with the expected annual electricity use.

3.2 Supply

The supply-side model involves firms deciding whether to submit bids to potential buyers and at what price. Sellers lack precise information about the number, characteristics, and prices of competing bids, though they can observe the total number of bids for an auction ex-post and know which firms use the platform in their area. Thus, I assume suppliers know the distribution of potential competition for a given project.

I model suppliers' bidding behavior as a two-stage process. In the first stage, each potential bidder $j \in \mathcal{N}(\mathbf{z}_i)$ must decide whether or not to enter the auction for the project i. At the time of entry, firms do not know their exact marginal cost of completing the project, but they know the distribution of possible costs they could incur. They also know the probabilities of each of their competitors entering the auction, the characteristics of those competitors, and the distribution of possible prices those competitors would submit. Additionally, they know the mean utility of the buyer (but not the random component of utility).[12] Therefore, each firm can form an expectation about their profits, conditional on the decision to enter the auction.

If seller j decides to enter the auction for the project, they incur a bid preparation cost η_{ij}, where $\eta_{ij} \sim Lognormal(\mu(\mathbf{z}_i, \mathbf{w}_j), \sigma^2(\mathbf{w}_j))$.[13] The expected bid preparation cost depends on both the project type and the seller's type. I assume the bid preparation cost is i.i.d. across projects and firms conditional on the seller's type and the project type and is private information of each potential bidder. If a firm decides to enter auction i, then the firm learns the non-price characteristics of their bid $\mathbf{x}_{ij}$, the capacity of the system to be installed q_{ij}, and the

[12] In particular, I assume that sellers know all of the parameters of the buyer's utility function, α, β, δ, and λ.

[13] The variance parameter allows random shocks to shift bid preparation costs across auctions. A low value of the variance parameter reflects that entry costs for firms of type $\mathbf{w}_j$ are relatively constant across auctions.

marginal cost of completing the project c_{ij}.

To keep the model empirically tractable, I assume that non-price characteristics, $\mathbf{x}_{ij}$, such as panel quality and inverter type, are not strategic choices by bidders. This implies firms cannot systematically change these characteristics in counterfactuals. This assumption is supported by the data, as installers typically use the same equipment for consecutive projects, with changes in hardware likely predetermined by inventory. Appendix Figure A.6 shows that installers use the same non-price characteristics as their previous bid over 74% of the time, with this probability remaining consistent across household demographics and competition levels.[14]

Analogously to the demand side, I assume that system capacity bids are not strategic choices for sellers. Although installers provide a recommended system capacity, there is little variation in capacity offers for a particular project, as installers typically size systems to match the household's annual energy usage. Supporting this assumption, the second column of Appendix Table A.6 shows that proposed capacities are not influenced by strategic factors. While the number of expected bids affects prices (Column 1), it is statistically unrelated to proposed system capacities (Column 2).

In formulating the sellers' bidding problem, I follow Levin and Smith (1994) and assume that prior to entering an auction, sellers know the project type and the joint distribution from which their marginal cost, non-price characteristics, and system capacity will be drawn, $F_{CXQ|\mathbf{w}_j,\mathbf{z}_i}$. Notably, the distribution depends on both the seller's type and the project type. However, firms only learn their exact marginal cost, non-price characteristics, and the capacity of the system after deciding to enter an auction. Intuitively, this means installers must exert some effort to prepare a customized bid and only learn about the exact marginal cost of a project by completing the bid preparation process. Although firms do not perfectly know their marginal costs prior to entry, they do know the distribution from which their marginal cost will be drawn. Therefore, sellers will know, for example, that buyers with large electric bills will be more likely to need a large system, but they will not know the exact size and cost

[14] The probability installers use the same hardware as their previous bid is 75% for households with homes valued below \$1 million and 72% for those with homes valued above \$1 million.

of the installation ex-ante. After the firms make their entry decisions in stage one, each firm's marginal cost and non-price characteristics are drawn from $F_{CXQ|\mathbf{w}_j,\mathbf{z}_i}$ and the installer then decides on a price bid during the second stage.

The assumption that installers do not know their marginal cost prior to entry is not clear-cut. For instance, Samuelson (1985) proposes an alternative model where marginal costs are known before entry, leading to selective auction participation based on private value realizations. In Appendix E, I investigate these competing models and fail to find evidence of selective entry, supporting the Levin and Smith (1994) model where costs are not perfectly known at the entry stage.[15]

Price Bidding: It will be helpful first to consider the firm's problem in the second stage after marginal costs and non-price characteristics are realized. Conditional on entering an auction, the firm j solves the following problem when setting a bid price for project i:

$$\max_{B_{ij}} \quad q_{ij}[B_{ij} - c_{ij}] \cdot \mathcal{P}_{ij}(B_{ij}|\mathbf{x}_{ij}, \mathbf{w}_j, \mathbf{z}_i) \tag{2}$$

Where q_{ij} is the system capacity, B_{ij} is firm j's per-unit price bid, and c_{ij} is firm j's marginal cost. $\mathcal{P}_{ij}(B_{ij}|\mathbf{x}_{ij}, \mathbf{w}_j, \mathbf{z}_i)$ is the equilibrium expected probability of winning the auction conditional on placing a bid price of B_{ij}. The equilibrium expected probability of being selected is also a function of the project type $\mathbf{z}_i$, the seller's type $\mathbf{w}_j$, and the non-price characteristics of the bid $\mathbf{x}_{ij}$. We work with expected probabilities because the seller does not know exactly which competitors they will face nor the bids of those competitors. We note that the solution to the bid pricing problem is not a function of the system capacity realization; q_{ij} enters the expected profit function multiplicatively and, therefore, does not directly influence the optimal per-unit bid price. However, the system capacity can indirectly affect the price bid if system capacity and marginal cost are correlated.

When formulating firms' expectations, I assume that all sellers make entry decisions simultaneously and submit their bids simultaneously. Therefore, the installers do not know the exact number of bidders they will be competing against nor the identities of their competi-

[15] Although the Levin and Smith (1994) model fits the data better than Samuelson (1985), other models might improve the fit further.

tors. Thus, firms' expectations (about the probability of winning) will only be a function of the project type, conditional on their bid price and non-price characteristics. In practice, firms on the platform submit bids at slightly different times. Although the identities of competing bidders are not visible to auction participants, firms can see how many bids have already been submitted for a given auction. Therefore, it is possible that firms could update their expectations based on the number of bids that have already been submitted. The assumption of simultaneous bidding is made primarily to simplify computation in the empirical exercise. However, I provide evidence that the assumption is a reasonable approximation of firms' behavior. In Appendix Table A.5, I regress bid price on the order that a bid was submitted, controlling for the total number of bids submitted for the project, installer fixed effects, CBSA fixed effects, and half-year fixed effects. The coefficient on "order of bid" is small and not statistically significant. As additional evidence, Table A.5 also shows that the "order of bid" is not associated with a change in the probability of that bid being selected. These regressions suggest firms are not making significant changes in bidding strategy based on the order they submit a bid, justifying the assumption of simultaneous bidding.[16]

Under the assumption of simultaneous bidding, a firm's expected probability of winning $\mathcal{P}_{ij}$ can be expanded as follows:

$$\begin{aligned}&\mathcal{P}_{ij}(B_{ij}|\mathbf{x}_{ij},\mathbf{w}_j,\mathbf{z}_i) = \mathbb{E}[Prob_{ij}(B_{ij};\mathbf{B}_{i,-j},\mathbf{X}_{i,-j},\mathbf{W}_{-j}|\mathbf{x}_{ij},\mathbf{w}_j,\mathbf{z}_i)] = \\ &\int Prob_{ij}(B_{ij};\mathbf{B}_{i,-j},\mathbf{X}_{i,-j},\mathbf{W}_{-j}|\mathbf{x}_{ij},\mathbf{w}_j,\mathbf{z}_i)\cdot dG(\mathbf{B}_{i,-j},\mathbf{X}_{i,-j},\mathbf{W}_{-j}|\mathbf{z}_i)\end{aligned} \tag{3}$$

Recall that $Prob_{ij}$ is the probability that buyer i selects firm j's bid conditional on a realized vector of competing price bids $\mathbf{B}_{i,-j}$, having a stacked vector of non-price characteristics $\mathbf{X}_{i,-j}$, and having types $\mathbf{W}_{-j}$. G represents the joint distribution function of $\mathbf{B}_{i,-j}, \mathbf{X}_{i,-j}$,

[16] For tractability, I also assume that bids submitted by sellers are binding. In rare cases, sellers will alter bid characteristics at a later stage (e.g., change the panel brand due to an inventory stock out), but such changes must be approved by the buyer. In such cases, only the final bid characteristics are observed. This is an inherent limitation of the data, and there exists a possibility that some bias exists in a small subset of the choice data due to these unobserved bid changes.

and $\mathbf{W}_{-j}$ occurring in equilibrium, conditional on the project being of type $\mathbf{z}_i$.[17] Since each firm's entry draw and marginal cost draw are assumed to be i.i.d., we can express dG as the product of the probabilities that each competing firm l decides to enter the auction and then bids B_{il} and has non-price characteristics $\mathbf{x}_{il}$.

I define the optimal bid function as $B^*_{il}(c_{il}|\mathbf{x}_{il}, \mathbf{w}_l, \mathbf{z}_i)$ and $H(\mathbf{w}_l, \mathbf{z}_i)$ as the probability that a potential seller l that is of type $\mathbf{w}_l$ enters an auction of type $\mathbf{z}_i$. Then we have:

$$dG(\mathbf{B}_{i,-j}, \mathbf{X}_{i,-j}, \mathbf{W}_{-\boldsymbol{j}}|\mathbf{z}_i) = \prod_{l \in \mathcal{N}(\mathbf{z}_i)\setminus\{j\}} H(\mathbf{w}_l, \mathbf{z}_i) \cdot dF_{CX|\mathbf{w}_l,\mathbf{z}_i}\big(B^{*-1}(B_{il}|\mathbf{x}_{il}, \mathbf{w}_l, \mathbf{z}_i), \mathbf{x}_{il}|\mathbf{w}_l, \mathbf{z}_i\big) \tag{4}$$

Where B^{*-1} represents the inverse bid function. The expression inside the product is the probability that firm l enters the auction multiplied by the probability that firm l bids B_{il} and has non-price characteristics x_{il}.

Firm j's first-order condition (FOC) for an optimal bid is given by:

$$(B_{ij} - c_{ij})\frac{\partial \mathcal{P}_{ij}(B_{ij}|\mathbf{x}_{ij}, \mathbf{w}_j, \mathbf{z}_i)}{\partial B_{ij}} + \mathcal{P}_{ij}(B_{ij}|\mathbf{x}_{ij}, \mathbf{w}_j, \mathbf{z}_i) = 0 \tag{5}$$

Given a vector of non-price characteristics, the optimal bid function $B^*_{ij}(c_{ij}|\mathbf{x}_{ij}, \mathbf{w}_j, \mathbf{z}_i)$ is defined implicitly by Equation 5.

Seller Participation: Now, consider the firm's decision of whether or not to enter an auction. Each firm will enter if the expected marginal profits conditional on entering are larger than the fixed cost of bid preparation η_{ij}. When firm j decides to enter auction i, they only know the project type, their own seller type, and their private entry cost draw. Firm j's expected profits conditional on entering the auction for project i can be expressed as follows:

[17] G is only a function of $\mathbf{z}_i$ because a seller's type $\mathbf{w}_j$ and non-price characteristics $\mathbf{x}_{ij}$ are private information at the time of bidding.

$$\mathbb{E}[\pi_{ij}|\mathbf{w}_j,\mathbf{z}_i] = \int \Big[q_{ij}\cdot(B^*_{ij}(c_{ij}|\mathbf{x}_{ij},\mathbf{w}_j,\mathbf{z}_i)-c_{ij})\cdot\mathcal{P}_{ij}(B^*_{ij}|\mathbf{x}_{ij},\mathbf{w}_j,\mathbf{z}_i)\Big]dF_{CXQ|\mathbf{w}_j,\mathbf{z}_i}(c_{ij},\mathbf{x}_{ij},q_{ij}|\mathbf{w}_j,\mathbf{z}_i) \tag{6}$$

Recall that $F_{CXQ|\mathbf{w}_j,\mathbf{z}_i}(c,\mathbf{x},q|\mathbf{w}_j,\mathbf{z}_i)$ is the joint distribution of non-price characteristics, marginal costs, and system capacity whose realization is not known to the firm at the time of entry. Therefore, the firm will enter the auction as long as:

$$\mathbb{E}[\pi_{ij}|\mathbf{w}_j,\mathbf{z}_i] \geq \eta_{ij} \tag{7}$$

Under the assumption that η_{ij} follows a lognormal distribution, the probability that firm j enters the auction for project i is:

$$H(\mathbf{w}_j,\mathbf{z}_i) = \Phi\left(\frac{ln\Big(\mathbb{E}[\pi_{ij}|\mathbf{w}_j,\mathbf{z}_i]\Big) - \mu(\mathbf{z}_i,\mathbf{w}_j)}{\sigma(\mathbf{w}_j)}\right) \tag{8}$$

Where Φ represents the cumulative distribution function for a standard normal random variable.

3.3 Equilibrium

For each seller j, a strategy consists of two functions: a participation strategy $\mathbf{w}\times\mathbf{z}\times\mathbb{R}_+\to\{0,1\}$, and a bidding strategy $\mathbf{w}\times\mathbf{z}\times\mathbf{x}\times\mathbb{R}_+\to\mathbb{R}_+$. Specifically, sellers use information about the project type, their seller type, and their entry cost shock to determine the binary choice of whether or not to enter. In the bidding stage, firms consider the project type, their seller type, their marginal cost draw, and their non-price characteristics to form a price bid. I follow the convention in the literature by focusing on type-symmetric pure strategy Bayesian equilibrium (Krasnokutskaya et al., 2020). That is, all sellers of the same type use the same participation strategy in equilibrium, and all sellers of the same type and the same non-price characteristics use the same bidding strategy in equilibrium. An equilibrium in the participation stage is a strategy profile such that all sellers satisfy Inequality 7, given the strategies of other firms. An equilibrium in the bidding stage requires that all firms satisfy Equation

5 given the other installer's strategies. Krasnokutskaya et al. (2020) prove the existence of a type-symmetric pure strategy Bayesian equilibrium of this game. However, there is no guarantee of a unique equilibrium in the participation stage. The next section describes the estimation procedure in detail.

4 Estimation

I estimate the structural parameters in three steps. First, I solve for the demand parameters via maximum likelihood. Second, I use the estimated demand parameters to simulate firms' first-order conditions for each bid in the data and recover bid-specific markups. Finally, I use the estimates from the first two steps to calculate each bidder's expected marginal profit from entering each auction and estimate the entry cost parameters using observed entry decisions. I discuss the details of each step in the following subsections.

4.1 Demand Estimation

From Equation 1 we can see that there are four sets of variables that affect a buyer's utility: (1) B, the bid price; (2) $\mathbf{z}^{(1)}$, household demographics that determine price-sensitivity; (3) $\mathbf{x}$, variables that characterize the non-price attributes of each participating installer's bid; and (4) $\mathbf{z}^{(2)}$, variables that shift the buyer's preference for all of the installation bids (i.e., shifts the likelihood of picking the outside option).

The bid price that enters buyers' utility for option j is measured in dollars per watt and is scaled to 70% of each installer's gross bid price to account for the 30% Investment Tax Credit (ITC). I refer to this after-incentive price as the "net price".[18] I allow for price sensitivity to vary across households with different home market valuations. In particular, I separate the sample into quartiles based on home market valuation and allow each quartile to have different price coefficients. I use home market valuation to proxy for wealth for a few reasons. First, home

[18]This specification assumes that buyers value a one-dollar reduction in the gross price equal to a one-dollar increase in the tax credit. This assumption is consistent with the existing literature (e.g., Langer and Lemoine, 2022; Pless and van Benthem, 2019). In most cases, the tax credit is paid out within one year of the purchase.

valuation is likely to be observable to the installers when placing bids. On the other hand, sellers are unlikely to observe household income. Second, Caceres (2019) shows that housing wealth is more closely correlated with total wealth than annual income among a large sample of U.S. households. Finally, there is more variation in the home market valuation due to the greater number of binned categories reported in the data.

The utility for each option is also a function of several non-price characteristics: dummies for premium and premium plus panel categories, a microinverter dummy, fixed effects for the installer's star rating category, and a set of fixed effects that measure the installer's installation experience. I also allow for additional heterogeneity in seller quality by including "permanent" installer fixed effects for each installer that placed over 300 total bids through the platform during the sample. These permanent sellers account for over 60% of the bids in the sample. In Appendix D, I discuss the robustness of the results to changes in the utility specification.

Outside Option: The outside option in this setting encompasses the possibility of either purchasing through an installer outside of the platform or not installing solar PV. As such, the net utility that the buyer obtains from choosing the outside option may also be affected by any hassle costs of contacting sellers directly. Moreover, the value of the outside option can also depend on local electricity prices, off-platform installation prices, and policies such as net energy metering, which all dictate the value of purchasing solar PV through the platform. Thus, I include fixed effects for each CBSA, fixed effects for each half year of the sample, fixed effects for each quartile of household monthly electricity expenditure, and a dummy variable for whether the household obtained off-platform quotes in the utility fucntion.[19] More specifically, I interact each of these fixed effects with an indicator variable for whether the choice represents a bid made through the platform (e.g., the inside options). Thus, the associated coefficients allow the relative value of each bid (relative to the outside option) to vary flexibly across households. Importantly, the CBSA fixed effects also control for any state or local incentives that could change the value of solar PV, including net metering rules that affect

[19]Projects that are outside a CBSA or in a CBSA with fewer than 100 total projects are placed into a new category by state. For example, a project located in Aspen, Colorado would be defined as "Other, CO"

households' electricity bills or up-front government rebates.[20]

In general, I cannot directly observe solar installation purchases made off of the platform. However, the platform did conduct exit surveys that asked potential buyers about off-platform purchase choices. I leverage these survey data to estimate probabilities of installing solar conditional on selecting the outside option for some of the counterfactual analyses.

4.2 Markup and Marginal Cost Estimation

After estimating demand, I calculate the markup embedded in each bid using the utility function estimates to form each firm's FOC for an optimal bid from Equation 5. Since the FOC involves expectations that cannot be expressed in a closed form, I evaluate these expectations by simulating the firm's probability of winning across different realizations of competitor sets and bid prices unknown to the installer at the time of bidding. The procedure is as follows:

1. *Estimate Entry Probabilities*: Calculate non-parametric entry probabilities for each project-seller type pair, $\mathbf{z}_i, \mathbf{w}_j$, as the ratio of auctions entered to total auctions for that type pair. Assume a seller is a potential entrant for auction i if they entered at least one auction of type $\mathbf{z}_i$.

2. *Simulate Entry Decisions*: Use the probabilities from (1) to simulate entry decisions for auction i by potential entrants in $\mathcal{N}(\mathbf{z}_i)$.

3. *Draw bids*: Draw price bids and non-price characteristics for each simulated entrant using the empirical distribution from similar auctions. If a type $\mathbf{w}_j$ seller enters a simulated auction of type $\mathbf{z}_i$; then draw a bid vector $\{B_{ij}, \mathbf{x}_{ij}\}$ from the pool of all bids placed by type $\mathbf{w}_j$ sellers in auctions of type $\mathbf{z}_i$.

4. *Evaluate Choice Probabilities*: Calculate the buyer choice probabilities $Prob_{ij}$ and demand semi-elasticities $\frac{\partial Prob_{ij}}{\partial B_{ij}}$ using the simulated bids and competitor characteristics.

[20] Most local incentives are invariant over the sample period. However, incentives in New York and Connecticut changed over time. In Section 4.5, I omit these states from the sample as a robustness check.

5. *Average Simulations*: Repeat the previous steps S times,[21] averaging the choice probabilities and demand semi-elasticities to obtain estimates for the two expectations in the FOC. Let s denote the simulation iteration, then the expressions are:

$$\widehat{\mathcal{P}_{ij}} = \frac{1}{S}\sum_{s=1}^{S} Prob_{ij}^{s}, \qquad \widehat{\frac{\partial \mathcal{P}_{ij}}{\partial B_{ij}}} = \frac{1}{S}\sum_{s=1}^{S} \frac{\partial Prob_{ij}^{s}}{\partial B_{ij}}. \tag{9}$$

6. *Calculate Marginal Costs*: Use the averaged choice probabilities and averaged demand semi-elasticities to compute the markup and marginal costs for each bid via the FOC:

$$\widehat{c_{ij}} = B_{ij} + \frac{\widehat{\mathcal{P}_{ij}}}{\widehat{\frac{\partial \mathcal{P}_{ij}}{\partial B_{ij}}}}. \tag{10}$$

This algorithm provides a unique marginal cost estimate for every bid, which I then use to form a non-parametric cost distribution for each seller-project type pair.

Defining project categories is crucial for credible markup estimates, balancing bias and variance. Too few categories can bias results if projects are heterogeneous, while too many can increase variance due to limited data. To avoid bias, I chose a high-dimensional project-type definition based on five variables: the CBSA, half-year, home market value quartile, household electricity expenditure quartile, and whether the buyer has off-platform quotes.

4.3 Entry Cost Estimation

In the final step, I use the estimated marginal costs to form each firm's *pre-entry* expected marginal profit from entering an auction i. For each bid in the data, I can calculate the firms' *post-entry* expected profit (before the buyer makes a choice) using the bid price, marginal cost, and probability of winning. The *post-entry* expected profit for seller j in auction i is equal to $q_{ij} \cdot (B_{ij} - \widehat{c_{ij}}) \cdot Prob_{ij}$. To calculate a seller's *pre-entry* expected profit $\widehat{\mathbb{E}[\pi_{ij}]}$ from entering an auction i, I take the average of all the realized *post-entry* expected profits for that seller's type $\mathbf{w}_j$ for projects of type $\mathbf{z}_i$. More precisely, the *pre-entry* expected profit is estimated as:

[21] I simulate 100 iterations of each auction type.

$$\widehat{\mathbb{E}[\pi_{ij}]} = \frac{1}{N(\mathbf{z}_i, \mathbf{w}_j)} \sum_{i \in \mathbf{z}_i} \sum_{j \in \mathbf{w}_j} q_{ij} \cdot (B_{ij} - \widehat{c_{ij}}) \cdot Prob_{ij}. \tag{11}$$

Where $N(\mathbf{z}_i, \mathbf{w}_j)$ is the total number of bids placed by type $\mathbf{w}_j$ sellers in auctions of type $\mathbf{z}_i$. I use $\sum_{i \in \mathbf{z}_i}$ to indicate the sum over all auctions of project type $\mathbf{z}_i$ and $\sum_{j \in \mathbf{w}_j}$ to indicate the sum over all bids submitted by sellers of type $\mathbf{w}_j$.

Next, I use the *pre-entry* expected profits $\widehat{\mathbb{E}[\pi_{ij}]}$ to maximize the following pseudo log likelihood function:

$$EntryPseudoLL(\mu, \sigma) = \sum_{i}^{M} \sum_{j \in \mathcal{N}(\mathbf{z}_i)} \Bigg\{ \mathbb{1}[j\ enters\ i] \cdot ln \left(\Phi \left(\frac{ln \left(\widehat{\mathbb{E}[\pi_{ij}]} \right) - \mu(\mathbf{z}_i, \mathbf{w}_j)}{\sigma(\mathbf{w}_j)} \right) \right) \tag{12}$$

$$+ \left(1 - \mathbb{1}[j\ enters\ i]\right) \cdot ln \left(1 - \Phi \left(\frac{ln \left(\widehat{\mathbb{E}[\pi_{ij}]} \right) - \mu(\mathbf{z}_i, \mathbf{w}_j)}{\sigma(\mathbf{w}_j)} \right) \right) \Bigg\}$$

Where $\mathbb{1}[j\ enters\ i]$ is an indicator function that equals one if seller j enters auction i and is zero otherwise. I specify that μ is a linear function of CBSA fixed effects, half-year fixed effects, installer star-rating fixed effects, installer experience fixed effects, and individual installer fixed effects for permanent sellers. I also allow σ to vary across installer star-rating categories.

4.4 Identification and Modeling Assumptions

To consistently estimate the demand parameters, it is necessary that all variables in the utility function, including bid price, are uncorrelated with the preference shocks ε_{ij} and ζ_{ig}. Additionally, the number of bids each buyer receives must be uncorrelated with these shocks. My identification strategy leverages household-level demographic data, including flexible fixed effects to control for household heterogeneity and a rich set of fixed effects to control for bid quality. Specifically, I use panel brand quality controls, inverter type controls, installer star-rating dummies, installer experience controls, and installer fixed effects. To account for buyer heterogeneity, I include electricity bill quartile dummies, a control for off-platform bids, CBSA fixed effects, and half-year fixed effects.

The price coefficients, α_i, are identified by variation in quoted prices after controlling for seller quality, hardware type, and common demand shocks across markets and time. This variation arises from differences in marginal cost conditional on buyer and seller type, such as input cost shocks due to roofing material differences. Despite the rich set of controls, there could be omitted variables correlated with both prices and unobserved preference shocks, which I address in detail in Appendix Section D.

With demand parameters identified, marginal costs are identified by Equation 10, which maps bid prices to costs. Entry cost parameters (μ and σ) are identified by variation in expected marginal profits, holding seller type constant. Identification of entry costs requires an exclusion restriction—an observed variable that affects the seller's ex-ante expected marginal profit before the entry decision but does not affect the entry cost distribution (Krasnokutskaya and Seim, 2011). I assume that the household-level demographics—home energy expenditure, home market valuation, and whether the household has off-platform bids—do not affect the firms' entry costs. This assumption is plausible if installers use their history of past bids to streamline new bids, making preparation costs constant across household demographics.

Having discussed the identification of the model parameters, I next highlight several critical assumptions that underlie my modeling approach. First, my model employs a static demand framework. Although dynamic models are commonly used for the solar PV market, there are several reasons why my *static demand assumption* may be reasonable in this context. Previous studies (e.g, Bollinger and Gillingham, 2019; De Groote and Verboven, 2019; Langer and Lemoine, 2022) used data when solar subsidies were decreasing, making dynamic incentives crucial. During my sample period, most US states had stable subsidies, with exceptions in Connecticut and New York, which I exclude in robustness tests. Additionally, Appendix Figure A.7 shows that pre-incentive solar prices had stabilized by my sample period, suggesting a relatively low incentive for consumers to delay investment for lower future prices.

Second, the model assumes that cost shocks are independent and identically distributed (i.i.d.) conditional on project and installer type. If unobserved factors, such as roofing type, induce correlation in cost shocks among installers, the *i.i.d. cost assumption* would be violated, leading to upwardly biased markup estimates. Appendix G provides evidence on the plausibility of the i.i.d. assumption.

Third, the demand model assumes consumers have full information about all alternatives, including the outside option. This implies that consumers know the prices and characteristics of off-platform installers. Under the *full information assumption*, the value of the outside option can incorporate additional hassle costs of off-platform procurement (e.g., time spent on contacting sellers), but it requires that consumers are aware of the utility they would receive from choosing an off-platform installer net of hassle costs. This assumption would be violated if, for example, consumer demand is characterized by a more complex search model in which consumers choose whether to undertake a costly effort to learn about offline installers. In such a model, consumer search effort may change endogenously in counterfactuals and bias the counterfactual predictions.

Lastly, the model treats sellers' entry and bidding decisions independently, ignoring joint decisions for simultaneously posted projects. Since only 13% of project postings occur in markets with more than 20 other projects weekly, this simplification is reasonable. However, if simultaneous postings influence seller entry, then my model will overestimate the variance of the marginal cost distribution. With these assumptions in mind, I now transition to discussing the model estimates in the following subsection.

4.5 Model Estimation Results

Demand Estimates: The top portion of Table 1 Panel A contains the estimates for the baseline utility specification. As expected, the base price coefficient is negative and relatively large in magnitude. We also see that households in the top three home value quartiles are relatively less price-sensitive. However, the interaction terms are not quite statistically significant (p-values of 0.14, 0.15, and 0.14, respectively). The middle portion of the table shows the mean own-price elasticity across all bids made to households in each home value quartile; we see that the bottom quartile is the most elastic (mean own-price elasticity of -2.43) despite receiving the lowest number of bids on average.

The parameters on the electricity bill quartile dummies reveal that households with higher monthly electricity expenditure obtain a lower utility (per unit capacity) from a solar installation. However, households with larger electricity expenditures typically install higher-capacity systems. We will see in Section 5 that the consumers in the highest electric bill quartiles do obtain higher total consumer surplus from the platform despite attaining lower consumer surplus per watt.

We also see that the coefficient associated with whether the household has off-platform quotes is also positive.[22] This result is consistent with off-platform quotes being positively correlated with preferences for rooftop solar and also that quotes on the platform tend to dominate off-platform installation options.

On the top right side of the table, we see that households value hardware characteristics, preferring higher-rated panel brands and systems with microinverters. We also see that buyers value installer characteristics. All else equal, sellers with a 4.5-star rating and those with ratings below 4.5 stars are less likely to be selected relative to an installer without ratings.[23] On the other hand, installers with a five-star rating are preferred to all other sellers. We also see that an installer's residential installation experience is highly valued by buyers; buyers are willing to pay over 20% more for an installer that has completed over 1000 installations compared to an installer that has completed less than 100 installations.

As discussed in Section 4.4, there are several threats to the identification of the utility parameters. Appendix Section D investigates the robustness of the coefficient estimates to adding a series of potential confounding variables into the utility specification. The robustness checks include adding controls for installer experience, panel brand fixed effects, household demographics, house characteristics, a discrete-continuous choice specification, and exclud-

[22]Relatedly, in the raw data, buyers with off-platform quotes are 33% more likely to select one of the bids from the platform compared to buyers without off-platform quotes.

[23]The point estimates suggest that sellers that are rated below 4.5 stars are preferred to sellers rated at 4.5 stars, although the difference is not statistically significant. Recall, that the utility includes fixed effects for installers that placed over 300 bids, so the star-rating coefficients are identified from the bids of transient sellers. The star-rating coefficients demonstrate a monotone pattern in specifications that omit installer fixed effects.

ing auctions from states with time-varying subsidies. The estimates are relatively stable across these alternative specifications.

Cost Estimates: Table 1 Panel B shows how average markups and marginal costs progressed throughout the sample period. Between the start of 2014 and the end of 2016, marginal costs fell by \$0.31 per watt (over \$2,200 on an average-sized system), and markups fell by \$0.21 per watt (over \$1,500 on an average-sized system). Costs and margins fell proportionally, and therefore, the (before-subsidy) Lerner index—calculated using all bids—remained relatively stable at about 0.45.

Although the estimates indicate that markups represent a substantial portion of installation prices, it is important to recognize that the estimated markups are gross of installers' fixed operating expenditures. These fixed expenditures include marketing and overhead for facilities and administration. Fu et al. (2016) calculate that installers should pay an average of \$0.33 per installed watt for marketing expenses and \$0.37 per watt for other overhead costs in 2016. Taking these estimates as given would imply that installers on the platform earn an average net profit margin of \$0.85 per watt—or 24.8% of installation prices in 2016.

Appendix Figure A.8a demonstrates that the estimated marginal cost reductions are explained mainly by the fall in wholesale solar PV hardware prices reported by Bloomberg Inc. Figure A.8a also indicates that hardware costs account for about half of the total marginal cost. In particular, the Bloomberg hardware cost index, together with the marginal cost estimates, imply that in 2016 H1 hardware costs made up about 28% of the solar installation prices (before subsidies), non-hardware costs such as installation labor and permitting made up 28%, and markups made up 44%. Appendix Figure A.8b shows how the marginal cost estimates compare to stated costs reported by publicly traded solar installation firms; the mean estimated marginal cost was slightly higher than the cost reported by SolarCity/Tesla but marginally lower than the costs reported by Sunrun and Vivint (Fu et al., 2016). Finally, we compare the estimated markups to other available estimates in the literature. Bollinger and Gillingham (2019) estimate static markups of about \$1.20/watt to \$1.45/watt using California data from before 2012, whereas the mean markup estimates in the current paper are slightly larger ranging from \$1.55-\$1.76/watt across 2014-2016.

I use the entry cost parameters, reported in Appendix Table A.7, to calculate the expected bid preparation cost (entry cost) conditional on participating. Table 1 Panel B shows that bid preparation costs fell from $40 in 2014 H1 to under $10 in 2016 H2. Appendix Figure A.9 shows that the bid preparation also becomes less variable over time, with the majority of bid costs in the $0-$20 range by the second half of the sample. Appendix F further investigates cost heterogeneity across installer, hardware, and household characteristics.

5 Welfare and Counterfactuals

In this section, I use the model estimates to evaluate consumers' welfare gains from using the platform. I then investigate the mechanisms driving the welfare results by simulating counterfactuals that measure the effect of increasing the number of bids per project on market outcomes. Finally, I solve a second set of counterfactuals to evaluate the impacts of solar subsidies.

5.1 Consumer Surplus Gains From Platform Access

I evaluate the extent to which the online platform improves consumers' expected welfare relative to their outside option using the following expression:

$$\mathbb{E}[CS] = \frac{1}{M}\sum_{i}^{M}\frac{1}{\alpha_i}\mathbb{E}[\max_{j\in\mathcal{J}_i\cup 0} \quad u_{ij} - u_{i0}] = \frac{1}{M}\sum_{i}^{M}\frac{1}{\alpha_i}\log\Big(1 + \big(\sum_{j\in\mathcal{J}_i}\exp\big(\frac{v_{ij}}{1-\lambda}\big)\big)^{1-\lambda}\Big)(\overline{q_i}). \tag{13}$$

Here, $\mathbb{E}[CS]$ is the expected consumer surplus that buyers obtain from their menu of options on the platform ($\mathcal{J}_i$) relative to their outside option. The last equality derives from the nested logit utility specification, where v_{ij} is the utility buyer i obtains from option j net of the taste shock, $v_{ij} = u_{ij} - \varepsilon_{ij}$. Lastly, recall that utility is measured in dollars per watt, so I scale the consumer surplus measure by each buyer's expected system size, $\overline{q_i}$, to obtain the expected *total* consumer surplus.

The above expression measures the value that consumers glean from the platform *relative to their outside option*. Thus, under the *full-information assumption*, the above estimate captures the added value the platform provides to buyers as an alternative means of procuring solar PV.

There are a number of caveats to keep in mind when interpreting the consumer surplus estimates. First, I estimate preferences among a selected sample of buyers who opted to shop for solar through an online website. Although we saw in Section 2 that these buyers appear relatively similar to the broader population of solar adopters— it's possible that these estimates relate to a sophisticated consumer segment that can elicit more value from using the online platform. Second, the consumer surplus measure is implicitly a function of the quality and pricing offered by installers off of the platform.[24] Even though the platform composed a small fraction of the overall solar installation market during the sample period, it is still plausible that offline installation price and quality offerings are enhanced in response to the competition from the platform. If so, these consumer surplus estimates would tend to understate the actual gains created by the platform because the calculation assumes that the value of the outside option remains fixed when the platform is removed (instead of decreasing). Third, it is possible that in a scenario where the platform was not available, buyers could contact the exact sellers that made a bid to them through the platform, therefore increasing the value of the outside option. However, most markets in the sample have dozens or even hundreds of operating solar installers, so adding a few additional sellers to the pool of possible off-platform sellers is unlikely to have a substantial impact on a buyer's value from the outside option.

Given the above caveats, Table 2 Panel A shows that the platform increased consumer surplus by $1,016 for the average household that shopped on the platform. For reference, this welfare gain is equivalent to making a payment of 6% of the mean bid price to each individual who used the platform. Panel B and Panel C demonstrate how consumer welfare varies across electricity expenditure quartiles and home valuation quartiles, respectively. Households in the top electricity expenditure quartile realize smaller per-unit surplus gains relative

[24]Sellers could also engage in more door-to-door sales or other marketing activities in the absence of the platform.

to households in the lowest quartile. However, these households purchase bigger systems and consequently attain larger total welfare gains. More specifically, households in the bottom electricity bill quartile reap \$754 in benefits from the platform relative to \$1,080, \$1,164, and \$1,075 for the top three quartiles, respectively. A similar pattern emerges in the distribution of gains across home values. The lowest-valued quartile of homes see gains of \$809 relative to \$1,030 for the most expensive quarile of homes.

These results indicate that the platform facilitated substantial gains for most consumers but that wealthier households appear to be the largest beneficiaries. This distributional result was not clear ex-ante because, on the one hand, wealthier households are less price-sensitive (Table 1) and therefore stand to benefit relatively less from a price reduction. On the other hand, wealthier households attract more bids, see bigger price reductions, and gain access to more distinct installers. The distribution of welfare gains in Table 2 Panel B and C, therefore, suggests a high value of obtaining additional installer choices.

5.2 Counterfactuals: Effects of Expanding Buyers' Choice Sets

The results presented in the previous section suggest that platforms can improve consumer outcomes in the residential solar market. However, the success of platforms going forward will hinge on attracting both sellers and buyers to participate. A platform will only reduce margins and prices if there are a sufficient number of sellers bidding through the platform. This raises several additional questions. First, how much of the platform welfare benefit can be explained by the buyers obtaining additional bids? Relatedly, how much does each incremental bid per project reduce solar installation prices? How much does solar adoption and associated environmental benefits increase if buyers obtain more bids? These questions are important for either policymakers or private companies that seek design platforms that reduce solar installation prices.

To investigate the above questions, I measure the effect of expanding buyers' choice sets, holding preferences fixed. In particular, I simulate counterfactuals in which I alter the number of installers that bid on each buyer's project. In the counterfactuals, installers are informed about the number of other competing sellers (if any), and each installer updates their optimal bid price based on the number of competitors they will face. In the counterfactuals, I assume that sellers know the number of competing bidders but not the identities of the other bidders. I provide additional details about the algorithm for solving counterfactual equilibria in Appendix H.1.

Table 3 displays the outcomes of changing the number of bids from one to five. I report all outcomes relative to the single-bid case (i.e., $\frac{y|bids=N}{y|bids=1}$). The top of the table shows that an increase from one to five bids leads to a 16.4% reduction in mean bid prices, a 25.2% reduction in the lowest bid, and a 15.5% fall in purchase prices (selected bids). These results imply a \$4,000 gross price decline (before subsidies) for a typical-sized system. The table also reveals a substantial decrease in the marginal effect of competition, namely, adding a second bid causes a much greater marginal bid price reduction (12% from the baseline) relative to adding a fifth bid (0.8% from the baseline).

Incremental bids can reduce prices through two channels: (1) reducing markups through increased competition and (2) reducing installation costs by connecting buyers to sellers with lower installation costs. The counterfactual results indicate that the majority of the price decline from incremental bids comes from reduced markups. More specifically, markups fall by over 40% when the number of bids increases from one to five, whereas marginal costs fall by only 2.5%.

In the second section of the table, I document changes in consumer and producer surplus as the number of bids per project expands. The estimates confirm that increasing the number of bids can deliver large consumer benefits. More specifically, providing a buyer with five bids causes a 360% increase in buyers' surplus from using the platform relative to the single bid case. Intuitively, buyers collect a relatively small benefit from using the platform if they receive only a single bid. Conversely, the platform can deliver substantial value for consumers when several sellers submit unique bids.

We also see that total producer surplus for on-platform installers increases over twofold if the number of bids increases from one to five. The increase in total producer surplus is driven primarily by the rise in the number of transactions that occur as the number of bids increases. Despite the increase in total surplus among platform sellers, the expected profit for each individual seller falls by over 50% as the number of bidders increases from one to five. Notably, the producer surplus estimates should be interpreted with some caution because the estimates only quantify changes in producer surplus for the sellers that are participating on the platform and do not account for changes that would accrue to installers operating off of the platform.

The third part of the table shows the impact of bid quantity on the number of solar PV installations. Evaluating counterfactual changes in solar adoption is especially challenging because I do not directly observe or model off-platform solar purchases. As a consequence, when a buyer chooses the outside option in the counterfactuals, this could either mean that they choose an off-platform installer or that they do not purchase a solar system. Therefore, I use data from platform exit surveys to predict the probability that buyers will adopt solar PV, conditional on selecting the outside option. Appendix Table A.8 shows that 27% of survey respondents elect to hire an off-platform installer conditional on choosing the outside option, and 73% chose not to install solar.[25] Additionally, buyers who collected quotes from off-platform sellers prior to arriving on the platform are much more likely to ultimately make off-platform purchases. As such, I specify the conditional probability of hiring an off-platform installer separately for each group of buyers—51.7% for households that already had off-platform quotes prior to using the platform and 19.7% for those who did not previously hold external quotes.

There are a few potential complications of using the exit survey data to predict off-platform purchase choices. For one, the survey represents a selected subset of the sample that may not be representative of the full platform buyer population. To characterize selective participation in the exit survey, I regress an indicator variable for whether each buyer completed the survey on a set of household characteristics in Appendix Table A.9. The regressions indicate that households with higher home values, high (or moderate) electricity usage, and those who receive more bids through the platform are the most likely to complete the survey. These selection patterns suggest that using the exit survey may provide an upper-bound estimate of the full sample probability that potential buyers hire off-platform installers conditionally

[25] The exit survey was completed by 11% of households that selected the outside option.

on choosing the outside option. A second possible limitation of using the off-platform purchase probabilities estimates above is that off-platform purchase behavior may vary with the number of bids that buyers obtain. For instance, buyers who receive fewer bids through the platform may search more off of the platform. To ease this concern, Appendix Figure A.10 illustrates that the off-platform purchase probability does not change systematically with the number of (platform) bids. Moreover, Appendix Table A.10 shows that there is not a statistically significant relationship between the number of bids and buyers' off-platform purchases across several regression specifications.

Acknowledging the potential challenges and additional assumptions required to estimate solar adoption effects, I find that expanding the bid set from one to five bids leads to at least a 21% increase in the number of households that adopt solar.[26] I also use estimates from Sexton et al. (2021) to calculate the net present value from avoided pollution damages resulting from these additional solar purchases.[27] I find that expanding buyers' choice sets from one to five bids leads to at least an 18% increase in external benefits via pollution reductions.

5.3 Counterfactuals: Market Impacts of Solar Subsidies

In the next set of counterfactuals, I use the model to assess the impact of government subsidies on market outcomes. Over the past few decades, subsidy programs have been a cornerstone of policymakers' efforts to expand renewable energy investment. The largest U.S. program promoting rooftop solar adoption has been the Solar Investment Tax Credit (ITC). The ITC was originally established by the Energy Policy Act of 2005 and allowed solar buyers to deduct

[26] The counterfactuals likely provide a lower bound estimate on the effect of an additional bid on solar adoption. The results are a lower bound because as the number of bids increases in the counterfactuals, we will see more substitution away from the outside option, and the calibrated solar adoption probability conditional on selecting the outside option is likely to be exaggerated due to selection into the exit survey.

[27] Sexton et al. (2021) estimate the annual pollution damages avoided per kilowatt of residential solar capacity separately for each ZIP code. The avoided pollution damage depends on the expected production of the solar PV system in the ZIP code and the pollution intensity of the power plants that reduce output due to a marginal increase in residential solar PV production.

30% of the solar installation price from their federal taxes. The history of the ITC has been marked with many contended extensions, planned step-downs, and other proposed policy alterations. The solar industry, environmentalists, and politicians have argued that renewable energy subsidies are critical to addressing climate change. On the other hand, opponents have countered that the tax credits are not cost-effective and place too large a burden on taxpayers.

To understand the effects of removing the ITC, I simulate counterfactual market outcomes both with and without the 30% ITC subsidy. In the counterfactual with the ITC, winning sellers earn 100% of the gross bid price, but consumers pay only 70% of the gross price. For the counterfactual without the ITC, buyers pay the entire gross bid price to selected sellers. In both counterfactual simulations, sellers update both participation and bidding strategies to account for the subsidy availability (or removal).[28] Importantly, the counterfactual removal of the ITC may also affect the value that buyers obtain from choosing the outside option through changes in off-platform prices. To account for these changes, I solve two specifications of the counterfactual that removes the ITC. In the first specification, I hold the normalized value of the outside option fixed ($v_{i0} = 0$). This specification corresponds to a 0% subsidy pass-through rate among installation prices outside the platform. In the second specification, I adjust the value of the outside option to characterize a 100% subsidy pass-through rate to off-platform prices. Specifically, I modify the utility of the outside option as $v_{i0} = 0 - 0.3\,\alpha_i * \overline{p_{it}}$, where $\overline{p_{it}}$ is the mean gross installation price among *all* installations in buyer i's local CBSA market at time t using Lawrence Berkeley National Lab data which includes off-platform transactions.[29] I discuss the algorithm used to solve the counterfactual equilibria in Appendix H.2.

Panel A of Table 4 shows average market outcomes for each of the counterfactuals. The first column shows results for the case where the ITC is available. In contrast, the second and third columns contain the results with the ITC removed—assuming a 0% off-platform pass-through rate and full pass-through, respectively. Notably, all of the outcomes in both the second and third columns are very similar, suggesting that the counterfactual results are

[28]The demand model controls for state of local incentives by including CBSA fixed effects. Therefore, the counterfactuals show how outcomes change when the ITC is removed, holding local policies fixed.

[29]I use data from Barbose et al. (2021) to calculate average per-watt prices among all installations within each CBSA for each half year. I set $\overline{p_{it}}$ as the statewide average price for CBSAs that are missing transaction prices.

relatively robust to altering the assumption about how removing the ITC affects the outside option. Focusing on the results in the first and third columns, we see that eliminating the ITC results in an 8% reduction in the number of bids per project from 3.49 to 3.24. Without the ITC, fewer installers find it worthwhile to submit bids because, for some projects, expected profits no longer cover their bid preparation costs. Removing the ITC also results in a 25.6% increase in the net price of solar bids from $2.47/watt to $3.10/watt. This net price increase of $0.63/watt implies a $4,600 increase on a typical-sized system. In the same fashion, the mean price of selected bids also increases by 23.7% with the elimination of the ITC. The consumer burden of removing the ITC is partly mitigated by sellers reducing their gross bid prices by $0.42/watt on average. Sellers find it optimal to reduce offer prices after the subsidy removal to recoup some sale quantity losses. If sellers did not change their bids in reaction to the ITC removal, the net bid price would increase by 42.8%.[30] All together, these price changes, along with reductions in seller participation, cause a 32% reduction in the number of purchases made through the platform absent the ITC.

In the lower part of Table 4—Panel B—I calculate the average change in various welfare outcomes per dollar of subsidy expenditures under the ITC. In particular, I estimate these values as $(\bar{Y}_{ITC} - \bar{Y}_{No})/\overline{Subsidy}_{ITC}$, where the numerator is the change in mean outcomes between the "ITC" and "No ITC" counterfactuals and the denominator is the mean subsidy expenditure (per potential buyer) when the subsidy is available. I calculate the above measures separately for each of the two counterfactual specifications removing the ITC. Again, focusing on the last column, we see that the ITC fosters substantial welfare increases for both producers and consumers using the platform. The ITC increases average consumer surplus by $0.55 per subsidy dollar and also raises sellers' gross marginal profits by $0.72 per subsidy dollar. On the other hand, the ITC slightly increases bid preparation costs by $0.03 per subsidy dollar by encouraging more bids. As an additional benefit, the ITC reduces pollution damage by

[30]The ITC covers 30% of the gross price. Therefore, with the ITC, the net price equals $7/10$ of the gross price, so removing the ITC without changing the gross bid price leads to a $10/7$ (42.8%) increase in net price.

at least 11.7¢ for each dollar of subsidy expenditure.[31] Summing all of these effects together and subtracting the $\$1.00$ subsidy cost, we obtain a net benefit of $\$0.35$ per subsidy-dollar ($\$0.55 + \$0.72 - \$0.03 + \$0.11 - \$1.00 = \$0.35$). Notably, the ITC provides sizable welfare gains for producers and consumers on the platform by reducing deadweight loss caused by market power in addition to correcting for environmental externalities. In particular, we have seen that solar installations are priced well above marginal cost. Therefore, the results suggest that a subsidy can promote efficiency gains by encouraging more transactions on the platform where buyers' willingness to pay exceeds the seller's marginal cost.

In addition to understanding the average welfare impacts of residential solar subsidies, an important question for policymakers is to determine where subsidies are likely to deliver the largest welfare gains. Table A.11 in the Appendix shows the five CBSAs in which platform users obtain the largest welfare gains and smallest welfare gains from the ITC per dollar of subsidy expenditure. The top CBSAs are located in Arizona, Texas, and Colorado. Platform users in these states obtain large gains from subsidies for two main reasons: First, these areas all have relatively few competing installers, which enables high markups. Additionally, Arizona, Colorado, and Texas all have abundant solar resources, so adding solar installations will generate more electricity and provide more external benefits from pollution reductions. On the other hand, the ITC subsidy provides more modest welfare gains in Connecticut and Massachusetts because there is stronger competition among installers and fewer solar resources in these areas. In sum, the results suggest that residential solar subsidies may deliver higher welfare gains in markets where external environmental benefits are larger but also in markets with higher markups.

There are several limitations and caveats to keep in mind when interpreting the results of the ITC subsidy analysis. First, the analysis above does not capture changes in producer

[31] Pollution damages depend on the probability that buyers who select the outside option hire an off-platform installer. To calculate pollution damages, I specify that buyers with (without) off-platform quotes hire off-platform installers with a probability of 0.517 (0.197) based on the exit survey. However, the probability that buyers choosing the outside option hire an off-platform installer would likely decrease if the ITC is removed. Thus, the estimates in Table 4 Panel B may be a conservative estimate of the pollution benefits of the ITC.

surplus that accrue to off-platform sellers. For example, if buyers substitute from on-platform sellers to off-platform sellers in the counterfactuals without the ITC, the producer surplus estimates above may overstate the aggregate producer surplus benefits of the ITC. On the other hand, if removing the ITC leads some buyers who previously chose off-platform installers to not adopt solar PV, then the estimates may understate the aggregate producer surplus benefits of the ITC. Second, I do not consider several potentially important externalities of solar installations such as electricity transmission and distribution costs (Feger et al., 2022), learning-by-doing (Bollinger and Gillingham, 2019), peer effects (Bollinger and Gillingham, 2012), or generation reserve costs (Gowrisankaran et al., 2016) in the welfare calculations. Third, the ITC policy covers all residential solar installations in the U.S., whereas the model is estimated using only solar installation projects that originated through the online platform. Buyer preferences and the intensity of bidding competition may be substantially different for projects that are remote from the platform. For this reason, we would expect equilibrium outcomes to respond differently to the ITC availability, yielding different quantitative welfare effects. Thus, we should be cautious about extrapolating the exact welfare estimates out of sample. Nonetheless, if competition for off-platform solar projects is less intense than the competition for projects on the platform–and therefore subject to higher markups—we would also expect substantial net benefits of subsidizing off-platform projects to constrain market power. Finally, the ITC also provides a tax incentive for utility-scale solar projects. Market structure in the utility-scale market is likely to differ from that of the residential market. Therefore, the welfare impacts of removing the ITC will also be likely to vary across these two markets.

6 Conclusion

Online platforms offer a convenient means for buyers and sellers to connect in markets with negotiated prices. Nonetheless, many such markets still widely operate via bilateral negotiations. In the solar PV market context, we have seen that online platforms can facilitate sizable welfare gains for consumers. A primary mechanism through which a platform can help consumers is by providing them access to additional bids, thereby lowering bid prices.

Reducing installation prices is particularly relevant in the solar PV market because (non-hardware) soft costs, which include installer markups, now account for over 70% of the price of a typical solar installation. Thus, policymakers aimed at reducing solar prices could consider informing the public about existing platforms or developing their own platforms to link buyers and sellers. Platforms could also yield similar benefits in other markets characterized by large hassle costs, such as home mortgages or building energy efficiency retrofits.

Notably, though, we have seen that welfare gains will not be evenly distributed across consumers when sellers can bid on projects selectively. In particular, households with higher home values obtain the most significant benefits because these wealthier households attract relatively more bids through the platform. These distributional effects are also important to keep in mind as other markets move more towards online platforms to link market participants.

The counterfactuals also provide new evidence on the welfare impacts of investment subsidies. Policymakers most commonly justify renewable energy subsidies based on positive environmental externalities. However, government subsidies are often introduced into markets with multiple existing distortions, such as imperfect competition, imperfect information, and environmental externalities. Robinson (1933) was the first to note that subsidies could improve welfare in imperfectly competitive markets, and Judd (2002) later argued that government subsidies could have particularly large welfare benefits in markets for capital-intensive goods. This paper investigates the removal of a prominent investment subsidy in the solar PV market and highlights that subsidies have the potential to improve welfare by constraining market power in addition to reducing pollution damages. These results have implications for tax and subsidy policy in other imperfectly-competitive markets.

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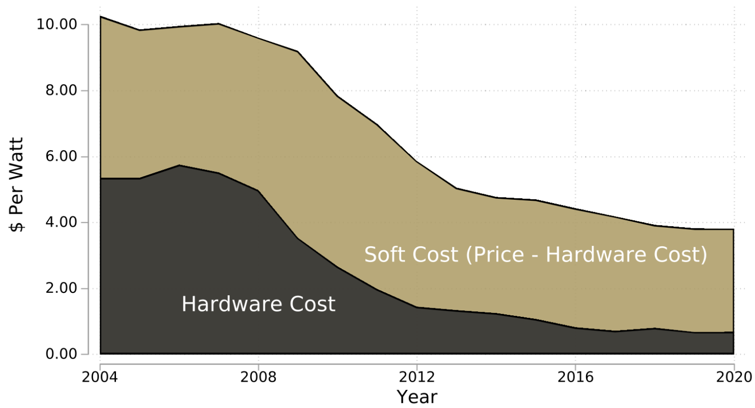
Figure 1: Residential Solar PV Installation Prices ($/Watt)



Notes: Figure constructed using data from Barbose et al. (2021). Each line shows the median cost in dollars per watt for residential solar installations in the U.S. Hardware costs include the panel, inverter, support structures, and electrical wiring.

Table 1: Demand and Cost Estimates

Panel A: Demand Estimates

Nesting Parameter		**Non-Price Bid Attributes**	
λ	0.372 (0.063)	Premium Panel	0.562 (0.076)
Price Coefficients		Premium Plus Panel	1.429 (0.150)
Constant	-0.717 (0.111)	Microinverter	0.370 (0.079)
$\times$ Home Mkt. Value - Quartile 2	0.068 (0.044)	**Installer Attributes**	
$\times$ Home Mkt. Value - Quartile 3	0.079 (0.051)	Star Rating ≤ 4	-0.260 (0.256)
$\times$ Home Mkt. Value - Quartile 4	0.089 (0.059)	Star Rating = 4.5	-0.409 (0.246)
Household Attributes ($\times$ **Inside Option**)		Star Rating = 5	0.281 (0.096)
Electric Bill - Quartile 2	-0.067 (0.098)	Installs Completed: 100-1000	0.697 (0.237)
Electric Bill - Quartile 3	-0.241 (0.102)	Installs Completed: >1000	0.749 (0.244)
Electric Bill - Quartile 4	-0.584 (0.111)		
Has Off-Platform Quotes	0.368 (0.092)		

Home Mkt. Value Quartile	**Mean Own-Price Elasticity**	**Avg Number of Bids**
1	-2.43	3.1
2	-2.25	3.47
3	-2.26	3.84
4	-2.26	3.86

Fixed Effects		**Log Likelihood**
CBSA Fixed Effects	Yes	-3823.542
Half-Year Fixed Effects	Yes	
Permanent Installer Fixed Effects	Yes	

Panel B: Mean Marginal Cost, Markups, Entry Costs

Half Year	# of Bids	MC ($/watt)	Markup ($/watt)	Lerner Index	Bid Prep Cost ($)
2014 H1	2.07 (0.07)	2.19 (0.34)	1.76 (0.34)	0.46 (0.09)	39.57 (10.32)
2014 H2	2.34 (0.06)	2.14 (0.34)	1.74 (0.34)	0.46 (0.09)	62.38 (13.15)
2015 H1	2.54 (0.04)	2.15 (0.33)	1.69 (0.33)	0.45 (0.09)	45.2 (8.84)
2015 H2	2.72 (0.04)	2.1 (0.34)	1.68 (0.34)	0.45 (0.09)	33.66 (6.99)
2016 H1	3.98 (0.04)	2.03 (0.32)	1.56 (0.32)	0.44 (0.09)	16.04 (3.58)
2016 H2	4.03 (0.02)	1.88 (0.32)	1.55 (0.32)	0.46 (0.09)	9.84 (2.17)

Notes: Panel A includes demand estimates with CBSA, half-year, and permanent seller fixed effects. Permanent sellers are those who submitted over 300 total bids. All project attributes, non-price attributes, and installer attributes are dummy variables. The star rating coefficients are relative to installers with no rating. The mean own-price elasticity is calculated based on the realized choice sets and does not account for ex-ante uncertainty in seller participation. Standard errors are in parentheses. Panel B shows the mean number of bids, mean marginal cost, mean markup, mean Lerner Index (markup/ gross price), and the expected bid preparation cost, conditional on submitting a bid for each half-year of the sample. Bayesian Bootstrap standard errors (Rubin, 1981) in parentheses. Bootstrap weights for each auction are drawn according to a Dirichlet distribution with $\alpha = 1$ across 100 bootstrap samples.

Table 2: Consumer Surplus Gains from Access to the Platform

Panel A: Consumer Surplus Summary - Full Sample

	Mean	Std. Dev.
Total Consumer Surplus Per Household ($)	1015.62 (190.29)	923.27 (181.47)
Consumer Surplus Per Unit ($/watt)	0.14 (0.03)	0.11 (0.02)
(Consumer Surplus)/(Mean Bid Price)	0.06 (0.01)	0.04 (0.01)

Panel B: Mean CS by Electricity Bill Quartile

Quartile	Bids	Total CS ($)	CS ($/watt)
1	3.12 (0.03)	754 (203.55)	0.15 (0.04)
2	3.54 (0.03)	1079.53 (315.04)	0.17 (0.05)
3	3.64 (0.03)	1164.29 (304.08)	0.15 (0.04)
4	3.85 (0.04)	1074.81 (325.84)	0.11 (0.03)

Panel C: Mean CS by Home Value Quartile

Quartile	Bids	Total CS ($)	CS ($/watt)
1	3.1 (0.03)	808.88 (229.36)	0.11 (0.03)
2	3.47 (0.03)	1087.17 (314.25)	0.15 (0.04)
3	3.84 (0.04)	1134.51 (363.7)	0.17 (0.05)
4	3.86 (0.04)	1033.1 (354.79)	0.16 (0.05)

Notes: Panel A reports the mean and standard deviation of each variable across all households in the sample. Each column in Panel B and Panel C reports the means value of the variable separately for each quartile. Bayesian Bootstrap standard errors (Rubin, 1981) in parentheses. Bootstrap weights for each auction are drawn according to a Dirichlet distribution with $\alpha = 1$ across 100 bootstrap samples.

Table 3: Effects of Number of Bids Per Project on Market Outcomes

	Counterfactual # of Bids Per Project				
	1 - Baseline	2	3	4	5
Relative Prices					
Mean Price Per Watt (All Bids)	1 (.)	0.88 (0.022)	0.855 (0.026)	0.842 (0.028)	0.834 (0.028)
Mean Price Per Watt (Lowest Bid)	1 (.)	0.834 (0.021)	0.788 (0.025)	0.762 (0.027)	0.745 (0.027)
Mean Price Per Watt (Selected)	1 (.)	0.904 (0.022)	0.874 (0.026)	0.857 (0.028)	0.845 (0.029)
Consumer & Producer Surplus (On Platform)					
Consumer Surplus ($)	1 (.)	1.859 (0.019)	2.502 (0.043)	3.089 (0.086)	3.597 (0.131)
Total Producer Surplus ($)	1 (.)	1.501 (0.063)	1.843 (0.126)	2.14 (0.178)	2.379 (0.224)
Producer Surplus Per Bid ($/bid)	1 (.)	0.75 (0.031)	0.614 (0.042)	0.535 (0.044)	0.476 (0.045)
Relative Quantities & Externalities					
# of Solar Installations	1 (.)	1.075 (0.006)	1.13 (0.007)	1.178 (0.01)	1.218 (0.012)
Pollution Damages Avoided ($)	1 (.)	1.064 (0.007)	1.111 (0.008)	1.152 (0.009)	1.186 (0.011)

Notes: Summary of counterfactual simulations varying the number of bids that each project receives. All outcomes are reported relative to the one-bid case. Bayesian Bootstrap standard errors (Rubin, 1981) in parentheses. Bootstrap weights for each auction are drawn from a Dirichlet distribution ($\alpha = 1$) across 10 bootstrap samples.

Table 4: Effects of Government Subsidies on Competition, Prices, and Welfare on Platform

Panel A: Market Outcomes

		Counterfactual	
	ITC	No ITC (0)	No ITC (1)
Bids Per Project	3.491 (0.039)	3.240 (0.058)	3.237 (0.058)
Gross Price Per Watt (All Bids)	\$3.523 (0.004)	\$3.123 (0.054)	\$3.098 (0.053)
Net Price Per Watt (All Bids)	\$2.466 (0.003)	\$3.123 (0.054)	\$3.098 (0.053)
Net Price Per Watt (Lowest)	\$2.252 (0.005)	\$2.842 (0.053)	\$2.819 (0.054)
Net Price Per Watt (Selected)	\$2.396 (0.008)	\$2.987 (0.04)	\$2.966 (0.042)
Purchases on Platform (Normalized)	1 (.)	0.669 (0.038)	0.679 (0.037)

Panel B: Change in Welfare per ITC Subsidy Expenditure (On Platform)

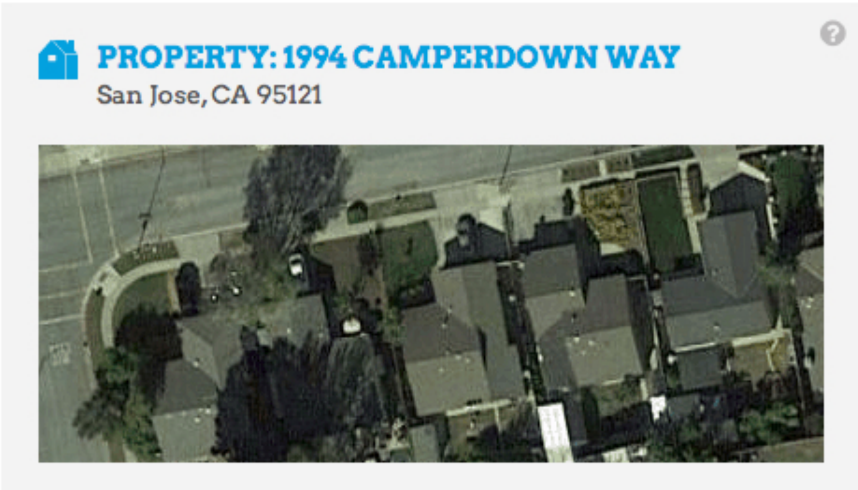
	(0)	(1)
Δ Consumer Surplus	\$0.570 (0.031)	\$0.552 (0.031)
Δ Gross Producer Surplus	\$0.711 (0.053)	\$0.718 (0.054)
Δ Bid Preparation Costs	-\$0.034 (0.005)	-\$0.033 (0.005)
Δ Pollution Damages Avoided	\$0.117 (0.013)	\$0.113 (0.013)
Δ Subsidy Cost	-\$1.000 (0)	-\$1.000 (0)
Δ Welfare (On Platform)	\$0.364 (0.014)	\$0.350 (0.013)

Notes: Panel A summarizes average outcomes across counterfactual market simulations with and without the federal investment tax credit. The second column, "No ITC (0)", assumes a 0% pass-through rate of the ITC removal to prices off of the platform. The third column "No ITC (1)" assumes a 100% pass-through rate of the ITC removal for prices off of the platform. Panel B calculates the relative change in welfare measures between the "ITC" and "No ITC" cases per dollar change in subsidy expenditure. Welfare estimates in Panel B do not include off-platform transactions. Bayesian Bootstrap standard errors (Rubin, 1981) in parentheses. Bootstrap weights for each auction are drawn from a Dirichlet distribution ($\alpha = 1$) across 10 bootstrap samples.

Online Appendix

A Additional Tables and Figures Referred to in Main Text

Figure A.1: Google Maps Photo of the Rooftop for a Potential Project



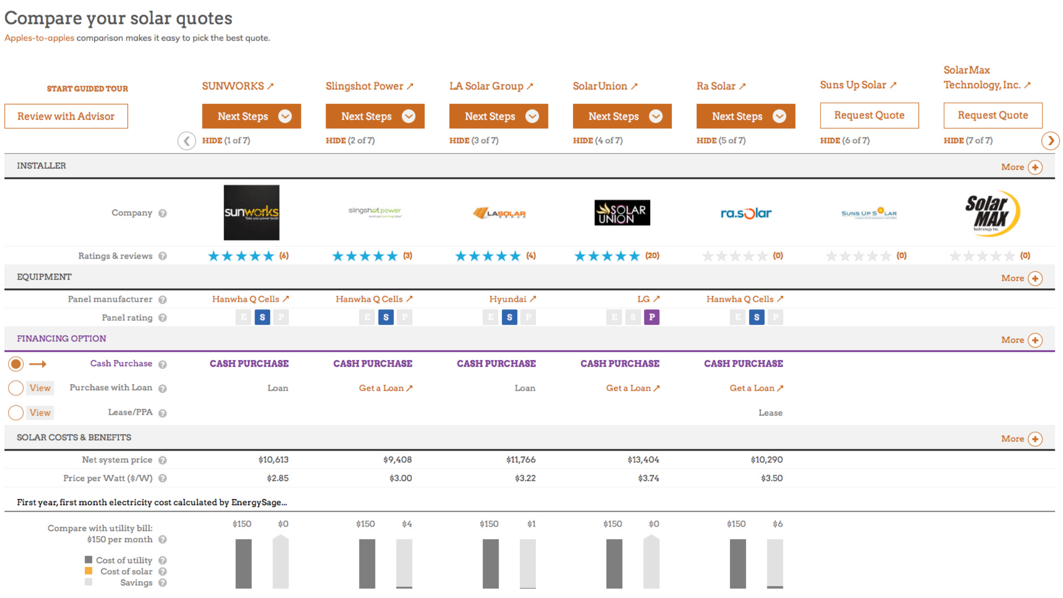
Notes: Figure shows an example of an EnergySage buyer profile. The profile allow potential bidders to see a Google Maps image of the buyer's roof.

Table A.1: Project Summary Statistics

	Mean	SD	25-%tile	50-%tile	75-%tile
Number of Bids	3.54	1.84	2.00	3.00	5.00
Home Market Value ($1,000s)	687.49	508.66	325.00	550.00	900.00
Age of Home	42.24	33.23	17.00	36.00	58.00
Home Size (sqft)	2238.57	863.92	1608.00	2100.00	2692.50
Env. Damage Avoided ($/KW-yr) - ZIP	46.69	18.42	26.12	51.84	53.34
Annual Solar Output (KWh/KW) - ZIP	1428.28	199.17	1198.72	1513.38	1559.34
Electricity Bill ($/month)	187.03	89.38	120.00	167.28	240.00
HH Head Age	51.86	13.86	42.00	50.00	62.00
HH Head Race - Asian (0,1)	0.12	0.32	0.00	0.00	0.00
HH Head Race - Black or Hispanic (0,1)	0.12	0.32	0.00	0.00	0.00
HH Head Holds Bachelor's Degree (0,1)	0.49	0.50	0.00	0.00	1.00
Has Off-Platform Quotes (0,1)	0.17	0.38	0.00	0.00	0.00

Notes: The number of bids, the household monthly average electric bill, and an indicator for whether the consumer has off-platform quotes are recorded and reported directly by EnergySage. Annual environmental damages avoided per kW capacity are calculated at the zip code level by Sexton et al. (2021). Additional variables come from Infinite Media's consumer database and were merged with the EnergySage data by property address.

Figure A.2: EnergySage Dashboard for Comparing Submitted Quotes

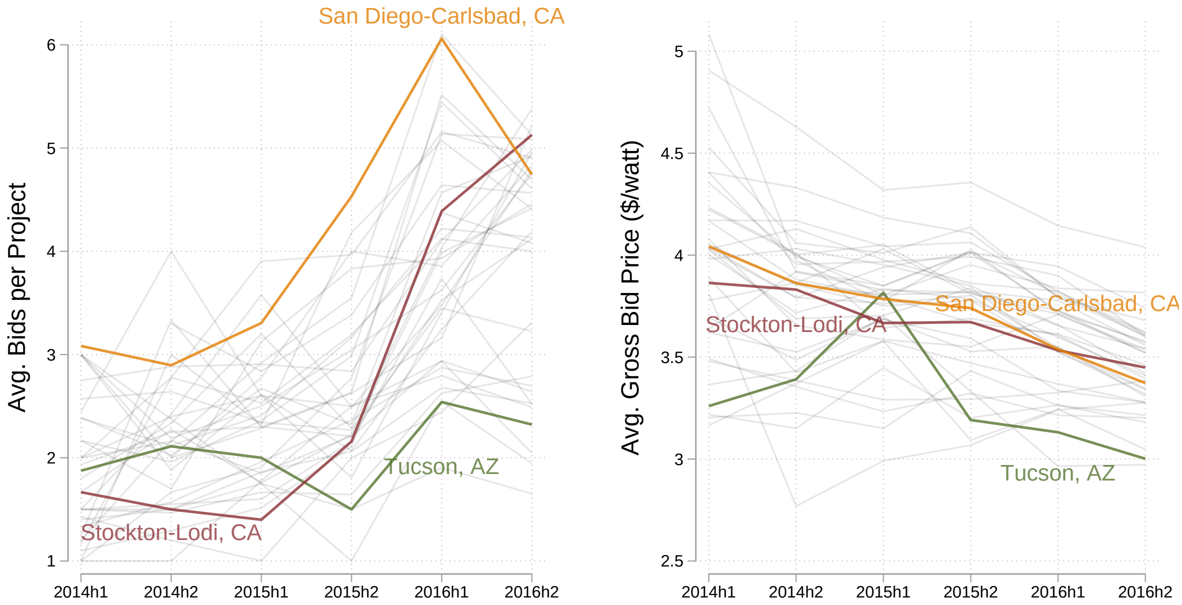


Notes: EnergySage quote comparison page in late 2016.

Table A.2: Project Count by Location and Year

	2014	2015	2016	Total
AZ	57	110	563	730
CA	353	1053	3417	4823
CO	30	140	365	535
CT	132	559	330	1021
MA	129	400	1025	1554
NY	62	173	698	933
TX	49	156	687	892
Total	812	2591	7085	10488

Figure A.3: Competition and Prices by Core-Based Statistical Area Over Time

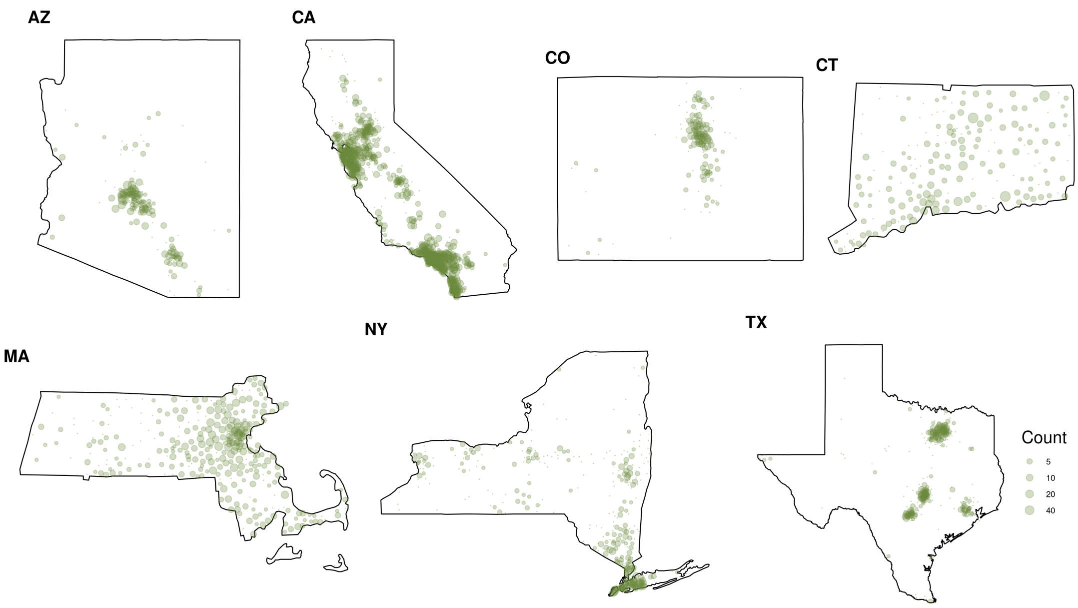


(a) Mean Bids Per Project

(b) Mean Bid Prices

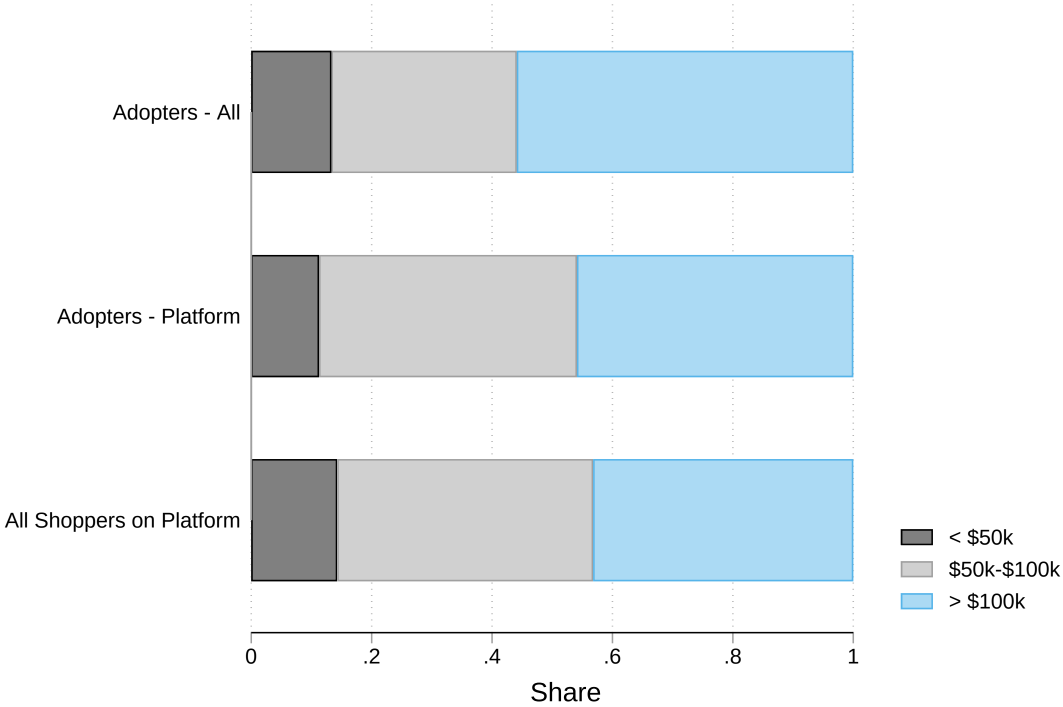
Notes: Each grey line represents a CBSA. Projects that are outside a CBSA or in CBSA with fewer than 100 total projects are placed into a distinct category by state. For example, a project located in Aspen, Colorado would be defined as "Other, CO".

Figure A.4: Potential Project Locations



Notes: Count is the total number of potential projects within a ZIP code during the full sample.

Figure A.5: Household Income Distributions - Platform Users vs. All Solar PV Adopters



Notes: The data on income distributions for off-platform solar adopters were obtained from Barbose et al. (2018). The household incomes in Barbose et al. (2018) are reported in $50k-width bins, so to make the two data sets comparable, I aggregate my income data for the platform shoppers into three income categories: "<$50k", "$50k-100k", and ">$100k". The figure displays the income distributions for three groups: (1) all solar PV adopters, (2) households that purchased a solar system through the platform, and (3) all households that used the platform, including those that did not buy a solar system.

Table A.3: Summary Statistics - Bid Characteristics

Panel A: Full Sample

	Mean	SD
Total Gross Price ($ 1000s)	25.79	(10.22)
Unit Price ($/watt)	3.57	(0.49)
System Capacity - KW	7.30	(2.88)
Premium Panel (0,1)	0.34	(0.47)
Premium Plus Panel (0,1)	0.04	(0.21)
Microinverter (0,1)	0.73	(0.44)
Installer Rating = 5 Star (0,1)	0.60	(0.49)
Installer Rating = 4.5 Star (0,1)	0.08	(0.27)
Installer Rating $\leq$ 4 Star (0,1)	0.18	(0.38)
No Ratings (0,1)	0.18	(0.38)
Experience: # of Installs (1000s)	2.40	(4.55)
Observations	37080	

Panel B: Los Angeles CBSA - 2016H1

	Selected Bid (0,1)			
	0		1	
	Mean	SD	Mean	SD
Total Gross Price ($ 1000s)	23.59	(8.83)	22.74	(7.03)
Unit Price ($/watt)	3.53	(0.29)	3.41	(0.22)
System Capacity - KW	6.72	(2.55)	6.60	(1.74)
Premium Panel (0,1)	0.54	(0.50)	0.64	(0.49)
Premium Plus Panel (0,1)	0.01	(0.10)	0.09	(0.29)
Microinverter (0,1)	0.78	(0.42)	0.86	(0.35)
Installer Rating = 5 Star (0,1)	0.67	(0.47)	0.73	(0.46)
Installer Rating = 4.5 Star (0,1)	0.01	(0.09)	0.00	(0.00)
Installer Rating $\leq$ 4 Star (0,1)	0.24	(0.42)	0.18	(0.39)
No Ratings (0,1)	0.24	(0.42)	0.18	(0.39)
Experience: # of Installs (1000s)	3.19	(3.88)	3.16	(3.83)
Observations	964			

Notes: The installer ratings and experience variables were recorded at the end of 2016 and, therefore, do not vary across auctions for a given installer.

Table A.4: Comparing On-Platform vs. Off-Platform System Attributes

	(1) ln($/watt)	(2) ln(Size)	(3) SunPower	(4) LG	(5) Microinverter
$\mathbb{1}$[Platform]	-0.152	0.00944	-0.0977	0.246	0.0818
	(0.00517)	(0.0116)	(0.0110)	(0.0168)	(0.0148)
Half Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
ZIP Code FE	Yes	Yes	Yes	Yes	Yes
N	156949	156949	156949	156949	156949
R^2	0.186	0.215	0.102	0.131	0.158

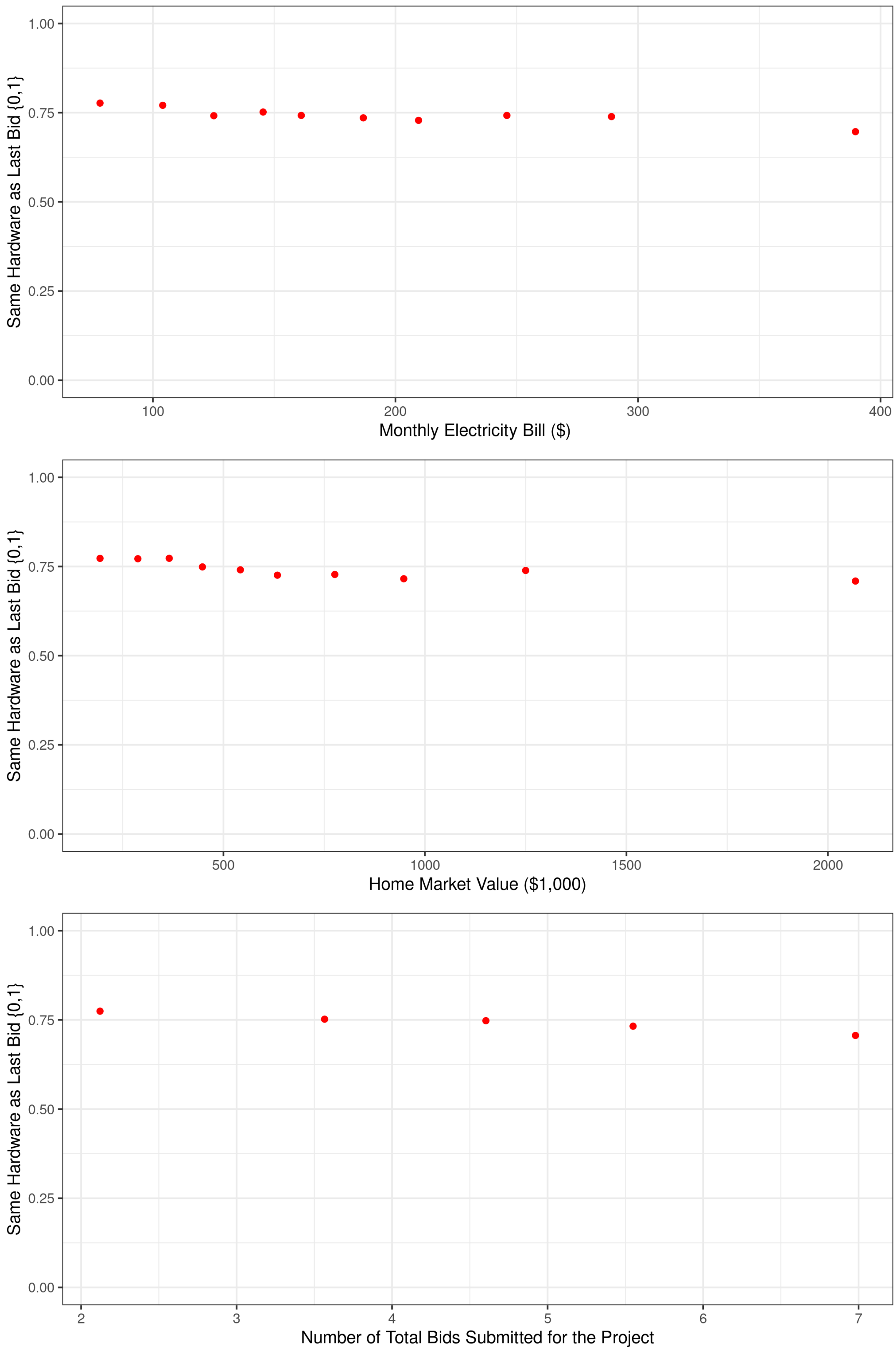
Notes: To compare system attributes of platform transactions with off-platform transactions, I append the LBNL's Tracking the Sun data with the EnergySage data for selected bids (EnergySage bids that a consumer chose). The regressions only include purchased residential systems between 2KW and 20 KW in size in both data sets. Likely, each of the EnergySage observations will also appear in the Open PV data. To deal with this issue, I use a matching procedure to pair each observation in the EnergySage data with an observation with similar observables in the Open PV data (same ZIP code, same time period, similar price, similar size) and drop the redundant observations. The dependent variable for each of the columns is (1) the logarithm of price per watt, (2) the logarithm of the system capacity in kW, (3) a dummy for whether the system manufacturer is SunPower, (4) a dummy for whether the system manufacturer is LG, and (5) dummy for whether the inverter manufacturer is either Enphase Energy or SolarEdge, respectively. Robust standard errors are in parentheses.

Table A.5: Bid Price ($/watt) and Selection Probability on Order of Bid

	(1) Bid ($/watt)	(2) Bid ($/watt)	(3) Selected Bid $\{0,1\}$	(4) Selected Bid $\{0,1\}$
Order of Bid	-0.00103	-0.000986	-0.000495	-0.000378
	(0.00148)	(0.00141)	(0.000528)	(0.000528)
Total Bids Control	Yes	Yes	Yes	Yes
System Size Control	Yes	Yes	Yes	Yes
CBSA FE	Yes	Yes	Yes	Yes
Half-Year FE	Yes	Yes	Yes	Yes
Installer FE	No	Yes	No	Yes
N	37080	37080	37080	37080
R^2	0.299	0.363	0.0111	0.0182

Notes: All standard errors listed in parenthesis are clustered by project id. Regressions control flexibly for the number of bids with a set of dummy variables indicating the total number of bids submitted for the project.

Figure A.6: Persistence of Non-Price Characteristics Across Installer Bids



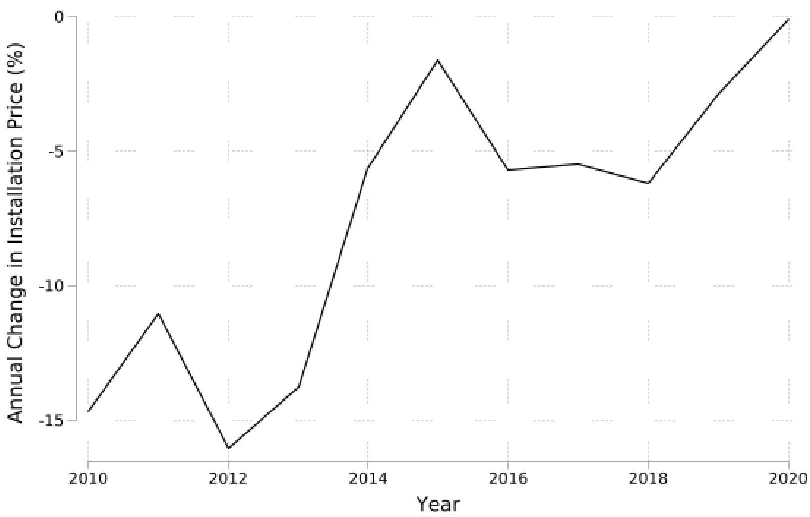
Notes: The binned scatter plots show the probability that installers bid the same non-price hardware characteristics as their most recent previous bid as a function of the household's monthly electricity bill, home value, and the total number of bids for the project.

Table A.6: Effects of Competition on Bid Prices and Proposed System Size

	Gross Price ($)	System Capacity (W)
Electric Bill ($/month)	6.066	22.40
	(0.783)	(0.803)
Home Value ($ 1000s)	0.391	0.162
	(0.153)	(0.146)
Mean # of Bids in Market	-364.9	15.11
	(32.39)	(31.68)
Mean # of Bids in Market × Electric Bill ($/month)	-0.938	-0.243
	(0.181)	(0.192)
Mean # of Bids in Market × Home Value ($ 1000s)	-0.0596	0.00773
	(0.0341)	(0.0340)
Capacity, Capacity^2 Controls	Yes	-
CBSA FE	Yes	Yes
Half-Year FE	Yes	Yes
Panel Brand FE	Yes	Yes
Inverter Brand FE	Yes	Yes
Installer FE	Yes	Yes
N	37080	37080
R^2	0.948	0.597

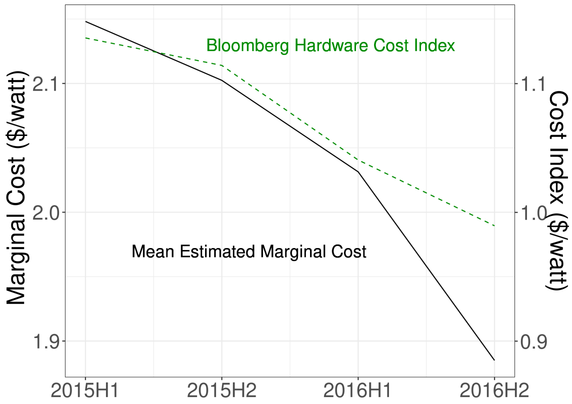
Notes: The mean number of bids in a market is defined as the average number of bids for all projects within the same CBSA and the same half-year. Household electric bill and home value variables are demeaned before running the regressions. Standard errors clustered by project are in parentheses.

Figure A.7: US Solar Installation Price Dynamics

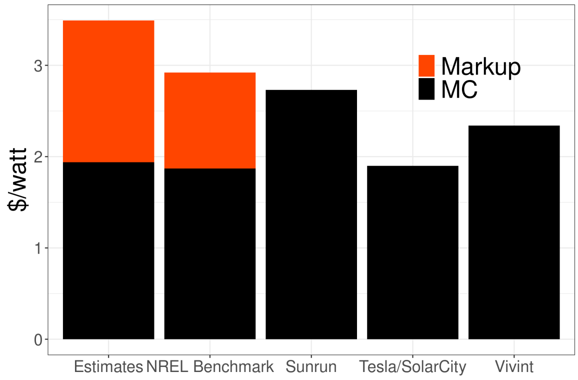


Notes: The line represents the annual percentage change in the median residential solar installation price (per watt). Figure constructed using data from Barbose et al. (2021). U.S. solar installation prices were declining at around 15% per year in the early 2010s. However, installation prices later stabilized, and by the start of this study's sample, the median installation price fell by only 2% between 2014 and 2015.

Figure A.8: Assessing Marginal Cost Estimates



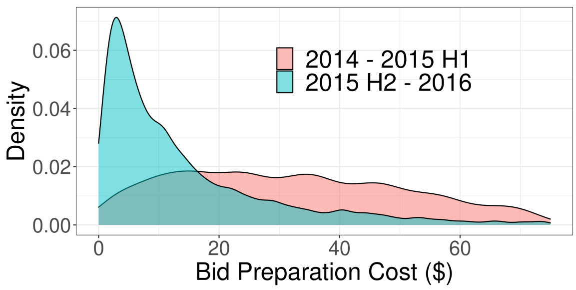
(a) Hardware Cost and MC Estimate



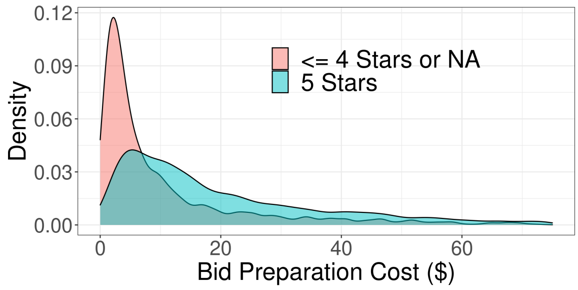
(b) MC Estimates vs. Stated Costs

Notes: Panel A.8a compares the evolution of estimated marginal costs (mean) to Bloomberg's solar PV cost index for the final two years of the sample. The Bloomberg cost index is the sum of Bloomberg's polysilicon panel cost index and Bloomberg's inverter cost index. Panel A.8b compares estimated marginal cost (mean) to NREL's 2016 cost benchmark and stated costs reported by three large publicly-trade installers (all cost estimates are from Fu et al. (2016)).

Figure A.9: Expected Entry Cost Distributions Conditional On Bidding



(a) Entry Cost Over Time



(b) Entry Cost by Seller Rating

Notes: A.9b shows density plots of the entry cost distribution across seller ratings. A.9a shows entry cost density plots for the first half vs the last half of the sample. The expected cost distributions are conditional on the seller deciding to enter a bid.

Table A.7: Entry Cost Estimates

$\boldsymbol{\mu}$		$\boldsymbol{\sigma}$	
Star Rating ≤ 4	4.347 (1.418)	Constant	4.732 (0.632)
Star Rating = 4.5	-2.819 (0.503)	Star Rating ≤ 4	3.569 (1.227)
Star Rating = 5	0.275 (0.241)	Star Rating = 4.5	-0.144 (0.480)
Installs Completed: 100-1000	0.952 (0.414)	Star Rating = 5	0.173 (0.315)
Installs Completed: >1000	1.101 (0.448)		

Installer Rating	**Mean Bid Preparation Cost**	**Share of Total Bids**
<= 4 Stars	$ 5.33	0.14
4.5 Stars	$ 13.27	0.08
5 Stars	$ 20.96	0.61
No Ratings	$ 18.62	0.16

Fixed Effects		**Pseudo Log Likelihood**
CBSA Fixed Effects in $\boldsymbol{\mu}$	Yes	-62191.95
Half-Year Fixed Effects in $\boldsymbol{\mu}$	Yes	
Permanent Installer Fixed Effects in $\boldsymbol{\mu}$	Yes	

Notes: The top panel shows several of the parameter estimates from the entry cost model. Coefficients for the CBSA fixed effects, half-year fixed effects, and permanent installer fixed effects in μ are not shown. The middle panel summarizes the expected bid preparation costs conditional on bidding. Bayesian Bootstrap standard errors (Rubin, 1981) in parentheses. Bootstrap weights for each auction are drawn according to a Dirichlet distribution with $\alpha = 1$ across 100 bootstrap samples.

Table A.8: Exit Survey - Outside Option and Off-Platform Purchases

Panel A: Exit Survey Sample Summary	
Exit survey responses from those choosing outside option	256
Survey response rate	0.11

Panel B: Off-Platform Installer Choices, Conditional on Outside Option

	Selected an Off-Platform Installer		
Already Had Off-Platform Quotes	No	Yes	All
No	159 (80.3%)	39 (19.7%)	198 (100%)
Yes	28 (48.3%)	30 (51.7%)	58 (100%)
All	187 (73%)	69 (27%)	256 (100%)

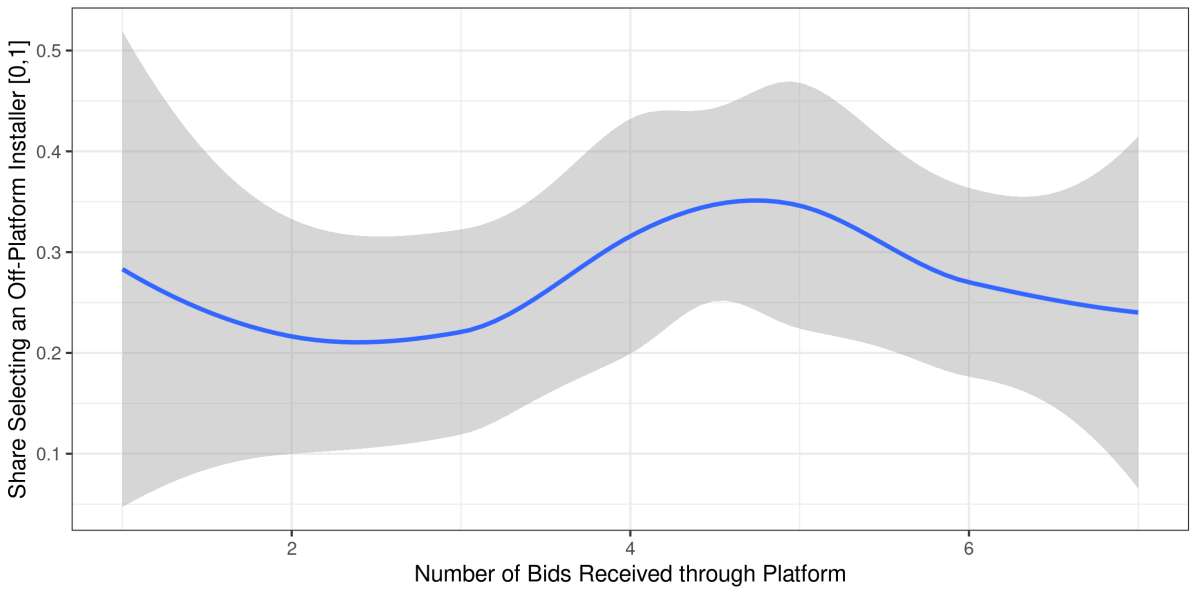
Notes: Panel A summarizes the sample size and response rate from EnergySage's exit survey. Each row indicates whether the survey respondent reported possessing external quotes when they initially created their account on EnergySage. Each column indicates whether each respondent reported using an offline installer conditional on selecting the outside option. Within each cell, the first number represents the number of respondents, and the second number in parentheses is the percentage share (summed across rows).

Table A.9: Selection into Exit Survey Participation

	Responded to Exit Survey {0,1}			
	(1)	(2)	(3)	(4)
(Intercept)	0.0306	0.0260		
	(0.0187)	(0.0234)		
Has Off-Platform Quotes {0,1}	0.0538	0.0532	0.0688	0.0668
	(0.0235)	(0.0239)	(0.0236)	(0.0238)
Home Market Value - Quartile 2 {0,1}	0.0276	0.0269	0.0468	0.0410
	(0.0202)	(0.0204)	(0.0225)	(0.0228)
Home Market Value - Quartile 3 {0,1}	0.0453	0.0443	0.0742	0.0692
	(0.0215)	(0.0218)	(0.0279)	(0.0279)
Home Market Value - Quartile 4 {0,1}	0.0706	0.0702	0.0846	0.0807
	(0.0248)	(0.0248)	(0.0324)	(0.0324)
Electric Bill - Quartile 2 {0,1}	0.0286	0.0278	0.0336	0.0281
	(0.0237)	(0.0239)	(0.0244)	(0.0245)
Electric Bill - Quartile 3 {0,1}	0.0273	0.0267	0.0318	0.0284
	(0.0222)	(0.0225)	(0.0225)	(0.0225)
Electric Bill - Quartile 4 {0,1}	0.0199	0.0192	0.0324	0.0276
	(0.0216)	(0.0218)	(0.0226)	(0.0228)
Number of Bids Recieved on Platform		0.0012		0.0112
		(0.0042)		(0.0049)
R^2	0.01326	0.01331	0.05355	0.05690
Observations	1,315	1,315	1,315	1,315
CBSA fixed effects			✓	✓
Half-Year fixed effects			✓	✓

Notes: The sample includes households invited to complete the EnergySage exit survey. The dependent variable is an indicator of whether the household completed the survey. Robust standard errors are in parentheses.

Figure A.10: Off-platform Installer Choice and Number of Bids Received through the Platform



Notes: The sample includes households that selected the outside option and completed the EnergySage exit survey. The y-axis is the share of households that purchased from an off-platform installer. The x-axis shows the number of bids the household received through the EnergySage platform. The line is constructed with a loess smoother, and the shaded area represents the 95% confidence interval.

Table A.10: Exit Survey - Number of Bids Received and Purchase from Off-Platform Installers

	Selected an Off-Platform Installer {0,1}			
	(1)	(2)	(3)	(4)
(Intercept)	0.2149			
	(0.0760)			
Has Off-Platform Quotes {0,1}	0.3211	0.3138	0.3147	0.3164
	(0.0719)	(0.0804)	(0.0822)	(0.0817)
Number of Bids Recieved on Platform	-0.0040	0.0116	0.0163	0.0939
	(0.0152)	(0.0210)	(0.0220)	(0.0794)
(Number of Bids Recieved on Platform)^2				-0.0081
				(0.0073)
R^2	0.09153	0.28027	0.29334	0.29794
Observations	256	256	256	256
CBSA fixed effects		✓	✓	✓
Half-Year fixed effects			✓	✓

Notes: The sample includes households that selected the outside option and completed the EnergySage exit survey. The dependent variable is an indicator of whether the household purchased from an off-platform installer. Covariates include a dummy for whether the household held off-platform quotes when they initially created their EnergySage account and the number of bids the household received through the EnergySage platform. Robust standard errors are in parentheses.

Table A.11: On-Platform Welfare Gains from ITC by CBSA

Panel A: CBSAs with Largest Welfare Gain Per Subsidy Expenditure (On Platform)

CBSA	Welfare Gain / Subsidy Cost
Other, TX	0.71
Phoenix-Mesa-Scottsdale, AZ	0.64
Denver-Aurora-Lakewood, CO	0.58
Tucson, AZ	0.58
Dallas-Plano-Irving, TX	0.57

Panel B: CBSAs with Smallest Welfare Gain Per Subsidy Expenditure (On Platform)

CBSA	Welfare Gain / Subsidy Cost
Providence-Warwick, RI-MA	0.22
Other, CT	0.24
Boston, MA	0.25
Other, MA	0.26
Bridgeport-Stamford-Norwalk, CT	0.27

Notes: The top panel shows the mean welfare gain among platform participants in dollars from the ITC subsidy (compared to no ITC counterfactual assuming 100% pass-through rate off of the platform) for the top 5 CBSAs and the bottom panel shows the five CSBAs with the lowest welfare gain among platform participants from the ITC. The welfare estimates do not include the external benefits or the subsidy costs associated with off-platform transactions.

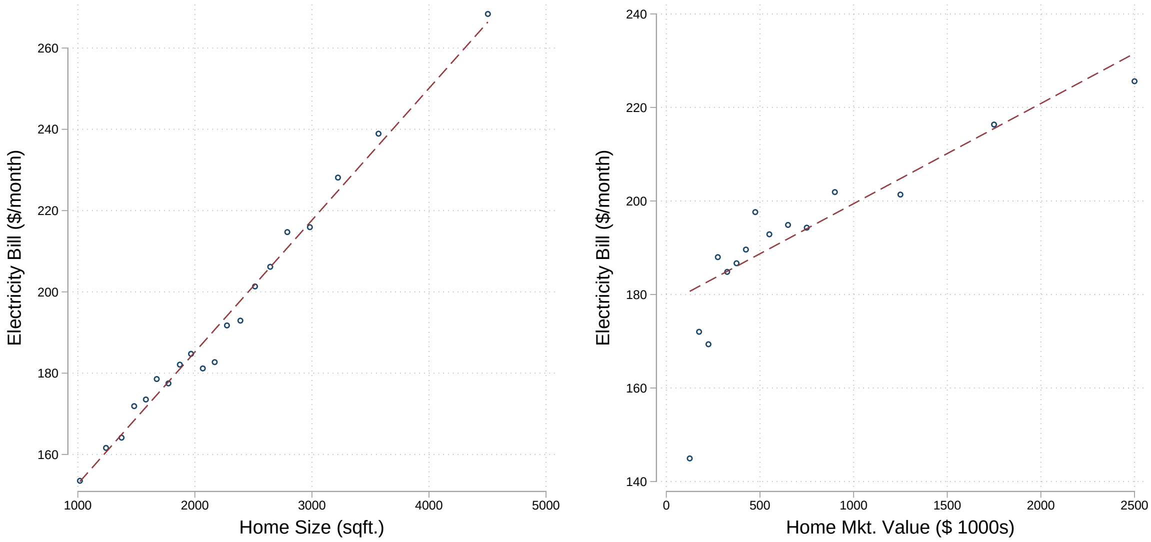
B Sample Construction

As demographic data were not collected directly by EnergySage, household data from Acxiom's Infobase were appended by Infinite Media, Inc. Infinite Media successfully appended demographic information for over 80% of the EnergySage households. I drop all households without a complete set of demographic variables and all projects where a lease agreement was selected. I drop these projects because comparing per-watt prices for leases vs. purchases is not straightforward. Furthermore, these projects compose less than 4% of the choices, and thus, discluding them is unlikely to have significant effects on the analysis. I also drop a handful of other observations that appeared to either be miscoded or outliers. In particular, I drop projects with system capacities (mean across bid proposals) under 3 kW and over 15 kW and drop price quotes under $2/watt or over $7/watt. I also drop households that reported monthly electric bills under $50 or over $500. Finally, I drop projects with a home market valuation below $100,000.

Additionally, I merge each project with environmental benefits estimates from Sexton et al. (2021) by ZIP code. Sexton et al. (2021) calculate the annual pollution damages avoided in dollars per kilowatt of residential solar capacity for each ZIP code. I scale the pollution damage estimate by the capacity of the system and assume a 20-year system life span with a 5% annual discount rate to determine the net present value of environmental damages avoided.

The Acxiom Infobase data contain two types of information about the households: (1) data on the home itself, such as the age of the structure, the square footage, the home's market valuation, and the house's primary roofing material, (2) information about the head of the household such as age, race, and whether they have a college degree. To verify the precision of the data merge, Figure B.1 plots a binned scatter plot of the home square footage from the Infinite Media consumer data against the monthly electricity expenditure reported by households directly to the platform. The figure shows that the variables from each data set are very highly correlated in the way that we would expect.

Figure B.1: Correlation of Variables from Different Data Sources



Notes: The binned scatter plots project the average monthly electricity bill as reported by consumers directly through the EnergySage website on the y-axis. Home square footage and home market value from Infinite Media, Inc. are plotted on the x-axis. Infinite Media, Inc. reports the home market value as a range of values for each household, and the middle value of the range is used.

C Descriptive Evidence: Selection & Price Discrimination

In this appendix section, I present several descriptive results about sellers' participation and bid prices that motivate the structural model.

There are a few mechanisms by which platforms could facilitate increases in solar PV adoption and improve consumer welfare. First, the availability of the platform could change the number of bids obtained by each household. An increase in the number of bids could increase solar adoption rates if sellers are differentiated in cost or quality. If sellers have heterogeneous costs, then more bids equate to giving each household more cost draws and consequently a lower expected minimum bid price even if sellers' pricing strategy is held fixed. Similarly, if sellers are vertically or horizontally differentiated, then more bids per project could lead to more solar purchases by linking buyers to higher quality or better-matched sellers. Seller quality could vary due to ratings, reviews, experience, warranties, and other service offerings. Additionally, a change in the number of bidders will change each firm's optimal pricing strategy. Thus, the equilibrium effects of the platform on prices, solar adoption, and consumer welfare hinges not only on how many sellers are registered for the platform but also on how sellers choose projects to bid on and how sellers set prices.

Figures C.1a and C.2a illustrate the variation in auction participation across two important household characteristics: home market valuation and monthly electricity expenditure. Figure C.1a depicts a binned scatter plot with the home market valuation on the x-axis and the mean number of bids obtained in each bin on the y-axis, as well as a quadratic fit line. We see that homes with higher market valuations attract more bids through the platform. Sellers bid 30% more frequently on homes valued over \$1 million compared to homes worth under \$300,000. In Figure C.2a we see an analogous pattern with electricity expenditure, households with monthly bills below \$100 get fewer than three bids on average, relative to nearly four bids for households with bills above \$300/month.

Figure C.1b (and C.2b) reveals disparities in the bid prices across households. The figure plots a binned scatter plot with the total installation price (before tax credits) on the y-axis. The total installation price for each observation is linearly adjusted for capacity (kW) and the time that the project originates (half year) so that each observation is more comparable.

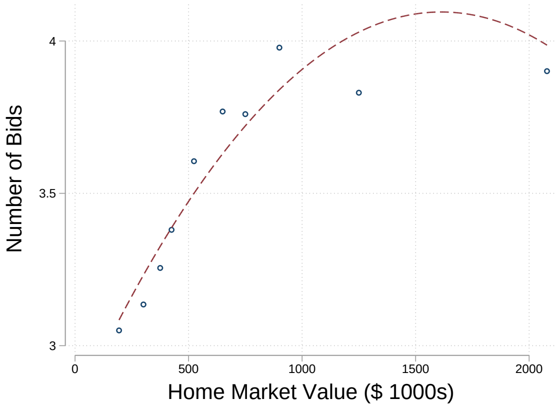
Therefore, the standardized prices should be interpreted as a bid price for a mean-sized system in the first half of 2016 (H1). We see that households with more expensive homes (and those with higher electricity bills, see C.2b) receive higher size-adjusted bid prices. These higher prices are despite the fact that these projects are more competitive on average, as shown in C.1a. These pricing disparities could be linked to systematic differences in costs (e.g., areas with more expensive homes face higher labor costs) or that installers are bidding higher prices to households that are likely to be more inelastic.

Figures C.1c and C.2c further investigate bid price differences across households. Figure C.1c, again, plots the relationship between bid prices and home market valuation but plots the relationship separately across markets with varying degrees of competition. I define a market as a CBSA-half-year. I then separate households into four categories based on the market in which they are located: markets with under 2 bids per project on average, markets with 2-3 bids, markets with 3-5 bids, and markets with over 5 bids on average. There are several notable patterns. Unsurprisingly, we see that bid prices made in more competitive markets are systematically lower across all home values. This relationship is also consistent with the correlation shown in Figure A.3 that bid prices fall over time as bidding competition increases. However, we see that the relationship between home valuation and bid prices changes with competition. In less competitive markets—those with fewer than three bids per project—there is a large increase in bid prices associated with both higher home values and higher electricity bills. In contrast, we see that bid prices are relatively constant across home valuations and energy bills in more competitive markets with more than three bids per project. An implication of these patterns is that more bidding competition is associated with a large reduction in bid prices for households with expensive homes or high electricity expenditures. These patterns in the data are also supported by the first column of Appendix Table A.6, which shows the results of a fixed effects regression of bid prices on the mean number of bids in the household's market, as well as interactions of the mean number of bids with household electricity expenditure and home valuation.

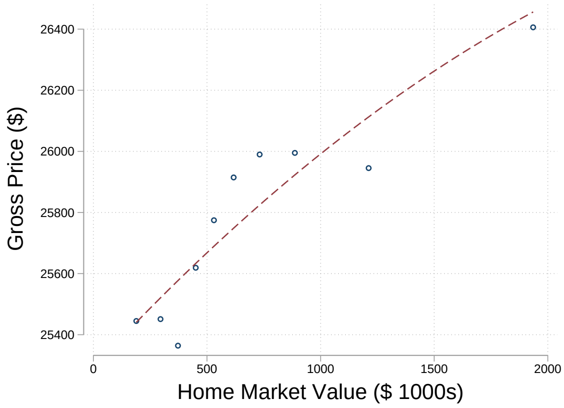
A plausible explanation of the heterogeneous relationship between competition and bid prices in Figure C.1c is differences in buyers' price-elasticities. For instance, if households with lower home valuations are more price sensitive, then sellers' optimal markups will be relatively lower if they are bidding against few or no competitors. In particular, if households are more price-sensitive then a higher bid by a monopolist or a duopolist will be more likely to be rejected by the buyer.

If home valuation and price elasticity are indeed negatively related, then the relative consumer welfare effects of the platform are ambiguous. On the one hand, wealthier households, in terms of home valuation, attract more bids (Figure C.1a) and larger bid price reductions from the added competition (Figure C.1c). However, if wealthy households are relatively less price sensitive (i.e., they value one dollar price reduction less than a low-income household), then they may obtain a relatively smaller consumer surplus gain compared to low-income households from using the platform despite obtaining a larger price reduction. Moreover, the relative consumer welfare effects of the platform will depend on whether a particular consumer group is marginal or infra-marginal with respect to the price change.

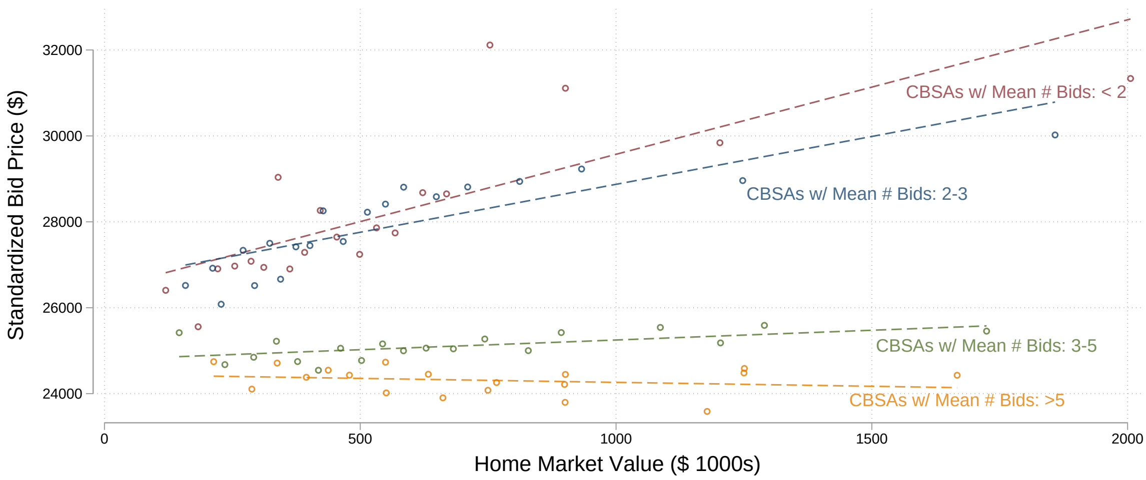
Figure C.1: Auction Participation and Pricing by Home Market Value



(a) # of Bids by Home Value



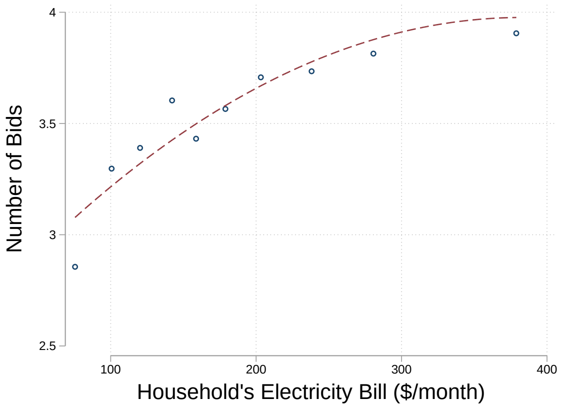
(b) Bid Prices by Home Value

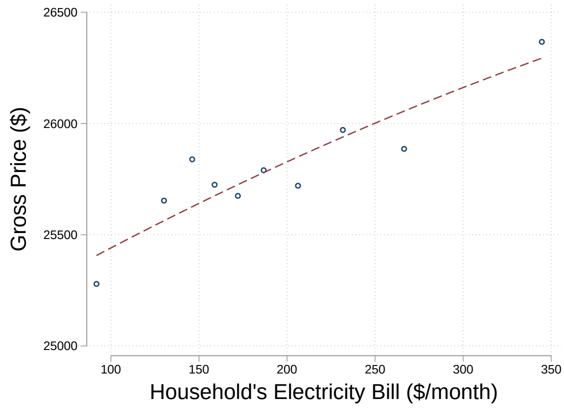


(c) Prices, Home Value, Mean Bids in CBSA

Notes: Panels B and C linearly adjust the prices for the capacity (kW) and the time (half year) the project occurred before plotting. In panel C, the mean bids in the market is the average number of bids across all projects within the same CBSA and the same half year.

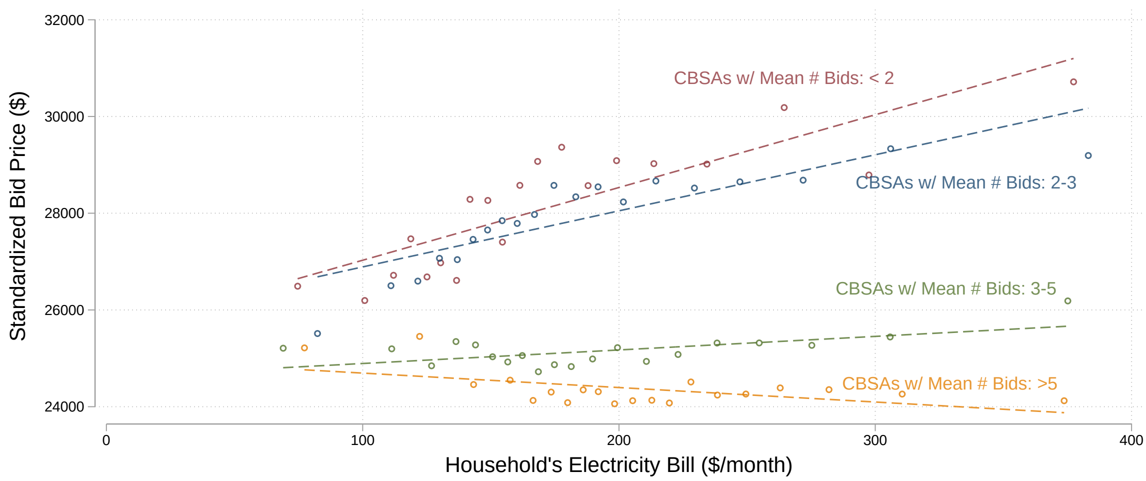
Figure C.2: Auction Participation and Pricing By Electricity Expenditure





(a) # of Bids by Elec. Bill

(b) Bid Prices by Elec. Bill



(c) Prices, Elec. Bill, Mean Bids in CBSA

Notes: Panels B, and C linearly adjust the prices for the size (kW) of the system size and the time (half year) the project occurred before plotting. In panel C, the mean bids in the market is the average number of bids across all projects within the same CBSA and the same half year.

D Demand Robustness Checks

Table D.1 investigates the robustness of the key coefficient estimates to adding a series of potential confounding variables into the utility specification. The baseline specification controls for star-rating and installer experience, as well as seller fixed effects for permanent sellers. A potential concern is that the star rating, experience, and even the seller fixed effects are imperfect controls if quality varies over time. For instance, star ratings can change as installers bid more and complete more projects through the platform. Column 2 of Table D.1 shows that both the price and nesting coefficients are robust to adding controls for the amount of time each installer has been active on the platform. In Column 3, I consider a utility specification with a full set of panel brand fixed effects in lieu of the more parsimonious controls for "premium" and "premium plus" rated panels. The key coefficients remain nearly unchanged after adding these additional hardware brand controls. In Column 4, I include additional household demographic variables that could be correlated with both prices and willingness to pay for solar. Namely, I include a control for whether the household head has a college degree, fixed effects for the race of the household head, and a dummy for if the household head is over 65 years old. The price coefficients are very similar after adding these demographic controls. Finally, the bid prices and the number of bids could both be correlated with factors that influence the viability of the specific rooftop. The age of the house, the size of the house, and the house's roofing material may affect the difficulty and cost of an installation, so I include a set of controls for the physical size of the house (square feet), the age of the house (years since built), and the house's primary roofing material. In particular, I add fixed effects for each home size quartile, fixed effects for each house age quartile, and fixed effects for the primary type of roofing material (Table G.2). The parameters and the implied price elasticities are again robust to these changes. For transparency, Table D.2 also shows how the estimates change if some of the installer attributes and household demographic variables are omitted from the utility specification.

It is conceivable that prices are correlated with other unobserved household characteristics that are also correlated with preferences; although these characteristics would need to be observable by the sellers through the platform, but at the same time, not collected and reported in Acxiom InfoBase's household marketing research database.

Another key assumption of the demand model is that the buyer's choice can be expressed as a function of utility per unit capacity. Effectively, this assumption abstracts away from the buyer's system capacity choice. This assumption could be problematic if buyers' choice is influenced by the proposed system capacity that each installer offers. For example, if buyers prefer bids for smaller systems and system capacity is correlated with price per watt due to installation economies of scale, then the price coefficients will be biased. In the second column of Table D.3, I add an explicit control for each installer's proposed system capacity as a non-price attribute in utility. The price coefficients are almost invariant to this change, suggesting the system capacity assumption is not consequential for the demand estimates.[32] In the third column, I consider an alternate functional form for buyers' utility function. Hanemann (1984) shows that if a buyer makes a discrete choice followed by a continuous choice, then the utility can be written as a function of the logarithm of price. The intuition is that the buyer should only care about the ratio of price to quality when choosing a product. Taking a log transformation leads to a linear utility function with a logged price term. I find the log-price specification leads to demand estimates that are slightly more elastic than the baseline model. However, I also find that the baseline model with linear prices better fits the data than the log-price model.

As a final robustness check, I re-estimated the demand model after removing auctions located in New York and Connecticut, the two states that offered time-varying subsidies during the sample period. Any state or municipal subsidies that are fixed over time are controlled for with the CBSA fixed effects in the baseline utility specification, however, time-varying subsidies could bias the estimated price elasticities if consumers are forward-looking. Table D.4 shows that removing Connecticut and New York does not substantially change the demand estimates. Removing these two states leads to slightly higher implied elasticities and a correspondingly lower mean markup of \$1.45/watt compared to \$1.59/watt estimated from the full sample.

[32]In other specifications not shown here, I find that adding the system capacity variable to utility has a large effect on the price coefficient if I also omit controls for household electricity expenditure.

Table D.1: Alternate Model Specifications - Adding Controls

	(1) - Base	(2)	(3)	(4)	(5)
λ	0.37 (0.06)	0.37 (0.06)	0.37 (0.06)	0.38 (0.06)	0.37 (0.06)
β - Price	-0.72	-0.72	-0.71	-0.71	-0.71
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
β - Price $\times$ Home Mkt. Value Q2	0.07 (0.04)	0.07 (0.04)	0.07 (0.04)	0.06 (0.04)	0.06 (0.05)
β - Price $\times$ Home Mkt. Value Q3	0.08 (0.05)	0.08 (0.05)	0.08 (0.05)	0.07 (0.05)	0.06 (0.06)
β - Price $\times$ Home Mkt. Value Q4	0.09 (0.06)	0.09 (0.06)	0.09 (0.06)	0.07 (0.06)	0.07 (0.07)
Mean Own-Price Elasticity	-2.27	-2.27	-2.26	-2.30	-2.29
Mean Markup ($/watt)	1.59	1.59	1.60	1.57	1.58
Log Likelihood	-3823.54	-3821.79	-3819.75	-3820.02	-3821.43
Installer Attributes					
Fixed Effects for Permanent Installers	Y	Y	Y	Y	Y
Installer Rating and Exper. Controls	Y	Y	Y	Y	Y
Experience/Time on Platform Controls	N	Y	N	N	N
Non-Price Bid Attributes					
Hardware Quality Controls	Y	Y	N	Y	Y
Panel Brand Fixed Effects	N	N	Y	N	N
Project Attributes $\times$ Inside Good					
Electric Bill Quartile Fixed Effects	Y	Y	Y	Y	Y
CBSA Fixed Effects	Y	Y	Y	Y	Y
Half-Year Fixed Effects	Y	Y	Y	Y	Y
Off-Platform Quote Fixed Effect	Y	Y	Y	Y	Y
Bachelor's Degree Fixed Effect	N	N	N	Y	N
Race Fixed Effects	N	N	N	Y	N
Over Age 65 Fixed Effect	N	N	N	Y	N
Home Sq. Footage Quartile Fixed Effects	N	N	N	N	Y
Home Age Quartile Fixed Effects	N	N	N	N	Y

Notes: The top panel displays the nesting parameter and price coefficients for the base model and alternate demand specifications. Standard errors are in parentheses. The middle panel shows the mean own-price elasticity and mean implied markup across all bids in the data. The bottom panel indicates which additional controls are included in utility. All models include fixed effects for all "permanent" installers, defined as any installer that submitted over 300 bids during the sample. All models include dummies for installers' star rating in 2016 and overall residential installation experience. The second model includes two dummies that indicate if the installer had 1) been bidding on EnergySage for at least 6 months, and 2) been bidding on EnergySage for over a year at the time the bid was submitted. All models include a microinverter dummy to control for hardware quality. Models 1,2,4, and 5 include dummies for "premium" and "premium plus" panel brands. The third model includes panel-brand dummies for the seven largest panel manufacturers. The fourth model includes additional demographic control variables such as the education, race, and age of the household head. The fourth model also controls for the home square footage quartile. All models include electric bill quartile fixed effects, CBSA fixed effects, and half-year fixed effects. All variables listed under *Project Attributes* are interacted with the "inside good". The fifth model interacts price with a dummy for whether the potential buyer stated that they already had quotes from another installer off of the platform. Standard errors are in parentheses.

Table D.2: Alternate Model Specifications - Removing Controls

	(1) - Base	(2)	(3)	(4)	(5)
λ	0.37 (0.06)	0.34 (0.06)	0.39 (0.06)	0.41 (0.06)	0.44 (0.06)
β - Price	-0.72 (0.11)	-0.71 (0.11)	-0.83 (0.11)	-0.59 (0.1)	-0.57 (0.09)
β - Price $\times$ Home Mkt. Value Q2	0.07 (0.04)	0.07 (0.04)	0.07 (0.04)		
β - Price $\times$ Home Mkt. Value Q3	0.08 (0.05)	0.09 (0.05)	0.08 (0.05)		
β - Price $\times$ Home Mkt. Value Q4	0.09 (0.06)	0.1 (0.06)	0.1 (0.06)		
Mean Own-Price Elasticity	-2.27	-2.14	-2.71	-2.16	-2.15
Mean Markup ($/watt)	1.59	1.68	1.33	1.67	1.68
Log Likelihood	-3823.54	-3840.94	-3887.81	-3849.38	-3867.63
Installer Attributes					
Fixed Effects for Permanent Installers	Y	Y	N	Y	Y
Installer Rating and Exper. Controls	Y	N	Y	Y	Y
Non-Price Bid Attributes					
Hardware Quality Controls	Y	Y	Y	Y	Y
Project Attributes $\times$ Inside Good					
Electric Bill Quartile Fixed Effects	Y	Y	Y	N	N
CBSA Fixed Effects	Y	Y	Y	Y	N
State Fixed Effects	N	N	N	N	Y
Half-Year Fixed Effects	Y	Y	Y	Y	Y
Off-Platform Quote Fixed Effect	Y	Y	Y	Y	Y

Notes: The top panel displays the nesting parameter and price coefficients for the base model and alternate demand specifications. Standard errors are in parentheses. The middle panel shows the mean own-price elasticity and mean implied markup across all bids in the data. The bottom panel indicates which additional controls are included in utility. Models 1, 4, and 5 include dummies for installers' star rating in 2016 and overall residential installation experience: one dummy indicates the installer has completed over 100 installs, and another dummy indicates over 1000 installs completed. Models 1, 2, 4, and 5 include fixed effects for all "permanent" installers, defined as any installer that submitted over 300 bids during the sample. All models include dummies for microinverter, "premium panel brand," and "premium plus panel brand" to control for hardware quality. Some models include electric bill quartile fixed effects, CBSA fixed effects, state fixed effects, and half-year fixed effects. All variables listed under *Project Attributes* are interacted with the "inside good". Standard errors are in parentheses.

Table D.3: Alternate Model Specifications - Functional Form and System Capacity Choice

	(1) - Base	(2)	(3)
λ	0.37	0.37	0.37
	(0.06)	(0.06)	(0.06)
β - Price	-0.72	-0.72	-1.92
	(0.11)	(0.11)	(0.29)
β - Price $\times$ Home Mkt. Value Q2	0.07	0.07	0.18
	(0.04)	(0.04)	(0.12)
β - Price $\times$ Home Mkt. Value Q3	0.08	0.08	0.2 (0.14)
	(0.05)	(0.05)	
β - Price $\times$ Home Mkt. Value Q4	0.09	0.09	0.23
	(0.06)	(0.06)	(0.16)
Mean Own-Price Elasticity	-2.27	-2.30	-2.44
Mean Markup ($/watt)	1.59	1.57	1.48
Log Likelihood	-3823.54	-3823.50	-3823.52
Price Variable	$/watt	$/watt	ln($/watt)
Seller Proposed System Capacity Control (W)	N	Y	N
Installer Attributes			
Fixed Effects for Permanent Installers	Y	Y	Y
Installer Rating and Exper. Controls	Y	Y	Y
Non-Price Bid Attributes			
Hardware Quality Controls	Y	Y	Y
Project Attributes $\times$ Inside Good			
Electric Bill Quartile Fixed Effects	Y	Y	Y
CBSA Fixed Effects	Y	Y	Y
Half-Year Fixed Effects	Y	Y	Y
Off-Platform Quote Fixed Effect	Y	Y	Y

Notes: The first column presents the baseline utility estimates with the price variable measured linearly in $/watt. The second column allows each seller's proposed system capacity (W) to enter as a non-price attribute in the buyer utility function. The final column estimates a demand with the natural logarithm of unit price entering utility. Standard errors are in parentheses.

Table D.4: Alternate Model Specifications - Drop States with Time-Varying Subsidies

	(1) - Base	(2)
λ	0.37 (0.06)	0.38 (0.07)
β - Price	-0.72 (0.11)	-0.78 (0.14)
β - Price $\times$ Home Mkt. Value Q2	0.07 (0.04)	0.06 (0.06)
β - Price $\times$ Home Mkt. Value Q3	0.08 (0.05)	0.08 (0.06)
β - Price $\times$ Home Mkt. Value Q4	0.09 (0.06)	0.1 (0.07)
Mean Own-Price Elasticity	-2.27	-2.47
Mean Markup ($/watt)	1.59	1.45
Log Likelihood	-3823.54	-3009.82
Sample	Full	Drop NY & CT
Installer Attributes		
Fixed Effects for Permanent Installers	Y	Y
Installer Rating and Exper. Controls	Y	Y
Non-Price Bid Attributes		
Hardware Quality Controls	Y	Y
Project Attributes $\times$ Inside Good		
Electric Bill Quartile Fixed Effects	Y	Y
CBSA Fixed Effects	Y	Y
Half-Year Fixed Effects	Y	Y
Off-Platform Quote Fixed Effect	Y	Y

Notes: The first column presents the baseline utility estimates. The second column shows estimates of the equivalent model but drops all auctions in New York and Connecticut. New York and Connecticut had changes in solar incentives during the sample period.

E Model of Entry

Much of the recent empirical auction literature has endogenized agents' decisions to participate in auctions in addition to the bid pricing problem. Empirical work has primarily focused on estimating one of two different models of entry behavior based on either Levin and Smith (1994) or Samuelson (1985). In the Levin and Smith (1994) model, agents must pay an entry cost in order to learn their private costs (values). Whereas in the Samuelson (1985) model, agents have to pay an entry cost to participate but their private costs are perfectly known prior to entry. A distinctive feature of the Samuelson (1985) model is that entry is *selective* in the sense that the entry game defines a threshold cost level under which bidders will enter. Both models also imply a different interpretation of the entry cost. Under selective entry, the entry cost only includes the costs associated with the bid preparation process (e.g., filling out documents and forms) while under non-selective entry (Levin and Smith, 1994), the entry cost also includes costs associated with information acquisition (e.g., researching the characteristics of the buyer and determining specifications of the work to be completed).

While many previous papers have imposed one of the two models of entry ex-ante, there are a few papers that explicitly test between the two competing models of entry in the context of traditional auctions (Li and Zheng, 2012; Marmer et al., 2013; Roberts and Sweeting, 2013). In Marmer et al. (2013), the authors propose the use of variation in the number of potential bidders, $\mathcal{N}$. Let $Q^*(\tau|\mathcal{N})$ be the τ-th quantile of active bidders' marginal cost conditional on $\mathcal{N}$. The authors show that, in the selective entry model (Samuelson, 1985), the selection effect manifests itself as the effect of $\mathcal{N}$ on $Q^*(\tau|\mathcal{N})$: in the face of greater potential competition, some potential entrants, who may be less efficient in the auction, will choose not to enter, and accordingly, the quantiles of those who do enter decrease: $Q^*(\tau|\mathcal{N}') \leq Q^*(\tau|\mathcal{N})$ for $\mathcal{N}' > \mathcal{N}$. The authors show that the inequality is strict in the (Samuelson, 1985) model, while $Q^*(\tau|\mathcal{N})$ does not depend on $\mathcal{N}$ in the (Levin and Smith, 1994) model so that there is no selection effect.

Unfortunately, the test from Marmer et al. (2013) cannot be directly applied in the context of multi-attribute auctions with heterogeneous bidders. In the first-price auction setting with selective entry considered by Marmer et al. (2013), potential bidders will participate in an auction if their private cost is below a certain threshold. However, in the multi-attribute auction setting, the allocation rule depends on other variables in addition to bid prices, so firms' entry decisions will be a function of non-price characteristics in addition to their marginal cost. Therefore, the entry cutoff threshold for a given auction will vary across seller types. For example, higher-quality sellers (as perceived by buyers) may have a higher cost threshold for entry relative to lower-quality sellers.

Therefore, I modify the test from Marmer et al. (2013) to test for selective entry in the multi-attribute auction setting. The original test developed by Marmer et al. (2013) compares the marginal costs across auctions with varying numbers of potential entrants, assuming all bidders are homogeneous.[33] If marginal costs decrease as the number of potential bidders increases, this provides evidence in favor of the selective entry model (Samuelson, 1985). However, in the multi-attribute setting, the marginal cost estimates should be compared across auctions with varying numbers of entrants while holding seller characteristics fixed. Therefore, I leverage the fact that many sellers submit bids in multiple markets and over time. Specifically, I estimate a regression of the estimated marginal cost for each bid on the number of potential bidders in the auction, controlling for installer fixed effects.[34] For these regressions, I restrict attention to permanent sellers that submit over 300 total bids. The estimated marginal costs (discussed in Section 3), are recovered based on the assumption of optimal price bidding conditional on entry but do not impose any restrictions on firms' entry behavior.[35] Importantly, the regression with installer fixed effects controls for differences in seller quality which could affect the marginal cost thresholds in which firms are willing to enter an auction. If selective entry occurs, we would expect installers' marginal costs (for bids they do submit) to be lower for projects that have more potential entrants. One challenge to identification is that the variation in the number of potential entrants is growing over time and marginal costs are also falling systematically over time due to technological improvement in solar PV

[33]Where the estimates of marginal cost are recovered from bid price data based on the assumption of optimal bidding conditional on entry.

[34]Recall that the number of potential entrants for a project is defined as the total number of sellers that submit at least one bid for projects of that same type.

[35]I simulate competition in the cost estimation step by estimating non-parametric entry probabilities for each project-seller type pair.

manufacturing. Therefore I also include time period fixed effects in the regression to control for changes in hardware input costs over time. Another concern is that markets with more potential entrants may have systematically different labor or materials costs. To address this concern, I also run an additional specification including CBSA fixed effects. The identifying assumption in this "triple-difference" style regression model is that changes in the number of potential entrants must be uncorrelated with shocks to installers' market-specific cost trends that are caused by other factors apart from the number of potential entrants. Finally, I run a third specification that adds controls for all other variables that enter the baseline model that could be correlated with the number of potential entrants and also related to marginal costs, these include electricity bill quartile fixed effects, home market value quartile fixed effects, and controls for the quality of the panels and the inverter associated with each bid.

The regression results from all three specifications displayed in Table E.1 indicate that a one-unit increase in the number of potential entrants has a negligible impact on marginal costs. If selective entry occurs we would expect that marginal costs would fall as the number of potential entrants rises. However, the point estimates are close to zero and even slightly positive which is inconsistent with the Samuelson (1985) model of selective entry. An increasing relationship between potential entrants and costs is not predicted by either the Samuelson (1985) model or the Levin and Smith (1994) model. The Levin and Smith (1994) model predicts that marginal costs should be invariant to the number of potential entrants.

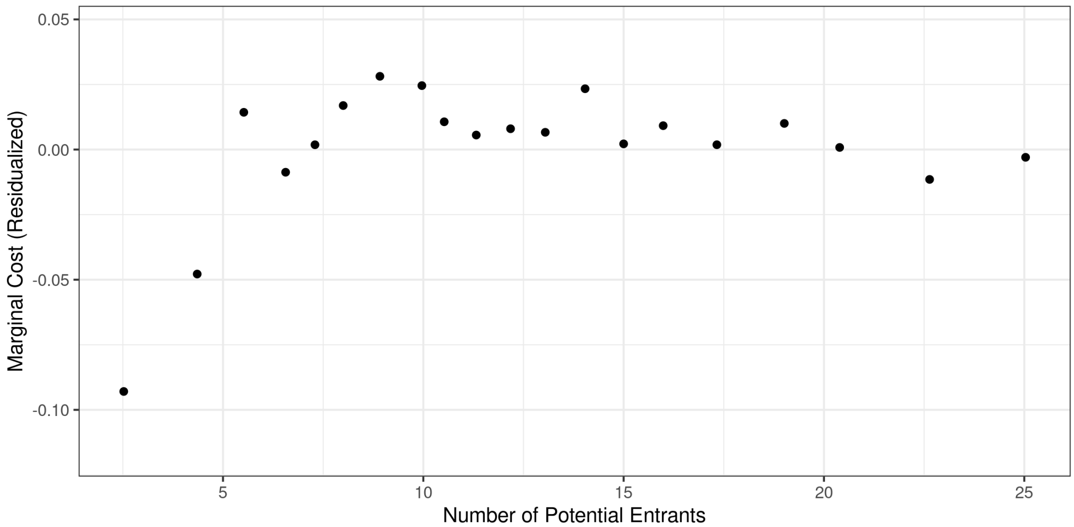
Table E.1: Testing for Selection into Entry

	Dependent variable:		
	Marginal Cost ($/watt)		
Number of Potential Entrants	0.006	0.003	0.004
	(0.0005)	(0.001)	(0.001)
Installer Fixed Effects	Yes	Yes	Yes
Half-Year Fixed Effects	Yes	Yes	Yes
CBSA Fixed Effects	No	Yes	Yes
Hardware Quality Controls	No	No	Yes
Home Value Quartile Fixed Effects	No	No	Yes
Electricty Bill Quartile Fixed Effects	No	No	Yes
Observations	23,197	23,197	23,197
R^2	0.392	0.425	0.495

Notes: The dependent variable is the estimated marginal cost in dollars per watt implied by the model in Section 3. Regressions only include bids from permanent installers that made over 100 bids and won at least one auction during the sample period. The number of potential entrants is defined by the number of sellers that submitted at least one bid for auctions of the same project type. Robust standard errors are included in parentheses.

To further investigate why marginal cost might be increasing slightly with the number of potential entrants, I run a regression equivalent to Column 3 of Table E.1 but excluding the number of potential entrants, and then create a binned scatter plot of the residuals as a function of the number of potential entrants. This plot is shown in Figure E.1. We see that the relationship between the marginal cost residuals and the number of potential entrants is essentially flat along the vast majority of the support. However, there are a few outlier observations with substantially negative marginal cost residuals for auctions with a very low number of potential entrants. In most cases, these represent markets towards the very beginning of the sample when installers and buyers were just starting to use the platform. Together, Table E.1 and Figure E.1 do not provide evidence in favor of a selective model of entry as we do not see a negative relationship between the number of potential entrants and marginal costs. In contrast, the relationship seems quite flat which provides justification for the entry model in the spirit of Levin and Smith (1994) used in this paper.

Figure E.1: Marginal Cost Residuals as a Function of the Number of Potential Entrants

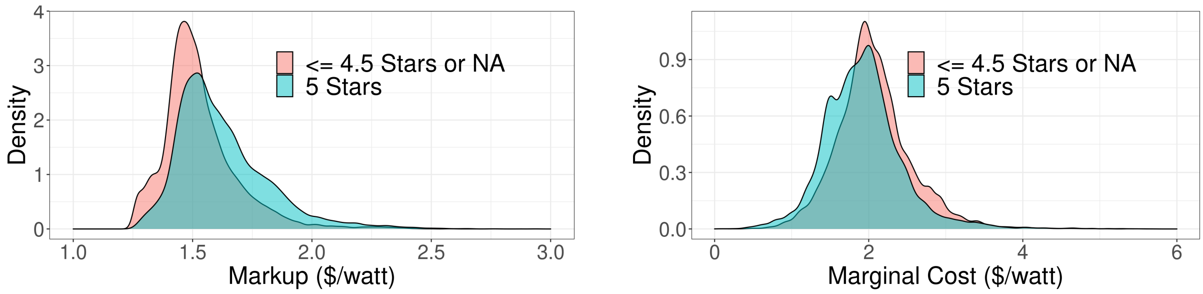


Notes: Marginal cost residuals are generated by running the regression in the third column of Table E.1 omitting the number of potential entrants variable.

F Additional Cost Heterogeneity Results

Figure F.1 shows the distribution of both markups and marginal costs across sellers with differing ratings. Figures F.1a and F.1b illustrate that five-star rated sellers are more likely to charge higher markups, however, these high-rated sellers are also more likely to have lower costs. The figures also illustrate substantial heterogeneity in both costs and markups across projects, and thus it is important to control for both seller-level and household-level heterogeneity.

Figure F.1: Marginal Cost and Markup Distributions



(a) Markup by Seller Rating (b) MC by Seller Rating

Notes: Kernel densities of the model implied marginal costs and markups.

To further investigate which variables are linked to higher costs and higher markups, I run regressions with both marginal costs and markups as dependent variables, including all of the variables in buyers' utility (besides price) as regressors. Table F.1 shows that the average installation costs are lower for households in the top 75% of home valuation, but these more expensive homes are also subject to much higher markups. We also see that households' electricity expenditure is both negatively correlated with marginal costs and markups. Additionally, the regressions show that higher-quality hardware (premium panels and microinverters) increases the marginal cost but also comes with higher margins. Consistent with Figure F.1, we also note that five-star sellers charge higher markups, but their prices are actually lower after accounting for their lower marginal costs. Sellers with more experience charge higher markups but do not have substantially lower costs after controlling for seller rating.

Table F.2 breaks down marginal costs by CBSA. The results indicate that CBSAs in Arizona and Texas tend to have lower installation marginal costs relative to California and the

Northeast, possibly due to lower labor costs in these areas.

Figure A.9b and Table A.7 also show a disparity in entry costs across sellers. Sellers with five-star ratings have higher bid preparation costs of \$20.96 compared to \$13.27 for sellers with a 4.5-star rating. Higher bid preparation costs for higher-quality sellers are consistent with higher opportunity costs. For instance, higher-rated sellers may have more project leads off the platform.

Table F.1: Marginal Cost and Markup Regressions

	Dependent variable:		
	MC (\$/Watt)	Markup (\$/Watt)	Gross Price (\$/Watt)
Household Attributes			
Home Mkt. Value - Quartile 2	−0.130 (0.006)	0.140 (0.002)	0.010 (0.006)
Home Mkt. Value - Quartile 3	−0.129 (0.008)	0.159 (0.002)	0.031 (0.007)
Home Mkt. Value - Quartile 4	−0.151 (0.009)	0.191 (0.002)	0.040 (0.008)
Electric Bill - Quartile 2	−0.037 (0.006)	−0.037 (0.002)	−0.074 (0.005)
Electric Bill - Quartile 3	−0.063 (0.006)	−0.049 (0.002)	−0.112 (0.005)
Electric Bill - Quartile 4	−0.075 (0.006)	−0.068 (0.002)	−0.143 (0.005)
Has Off-Platform Quotes	0.0001 (0.005)	−0.001 (0.001)	−0.001 (0.005)
Non-Price Bid Attributes			
Premium Panel	0.066 (0.005)	0.084 (0.001)	0.150 (0.005)
Premium Plus Panel	0.744 (0.011)	0.256 (0.003)	1.000 (0.010)
Microinverter	0.086 (0.006)	0.053 (0.002)	0.139 (0.005)
Installer Attributes			
Star Rating ≤ 4	0.017 (0.022)	−0.068 (0.006)	−0.051 (0.020)
Star Rating = 4.5	−0.034 (0.016)	−0.061 (0.004)	−0.095 (0.014)
Star Rating = 5	−0.143 (0.008)	0.066 (0.002)	−0.077 (0.007)
Installs Completed: 100-1000	−0.035 (0.012)	0.083 (0.003)	0.048 (0.011)
Installs Completed: >1000	0.025 (0.013)	0.095 (0.004)	0.120 (0.012)
Permanent Installer FE	Yes	Yes	Yes
CBSA FE	Yes	Yes	Yes
Half-Year FE	Yes	Yes	Yes
Observations	37,080	37,080	37,080
R^2	0.402	0.675	0.494

Notes: Robust standard errors in parentheses. The dependent variables are the model-implied marginal cost (\$/watt), the model-implied markup (\$/watt), and the observed bid price before tax credits (\$/watt). All variables that enter consumer utility are included as covariates including the Home Market Value Quartile dummies which are interacted with price in consumer utility.

Table F.2: Marginal Costs Across CBSAs

Panel A: Lowest Marginal Cost CBSAs in 2016 H1

CBSA	MC (Mean)	MC (SD)
Phoenix-Mesa-Scottsdale, AZ	1.46	0.58
Tucson, AZ	1.58	0.36
Other, TX	1.62	0.47
Austin-Round Rock, TX	1.68	0.41
Other, CO	1.68	0.35
Other, AZ	1.7	0.4
Fort Worth-Arlington, TX	1.72	0.36
Dallas-Plano-Irving, TX	1.74	0.43
Denver-Aurora-Lakewood, CO	1.74	0.34
San Antonio-New Braunfels, TX	1.86	0.34

Panel B: Highest Marginal Cost CBSAs in 2016 H1

CBSA	MC (Mean)	MC (SD)
New York, NY	2.42	0.7
Providence-Warwick, RI-MA	2.4	0.42
Other, CT	2.36	0.68
Hartford, CT	2.28	0.46
New Haven-Milford, CT	2.28	0.43
Worcester, MA-CT	2.28	0.4
Other, NY	2.26	0.62
San Jose-Sunnyvale-Santa Clara, CA	2.26	0.5
Other, MA	2.25	0.52
Bridgeport-Stamford-Norwalk, CT	2.23	0.45

Notes: The top panel shows the mean and standard deviation of marginal cost for the ten lowest-cost CBSAs in 2016 H1. The lower panel shows the mean and standard deviation of marginal cost for the ten highest-cost CBSAs in 2016 H1.

G Heterogeneity in Installation Costs and Unobservables

The identification of the demand parameters, particularly the price coefficient and the nesting parameter, requires exogenous shifts in bid prices and auction participation that are uncorrelated with buyer preferences. As such, installation cost shifters can provide a potentially valuable source of variation to estimate demand. In this appendix section, I show suggestive evidence that this type of variation exists in the data. I also discuss how correlated unobservable cost shocks could bias the supply-side parameters. Moreover, I provide several sensitivity checks to test if the main results are likely to be robust to the presence of correlated cost shocks that are observable to sellers but unobservable to the econometrician.

Heterogeneity in costs can arise because some rooftops are more suitable for a rooftop solar installation. For example, some roofing materials make mounting a rooftop solar installation more costly because they require additional labor or materials. Some of the most common roofing materials—asphalt shingle, composite shingle, and metal—are easier for installers to work with. In contrast, tile, gravel, and wood shake roofs require additional labor and materials to properly mount a solar PV system.[36] Moreover, installation costs may vary across sellers depending on their specific installation experience and the characteristics of the home. To investigate the importance of roofing material on bidding behavior, I collect additional data on each household's roof material from Acxiom Infobase. Acxiom reports roof type for approximately 50% of the households in the sample. Accordingly, I categorize each project into one of three roof types: (1) asphalt shingle, composite shingle, or metal; (2) tile, gravel, shake, or wood shingle; and (3) other or unknown. Here, the second group represents homes that are expected to have more difficult installations due to their roof type and the third category includes uncommon roof types and all houses whose roof material was not reported by Acxiom.

To test whether roof type affects bidding behavior, I run two descriptive regressions to measure how roof type is associated with bid pricing and the number of bids that a household receives. The results show that bids made to households with tile, gravel, or wood shake

[36]See https://purepointenergy.com/most-common-roof-types-for-solar-and-their-pros-and-cons/ for a more extended discussion.

roofs are about \$0.01 per watt higher than similar households with asphalt, composite, or metal roofs (the omitted category), although the coefficient is not statistically significant (p-value=0.32). The second regression indicates that households with tile, gravel, or wood shake roofs obtain an average of 0.16 fewer bids than similar households with asphalt, composite, or metal roofs. These regressions provide some suggestive evidence that supply-side shocks at the project level could provide a credible source of variation to identify the price coefficient and the nesting parameter λ.

Table G.1: Effects of Roof Material on Bid Prices and Auction Participation

	Dependent variable:	
	Bid Price	Number of Bids
Roof Material = Other/Unknown	0.007	−0.170
	(0.008)	(0.052)
Roof Material = Tile/Gravel/Wood Shake	0.010	−0.160
	(0.010)	(0.067)
Full Set of Controls	Yes	Yes
Observations	37,080	10,488
R^2	0.494	0.470

Notes: The first column reports results for regressions with gross bid price in dollars per watt as the dependent variable. The first regression controls for all variables that enter the main utility specification such as the project type (e.g., CBSA fixed effects and electricity bill quartile fixed effects), the non-price characteristics (e.g, panel brand quality), and installer type (e.g. installer FEs for permanent installers and installer ratings for transient installers). In the second column, the dependent variable is the number of bids obtained for the project, controlling for all variables that determine the project type in the main specification. In both regressions, the omitted roof material category is "Asphalt/Composite/Metal".

Supply-side shocks will provide a credible source of variation to identify the demand parameters as long as the shocks are not correlated with buyers' preference shocks. I test whether these supply-side shocks are correlated with preferences by re-estimating the utility model including dummies for each of the three roof type categories in the utility function. The results are shown in Table G.2.

We see that the price coefficients and the nesting parameter are nearly identical across the two models. Moreover, the coefficients on the roofing material dummies are not statistically distinguishable from zero. Put differently, we cannot reject the null hypothesis that supply-

Table G.2: Alternate Demand Specifications - Roofing Material Controls

	(1) - Base	(2)
λ	0.37 (0.06)	0.37 (0.06)
β - Price	-0.72 (0.11)	-0.72 (0.11)
β - Price $\times$ Home Mkt. Value Q2	0.07 (0.04)	0.07 (0.04)
β - Price $\times$ Home Mkt. Value Q3	0.08 (0.05)	0.08 (0.05)
β - Price $\times$ Home Mkt. Value Q4	0.09 (0.06)	0.09 (0.06)
γ - Roof Material = Other/Unknown		-0.06 (0.15)
γ - Roof Material = Tile/Gravel/Wood Shake		-0.19 (0.21)
Mean Own-Price Elasticity	-2.27	-2.28
Mean Markup ($/watt)	1.59	1.59
Log Likelihood	-3823.54	-3823.11
Installer Attributes		
Fixed Effects for Permanent Installers	Y	Y
Installer Rating and Exper. Controls	Y	Y
Non-Price Bid Attributes		
Hardware Quality Controls	Y	Y
Project Attributes $\times$ Inside Good		
Electric Bill Quartile Fixed Effects	Y	Y
CBSA Fixed Effects	Y	Y
Half-Year Fixed Effects	Y	Y
Off-Platform Quote Fixed Effect	Y	Y

Notes: The top panel displays the nesting parameter and price coefficients for the base model and an alternate demand specification that includes controls for the household's roofing type. Standard errors are in parentheses. The middle panel shows the mean own-price elasticity and mean implied markup across all bids in the data. The bottom panel indicates which additional controls are included in the utility function. Both models include dummies for installers' star rating in 2016 and overall residential installation experience: one dummy indicates if the installer has completed over 100 installs, and another dummy indicates over 1000 installs completed. Both models include fixed effects for all "permanent" installers, defined as any installer that submitted over 300 bids during the sample. Both models include dummies for microinverter, "premium panel brand" and "premium plus panel brand" to control for hardware quality. Both models include electric bill quartile fixed effects, CBSA fixed effects, and half-year fixed effects.

side shocks (related to roofing material) that could affect bid pricing and auction participation are uncorrelated with unobserved buyer preferences. This suggests that these types of shocks can provide credible variation for identifying the demand parameters.

Even if the demand estimates are unbiased, another related concern is that unobserved heterogeneity that affects project costs such as roofing type could bias the supply-side estimates of markup and marginal costs. One of the key assumptions in the bidding model is that cost shocks are i.i.d. conditional on the project type and the installer's type. However, if there are factors (such as rooftop characteristics) that are observable to installers but are not observable in the data, this could induce a correlation in cost shocks among installers bidding for the same project, violating the i.i.d. assumption on costs. Put simply, installers may know that projects that they view as more difficult and costly, are also more likely to be costly for other competing installers. If true, installers' modeled expectations about the dispersion of competing bids will be larger than they are in reality. This could lead to upward-biased estimates of the optimal markup because a marginal increase in a seller's bid price will lead to a relatively smaller decrease in the probability of winning the auction because other installers will also be likely to submit higher bids.

I test the robustness of the estimated markups to project-level cost heterogeneity by explicitly allowing the roof-type variable to enter $\mathbf{z}_i$ as a determinant of project type. Therefore, sellers' expectations about competitors' entry probabilities and expected bid prices are allowed to vary across projects with differing roof types. The lower panel in the table also confirms that the mean markup is nearly the same between the baseline model and the model that allows the roofing type to enter both the supply and the demand model.

However, there are several other factors that are not directly observed that could affect installation costs, such as the pitch of the roof. This set of results provides suggestive evidence that unobserved cost heterogeneity is unlikely to lead to substantial bias of either the demand or supply parameters.

H Algorithms for Solving Counterfactuals

H.1 Algorithm for Solving Counterfactuals with Fixed # of Bids

In the counterfactuals, I assume that sellers know the number of competing bidders but not the identities of the other bidders. I draw the identities of the bidders randomly with the probabilities weighted by seller entry probabilities observed in the data.[37] After I draw the installers for each project, buyers choose from competing bids and the outside option.[38]

The algorithm to solve these counterfactuals is as follows:

1. For each project i, start with a vector of all bids submitted for projects of that type ($\mathbf{B_0}$), a fixed number of bids (N), and entry probability weights for each potential seller for that auction type ($\mathbf{E_0}$).

2. Calculate each firm's optimal price given the current distribution of prices and entry probabilities from step one. Store the new vector of bids $\mathbf{B_1}$.

    - Equation 5 is the first order condition for each firm's optimal price. The first-order condition does not have a closed form, so simulate S=100 iterations of each auction type to approximate the integrals numerically.

3. Measure the difference between each of the original prices and the updated prices. Stop if $||abs(\mathbf{B_1} - \mathbf{B_0})||_\infty < \delta_b$. Otherwise, replace $\mathbf{B_0}$ with $\mathbf{B_1}$ and then start over at Step 1.

    - I set $\delta_b = .00001$

[37]The seller entry probabilities are calculated separately for each project type. I also assume that installers know the entry probabilities of each competitor.

[38]I simulate 100 iterations of each project and measure the average outcome across all iterations to reduce simulation noise.

H.2 Algorithm for Solving ITC Counterfactuals with Endogenous Bidding

1. For each auction type, start with a vector of all bids submitted for projects of that type ($\mathbf{B_1}$) and start with an entry probability for each potential entrant for that auction type ($\mathbf{E_0}$).

2. Draw S=100 vectors of non-price characteristics for each potential entrant. Draw each vector of non-price characteristics at random from the list of all bids made by that project-seller type pair.

3. Draw S=100 uniform draws for each potential entrant to determine random entry for each simulation iteration.

   - Choose entrants for each simulation iteration by determining if the random uniform draw is less than $\mathbf{E_0}$
   - *Note: To ensure convergence, I hold the initial S=100 sets of simulated entrants fixed throughout the algorithm even though the entry probabilities will change in the counterfactuals. I use an importance sampling approach similar to Guerre et al. (2000) to adjust for the fact that I do not update the sets of entrants at each step.*

4. Set $\mathbf{E_0}$=$\mathbf{E_1}$

5. Calculate each firm's optimal price given the current distribution of prices $\mathbf{B_1}$ and entry probabilities $\mathbf{E_1}$. Store the new vector of bids $\mathbf{B_2}$.

   - Equation 5 is the first order condition for each firm's optimal price. The first-order condition does not have a closed form, so use the S=100 simulation iterations of each auction type to approximate the integrals numerically. When calculating the averages, I use importance weights to adjust for the fact that the competitors were drawn according to $\mathbf{E_0}$ instead of $\mathbf{E_1}$.

6. Use the updated prices (and conditional winning probabilities) from Step 2 to calculate each potential entrant's expected marginal profit of entering the auction. Then use

the new expected profits to update each firm's entry probability. Store the new entry probabilities $\mathbf{E_2}$.

7. Measure the difference between each of the original prices and the updated prices and measure the difference between the original and updated entry probabilities. Stop if $||abs(\mathbf{B_2} - \mathbf{B_1})||_\infty < \delta_b$ and $||abs(\mathbf{E_2} - \mathbf{E_1})||_\infty < \delta_e$. Otherwise replace $\mathbf{B_1}$ with $\mathbf{B_2}$ and $\mathbf{E_1}$ with $\mathbf{E_2}$ and then start over at Step 5.

    - I set $\delta_b = 0.00001$ and $\delta_e = .0.00001$.

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