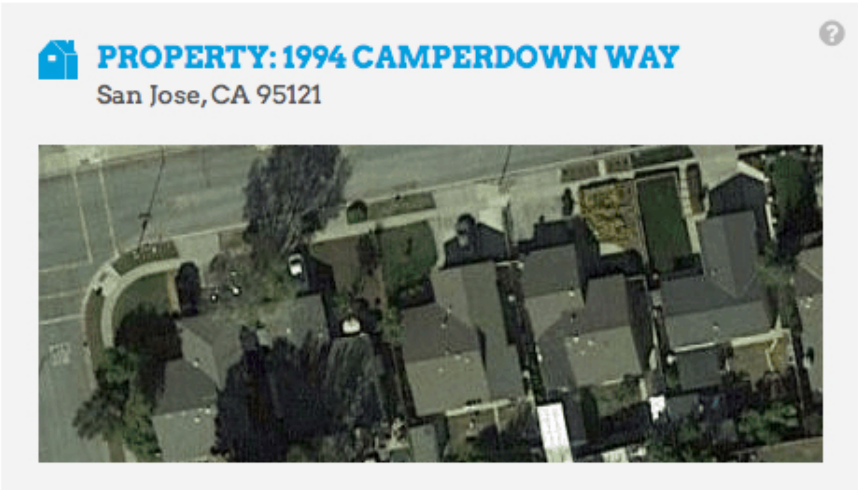
Online Appendix

A Additional Tables and Figures Referred to in Main Text

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



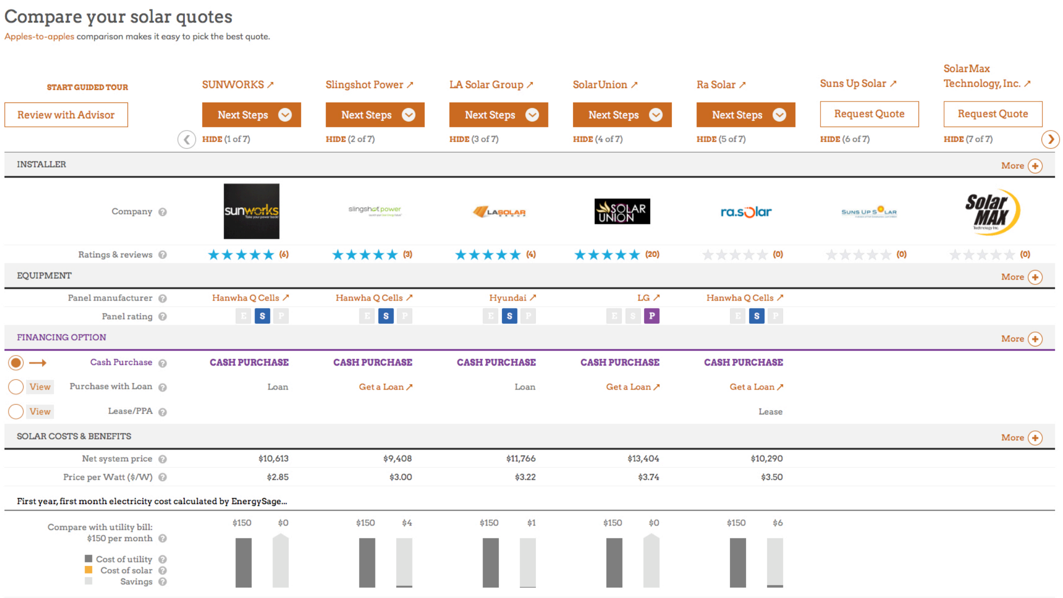
Notes: Figure shows an example of an EnergySage buyer profile. The profile allow potential bidders to see a Google Maps image of the buyer's roof.

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

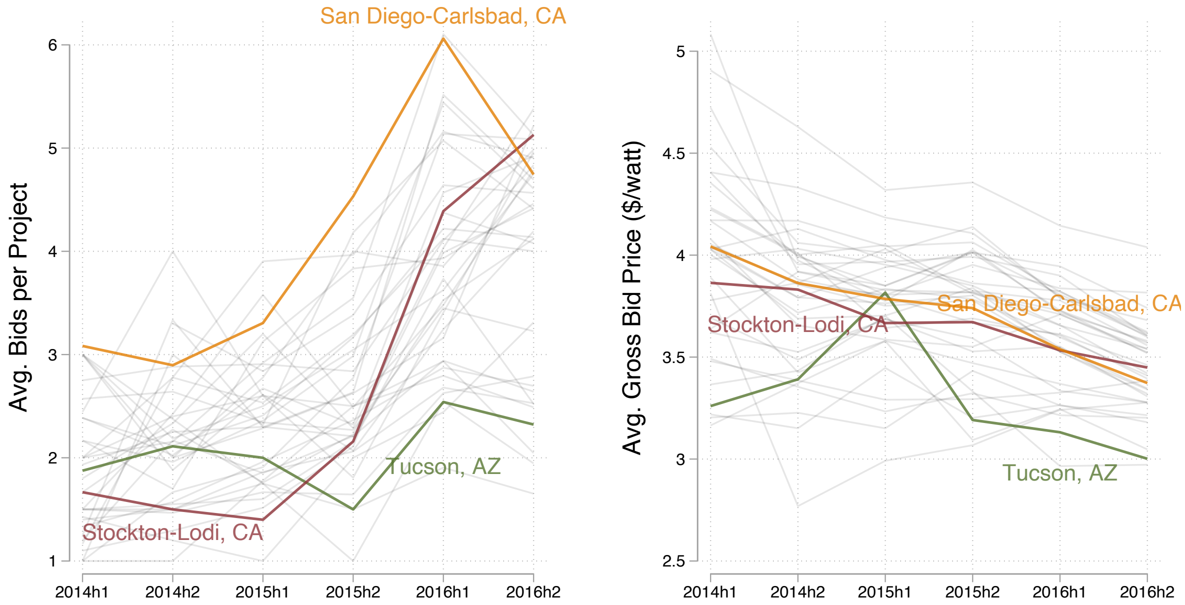


Notes: EnergySage quote comparison page in late 2016.

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

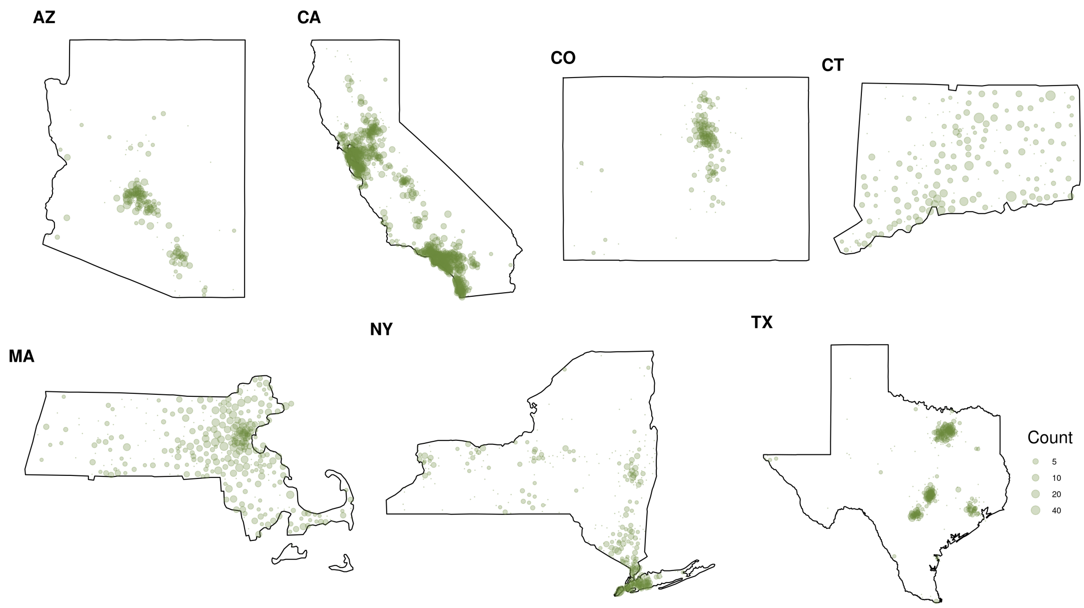


(a) Mean Bids Per Project

(b) Mean Bid Prices

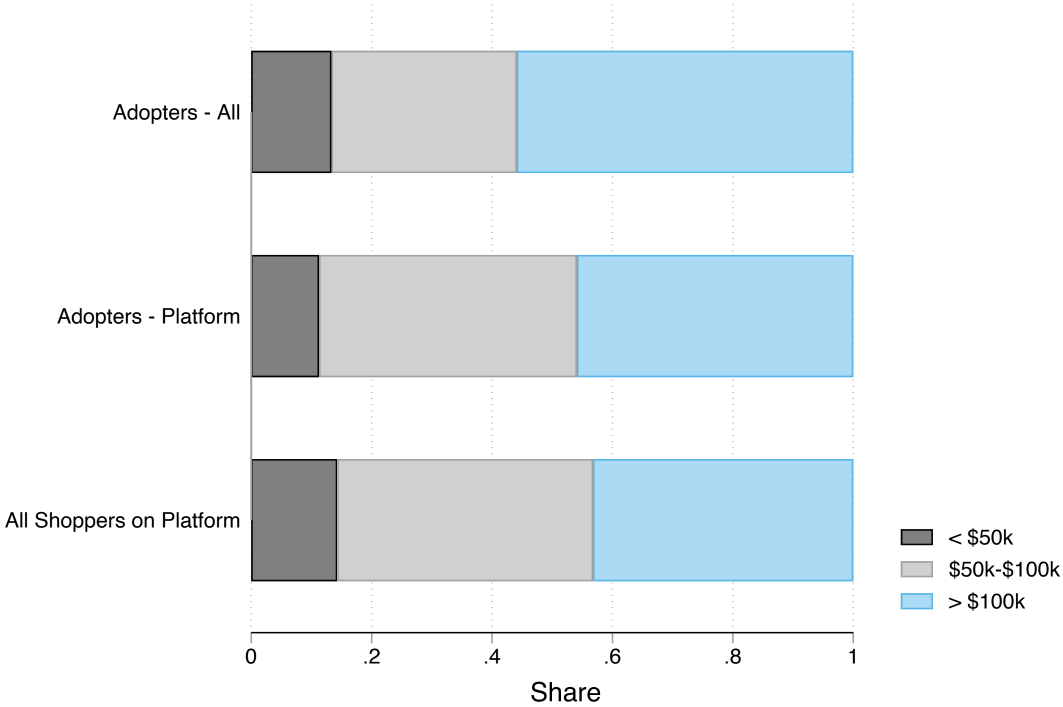
Notes: Each grey line represents a CBSA. Projects that are outside a CBSA or in CBSA with fewer than 100 total projects are placed into a distinct category by state. For example, a project located in Aspen, Colorado would be defined as "Other, CO".

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

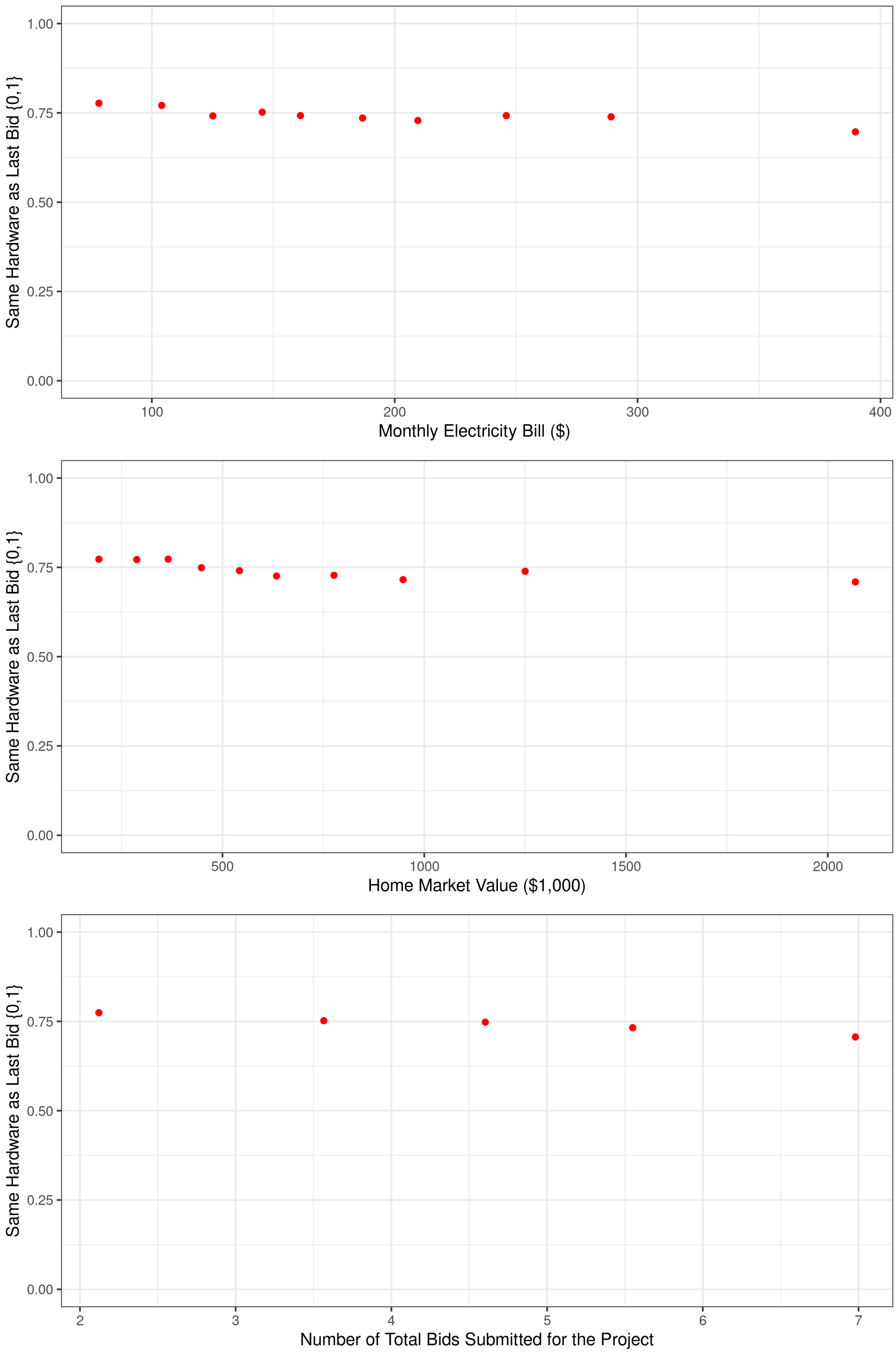
Notes: To compare system attributes of platform transactions with off-platform transactions, I append the LBNL's Tracking the Sun data with the EnergySage data for selected bids (EnergySage bids that a consumer chose). The regressions only include purchased residential systems between 2KW and 20 KW in 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



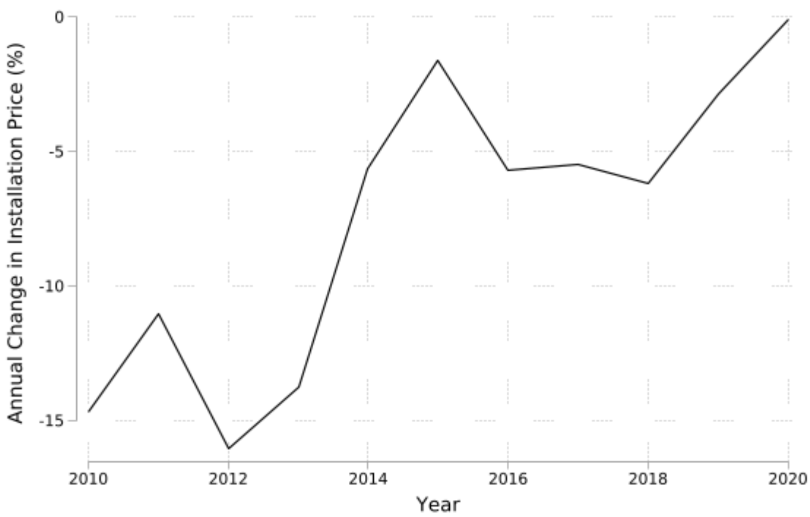
Notes: The binned scatter plots show the probability that installers bid the same non-price hardware characteristics as their most recent previous bid as a function of the household's monthly electricity bill, home value, and the total number of bids for the project.

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

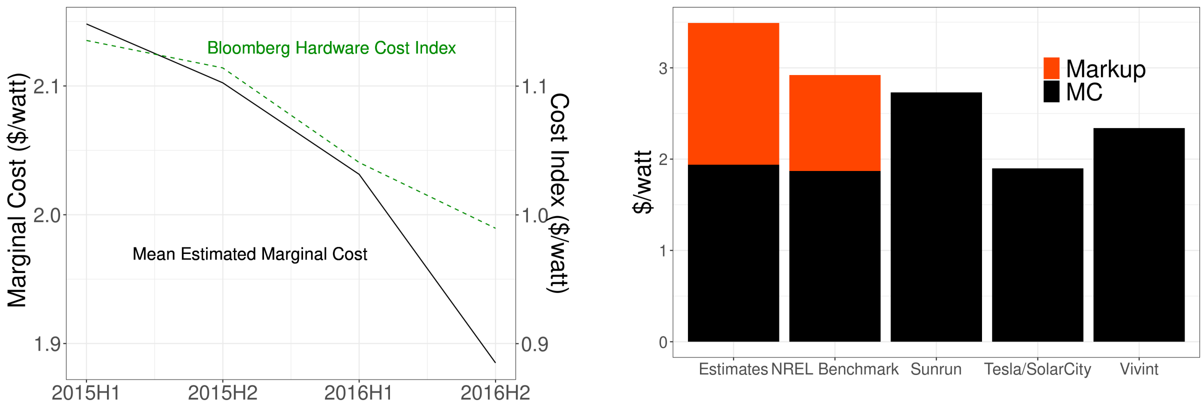
Notes: The mean number of bids in a market is defined as the average number of bids for all projects within the same CBSA and the same half-year. Household electric bill and home value variables are demeaned before running the regressions. Standard errors clustered by project are in parentheses.

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

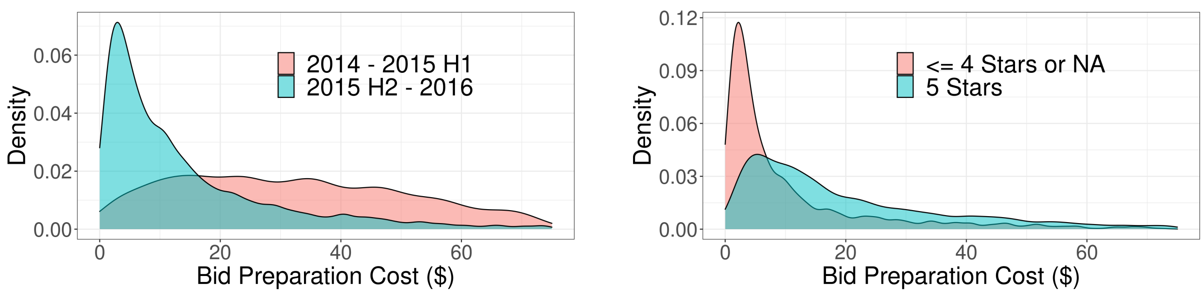


(a) Hardware Cost and MC Estimate

(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%)

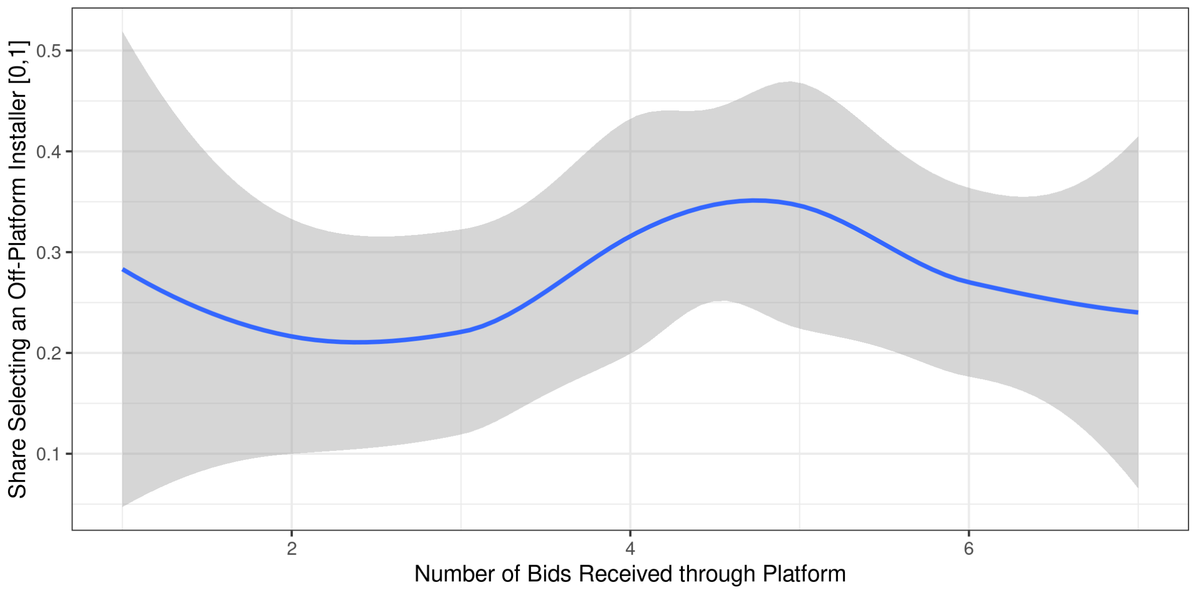
Notes: Panel A summarizes the sample size and response rate from EnergySage's exit survey. Each row indicates whether the survey respondent reported possessing external quotes when they initially created their account on EnergySage. Each column indicates whether each respondent reported using an offline 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.

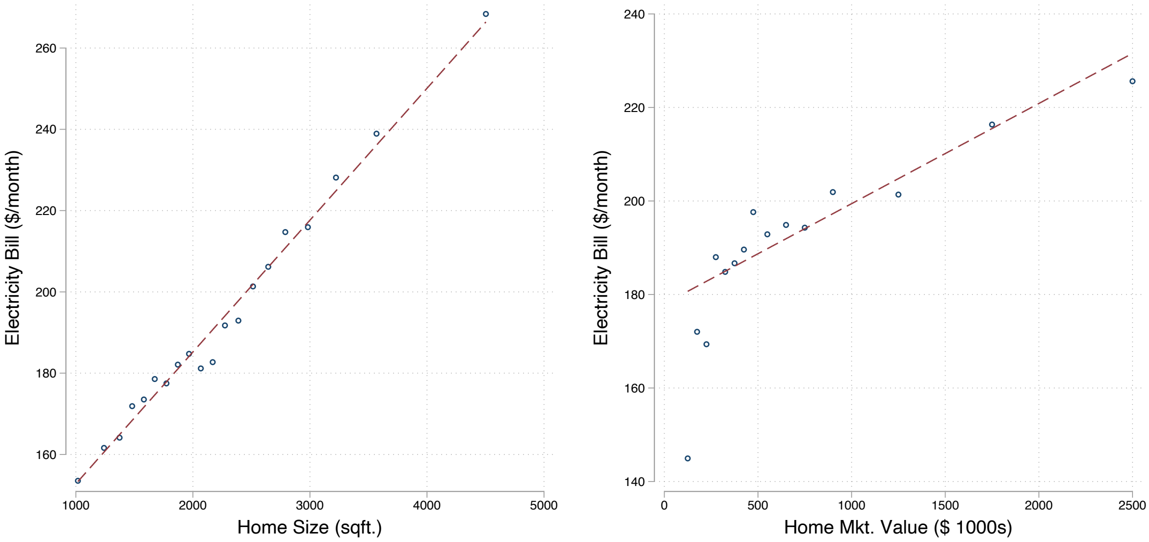
B Sample Construction

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.

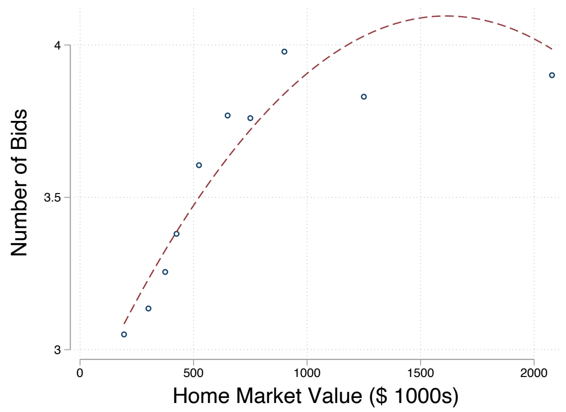
Therefore, the standardized prices should be interpreted as a bid price for a mean-sized system in the first half of 2016 (H1). We see that households with more expensive homes (and those with higher electricity bills, see C.2b) receive higher size-adjusted bid prices. These higher prices are despite 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.

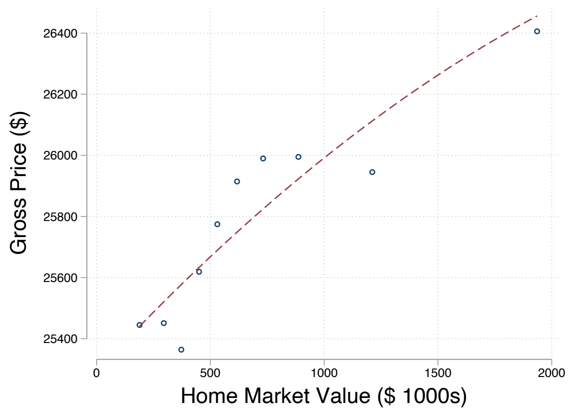
A plausible explanation of the heterogeneous relationship between competition and bid prices in Figure C.1c is differences in buyers' price-elasticities. For instance, if households with lower home valuations are more price sensitive, then sellers' optimal markups will be relatively lower if they are 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.

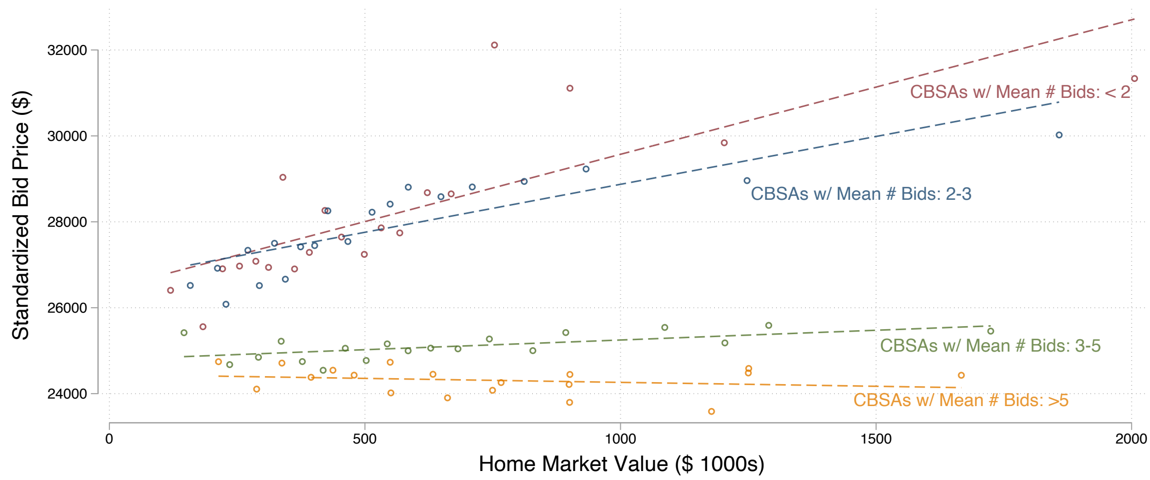
Figure C.1: Auction Participation and Pricing by Home Market Value



(a) # of Bids by Home Value



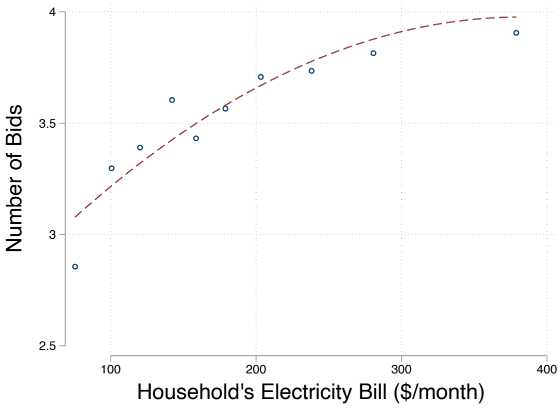
(b) Bid Prices by Home Value



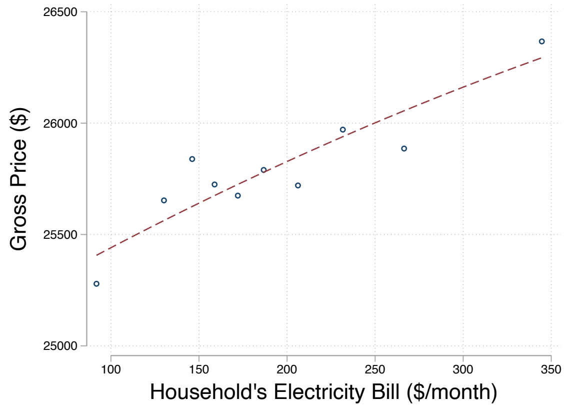
(c) Prices, Home Value, Mean Bids in CBSA

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.

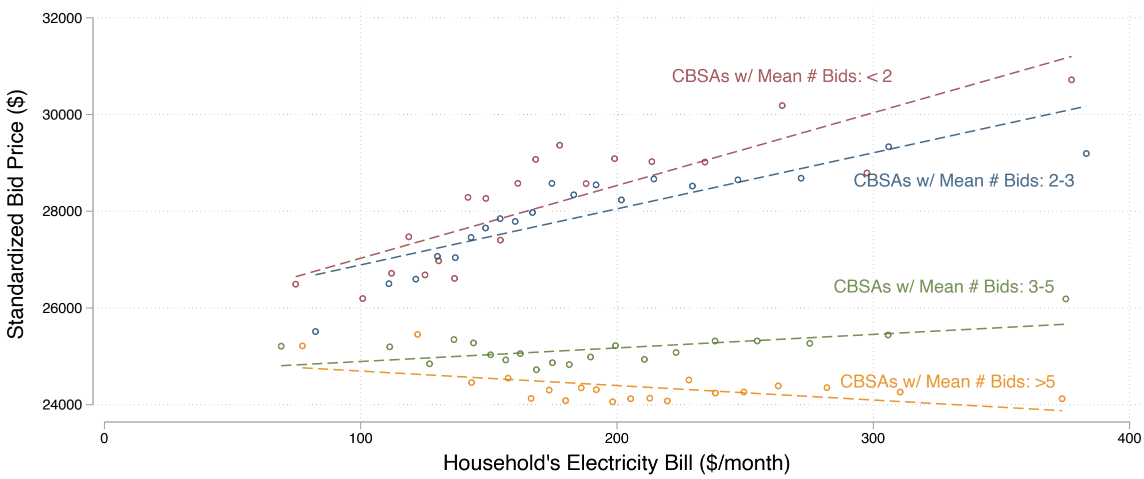
Figure C.2: Auction Participation and Pricing By Electricity Expenditure



(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.

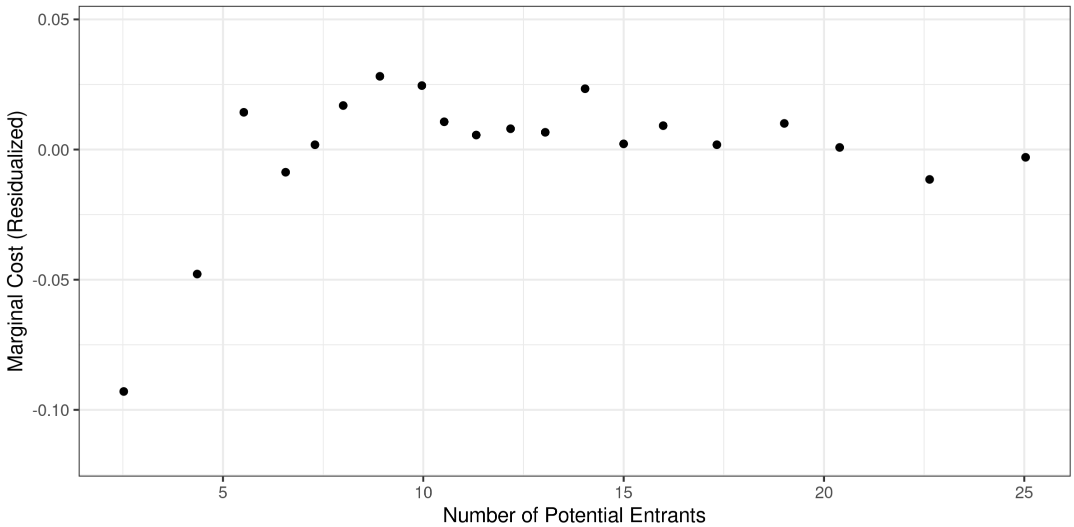
Table E.1: Testing for Selection into Entry

	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

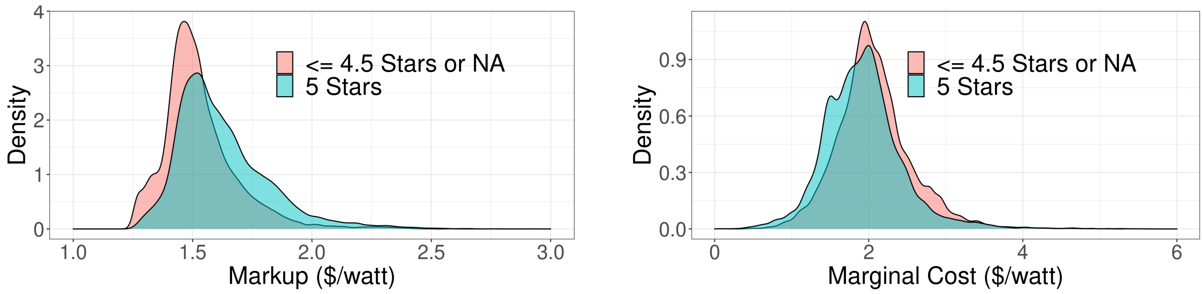


Notes: Marginal cost residuals are generated by running the regression in the third column of Table E.1 omitting the number of potential entrants variable.

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 $\leq$ 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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