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Publication Date
2016-08-30

LBNL- 1006193

ERNEST ORLANDO LAWRENCE
BERKELEY NATIONAL LABORATORY

What Factors Affect the Prices of Low-Priced U.S. Solar PV Systems?

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08/2016

This work was supported by the Office of Energy Efficiency and Renewable Energy (Solar Energy Technologies Office) of the U.S. Department of Energy under Contract Nos. DE-AC02-05CH11231(LBNL) and DEAC36-08GO28308 (NREL).

Disclaimer

Acknowledgements

This work was supported by the Office of Energy Efficiency and Renewable Energy (Solar Energy Technologies Office) of the U.S. Department of Energy under Contract Nos. DE-AC02-05CH11231(LBNL) and DE- AC36-08GO28308 (NREL). For supporting this work, we thank Elaine Ulrich, Odette Mucha, Ammar Qusaibaty, Joshua Huneycutt, Dan Boff and the entire DOE Solar Energy Technologies Office team.

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Abstract

The price of solar PV systems has declined rapidly, yet there are some much lower-priced systems than others. This study explores the factors leading some systems to be so much lower priced than others. Using a data set of 42,611 residential-scale PV systems installed in the U.S. in 2013, we use quantile regressions to estimate the importance of factors affecting the installed prices for low-priced (LP) systems (those at the 10th percentile) in comparison to median-priced systems. We find that the value of solar to consumers–a variable that accounts for subsidies, electric rates, and PV generation levels–is associated with lower prices for LP systems but higher prices for median priced systems. Conversely, systems installed in new home construction are associated with lower prices at the median but higher prices for LP. Other variables have larger cost-reducing effects on LP than on median priced systems: systems installed in Arizona and Florida, as well as commercial and thin film systems. In contrast, the following have a smaller effect on prices for LP systems than median priced systems: tracking systems, self-installations, systems installed in Massachusetts, the system size, and installer experience. These results highlight the complex factors at play that lead to LP systems and shed light into how such LP systems can come about.

Keywords: subsidies; solar; PV; price dispersion; technological change

1. Introduction

The global deployment of solar photovoltaics (PV) is on the rise, motivated by a variety of policy interventions and by the dropping cost of solar (Baker et al. 2013, Bazilian et al. 2013, REN21 2016). But the degree to which solar continues its rapid pace of deployment and its resulting role in climate mitigation will depend on future cost reductions (IPCC 2011, Luderer et al. 2014, Pietzcker et al. 2014). Increasingly lower costs will be important to help overcome the inherent grid-integration limitations to time-variable PV output and to counteract declining incentives and compensation rates(Mills and Wiser 2013, Hirth 2015, Denholm et al. 2016, Sivaram and Kann 2016). As such, a key goal for the solar industry, policymakers, and other decision makers—as exemplified by the U.S. Department of Energy's *SunShot* Initiative—is to foster continued, dramatic declines in solar costs, in order to ensure a sizable future role for this technology in meeting energy supply needs under carbon constraints.

A surprising feature of the solar market is that while the mean installed price has been decreasing rapidly, there is also considerable heterogeneity in the prices of installed systems, both across and within markets. For example, in Germany, the average installed price of a residential system in 2014 was \$1.75/W (Wirth 2016); in the U.S., meanwhile, the average installed price for residential systems in 2014 was much higher, above \$4/W. Seel et al. (2014) explore some of the drivers for these installed price variations across markets. Even within the United States, however, we see a large number of much lower priced systems than others. Barbose and Darghouth (2015), for example, show a spread in the installed prices of smaller residential PV systems in the U.S. in 2014 of \$3.50/W (20th percentile) to \$5.30/W (80th percentile).

Researchers have begun exploring some of the reasons for this heterogeneity in PV pricing in the U.S., focusing on factors that influence prices at the median. Gillingham et al. (2016), for example, broadly assess factors influencing PV system price differences, including search costs, market competition, installer experience and market share, incentive levels, market characteristics, solar policy design, and PV system characteristics. Burkhardt et al. (2015) and Dong and Wiser (2014), meanwhile, evaluate the influence of local permitting and regulatory processes on PV system prices. Still other work has investigated the impact of solar incentives on prices (Podolefsky 2013, Shrimali and Jenner 2013, Dong et al. 2014) and the influence of third-party ownership (TPO) (Davidson and Steinberg 2013). All of this previous work has focused on understanding trends for mean or median PV systems. Most recently, however, research has begun to specifically explore the characteristics of low-priced (LP) systems. In particular, Nemet et al. (2016) provide a first assessment of LP PV systems, finding that system characteristics, location, and policies have significant effects on whether the systems are priced below the 10th percentile of the price distribution.

This study builds on the past literature by continuing the focus on low-priced systems. We extend the work of Nemet et al. (2016) by statistically evaluating what might drive LP systems to be *even lower* priced. This is important since one of the key pathways to a large-scale climate solution would be to continue to drive the prices of solar PV lower to allow for widespread adoption. Our research questions are thus: (1) What factors are associated with lower prices among LP PV systems, and (2) Are those factors different from those for median priced systems?

In conducting this work, we analyze 42,611 residential-scale PV systems installed in the United States in 2013, estimating the factors affecting installed prices for LP systems. We leverage the sizable data set of system-level PV prices managed by Lawrence Berkeley National Laboratory (LBNL).[1] In order to help gauge the possible drivers for achieving even lower prices, as might be needed if solar is to play a major role in climate mitigation, we are especially interested in knowing whether these factors are different from those affecting PV systems at the middle of the price distribution. As such, we use quantile regressions to compare effects for LP to those at the median.

2. Methods and Data

Our overall approach in addressing these questions is to apply quantile regressions to data on U.S. residential-scale PV installations.

1.1.Data sources

We begin with data from LBNL's *Tracking the Sun* (TTS) report series (Barbose and Darghouth 2015). For TTS, individual PV system installation data is collected for over 400,000 systems from 59 PV incentive programs, accounting for about two thirds of all PV installations in the US since 1998. The data includes the systems' total system transaction price, which is the principal variable of interest in this analysis, installation date, location (zip codes or street addresses), incentive levels, customer segment, third party ownership, installer information, as well as a number of other system characteristics. Barbose and Darghouth (2015) contains a comprehensive description of the TTS data set.

We extend the TTS dataset for this analysis by constructing new variables from installation dates, locations, and installer information. This includes the number of active installers in the county; the aggregate, discounted county-level experience for installers; the consumer value of solar (present value of all incentives and electricity bill savings over the lifetime of the system, based on simulated PV generation, average utility electricity rates, calculated and reported incentive levels); module and inverter price indices from SEIA/GTM (2014); and a number of socio-economic and demographic variables associated with the zip code or county where the PV system is installed, such as household density, income, and wages from the U.S. Census (2014) and the U.S. Bureau of Labor Statistics (2014). We include variable definitions in the Supporting Information (SI).

1.2.Variables and restrictions

We restrict this data set by including only systems with the following characteristics: installed in

[1] This paper is part of a larger body of research conducted by LBNL, University of Texas—Austin, University of
Wisconsin—Madison, Yale University, and the National Renewable Energy Laboratory that is exploring U.S. PV system price variability.

2013 (for the most recent data), between 1-15 kW_{DC} (for residential scale), and with installed prices between $1 and $25/W (to eliminate outliers). Further, we drop systems with incomplete information, e.g., on county and installer name. We include Third Party Owned (TPO) systems but exclude those with prices based on "appraised" value (n=19,765). Rather than reflecting actual transactions, appraised value prices are based on companies' idiosyncratic formulae and thus do not convey meaningful information about the transacted price of an installation; these are reported by vertically integrated solar installers who install and own TPO systems and hence do not have transaction prices to report. Exclusion of appraised value systems increases our confidence in the modeled results (see SI). The resulting data set includes complete information on 42,611 installed residential-scale systems[2], and consists of customer-owned PV systems and TPO systems that do not report appraised values but instead report transaction prices between the installer and the third-party owner. Figure 1 shows the probability distribution of installed prices for these systems. We include summary statistics for all variables in the SI.

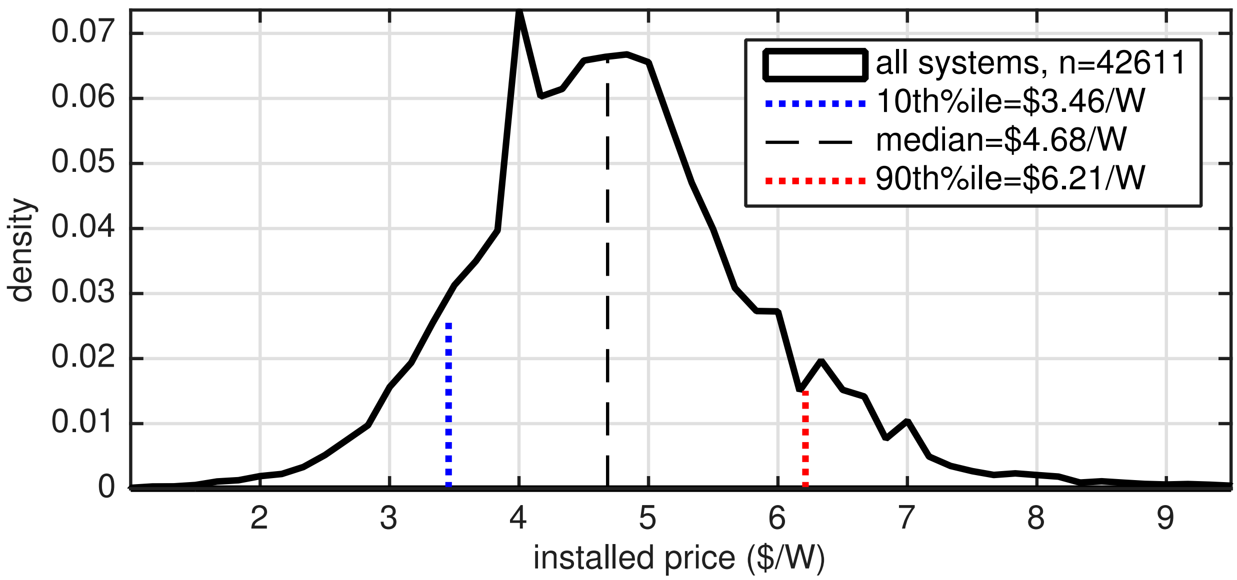

Figure 1. Probability distribution of installed PV prices 2013.

1.3. Quantile regression approach

Because we are particularly interested in understanding the factors that affect systems with the lowest prices, we use a quantile regression approach (Koenker 2005). Rather than estimating a model to predict the conditional mean price, this approach weighs positive and negative error terms differently to predict outcomes at any quantile. For example, we can target prices with larger negative error terms, such as the 10th percentile. To represent LP systems, we use the 10th percentile, where installed price, P=$3.46/W, and employ the specification used in Nemet et al. (2016), which uses regressors for competition variables (COMP), firm (FIRM) and market (MKT) characteristics, policies (POL), PV system attributes (SYSTEM), and binary variables (B):

[2] Included in the dataset are only systems 1-15 kW in size, typical of residential installations but also including smaller commercial installations.

$$P_{ijst} = \beta_0 + \beta_1 COMP_{ist} + \beta_2 FIRM_{jst} + \beta_3 MKT_{ist} + \beta_4 POL_{ist} + \beta_5 SYSTEM_{ist} + B + e_{ijst} \quad (1)$$

for each installation *i*, installer firm *j*, state *s*, and date *t*. COMP is a vector of competition variables, which consists of the number of active installers and county-level concentration Herfindahl-Hirschman index (HHI). FIRM includes county-level experience, market share, and installer scale. MKT includes: household density; whether the customer is residential, commercial, or other; whether the system is third-party or customer owned; as well as income for the zip code. POL includes four policy variables: the value of solar to consumers (discussed below and in SI), percent of incentives coming from solar renewable energy credits (SREC), interconnection score, and sales tax. SYSTEM is a vector of installation characteristics including system size (and size squared), average module and inverter hardware costs, a zip-code level wage index, and module efficiency. It also includes binary variables for tracking, building integrated PV (BiPV), new construction, battery backup, self-installation, micro-inverters, Chinese panels, and thin-film panels. We add separate binary variables, B, for the state and the month of application for the installation. We arrange our specifications to avoid including highly collinear pairs, e.g., installer scale and experience; zip-code-level education, income, and wages. The supplementary information contains further details on the variable definitions.

3. Results

1.4. Descriptive Comparisons

Before interpreting the quantile regression results, it helps to understand two aspects of the data descriptively, the consumer value of solar and third party ownership-the first because it is important for the research questions and results, and the second because it bifurcates the data set. The following descriptives provide context for interpreting the subsequent regression results.

1.1.1. Consumer value of solar

Consumer value of solar (VoS) measures the sum of up-front tax credits and rebates (federal investment tax credit [ITC], state ITC, rebates) and lifetime revenue streams (utility bill savings, SRECs, performance-based incentives, feed-in tariffs) accruing to a system (Figure 2).

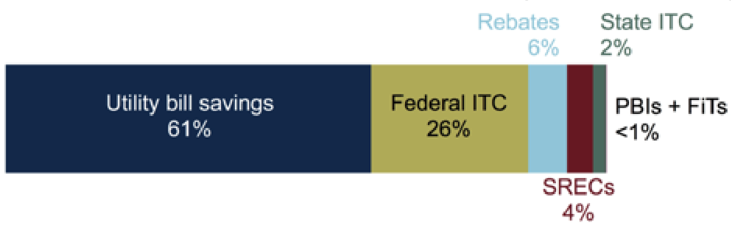

Figure 2. Components of the consumer value of solar for all systems.

VoS varies geographically according to incentive availability, local retail rates, and local solar resources (Figure 3). Utility bill savings are the primary contributor to VoS in most states, comprising about 61% of the VoS of an average system—highest in California, lowest in Florida (utility bill savings in Florida are replaced by feed-in tariff revenue).

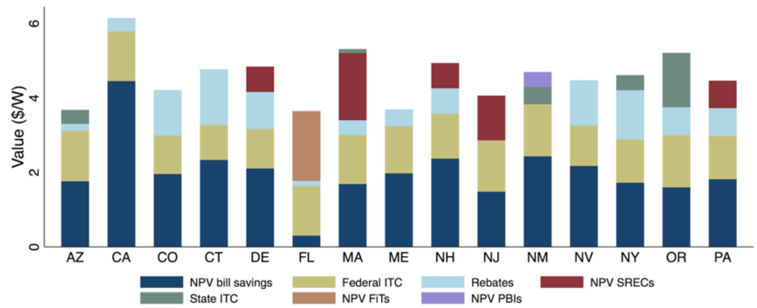

Figure 3. Disaggregation of VoS components by state.

The mean VoS of LP systems is about $0.68/W lower than non-LP systems (t=27), due primarily to a $0.67/W difference in mean utility bill savings (t=24) (Figure 4). However, previous work has found that LP systems are associated with higher VoS when controlling for state fixed effects and other covariates (Nemet et al. 2016). This change in effect is driven strongly by dynamics in California. Due in part to steeper tiered rate structures in northern California (the PG&E utility service area), average utility bill savings are about $2.70/W higher in California than in other states (Figure 3). California's disproportionate representation among non-LP systems (about 68% of non-LP systems compared to 34% of LP systems) drives a negative VoS/LP relationship without state fixed effects (Nemet et al. 2016), indicating that PV systems with higher VoS are more likely to be non-LP. However, within California, utility bill savings are about $0.79/W higher for LP than for non-LP systems (t=21), contributing to a sign flip for the VoS/LP relationship when including state fixed effects. In the quantile regressions, we assess the VoS/LP relationship further, and in the discussion consider differences between northern and southern California.

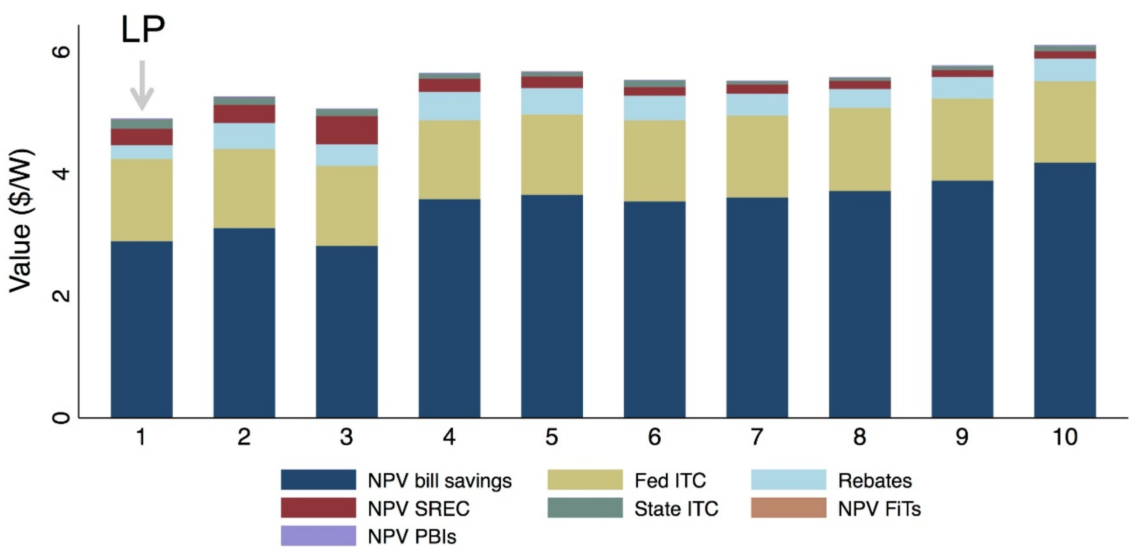

Figure 4. VoS disaggregation by system price decile.

Spatially variable factors, such as VoS, can drive geographic price variability. In general, system prices are higher in California, especially southern California, and relatively lower in other major markets such as Arizona and New Jersey (Figure 5). Low prices in Arizona and New Jersey, which also happen to be relatively low VoS states, further drive a negative VoS/LP correlation at the national level. However, our quantile regression models, which include state fixed effects to control for unobserved state differences, effectively measure state-level relationships between VoS and installed prices. The most prominent state-level VoS/price relationship is in California, a relationship we discuss in the concluding section.

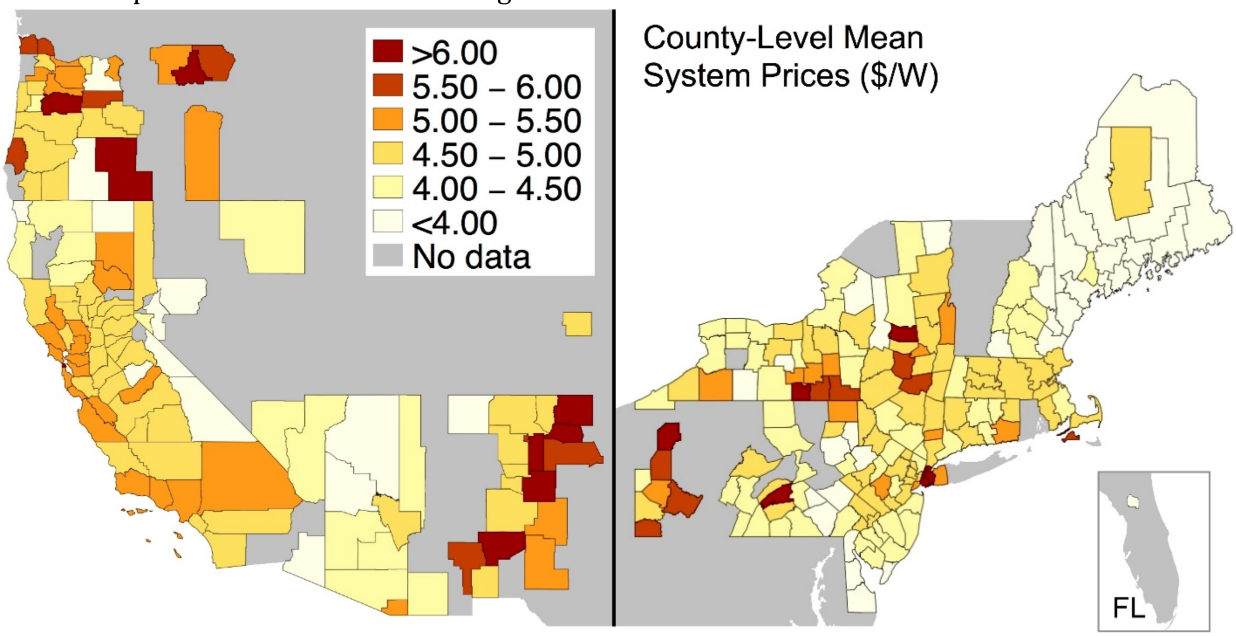

Figure 5. County-level mean system prices ($/W). Left panel shows 5 western states and right panel shows 8 eastern states.

1.1.2. Third party ownership

System ownership (host-owned vs. TPO) is another spatially heterogeneous factor that could explain geographic price variation. System ownership trends vary considerably across states, from six states with no TPO (due in part to restrictive state policies) to as high as 87% TPO in New Jersey (Figure 6). Of the five states with at least 100 TPO systems in the data, TPO systems are less likely to be LP in two states (CA, NY) and more likely to be LP in three states (AZ, MA, NJ). As noted above, these data exclude appraised value TPO systems.

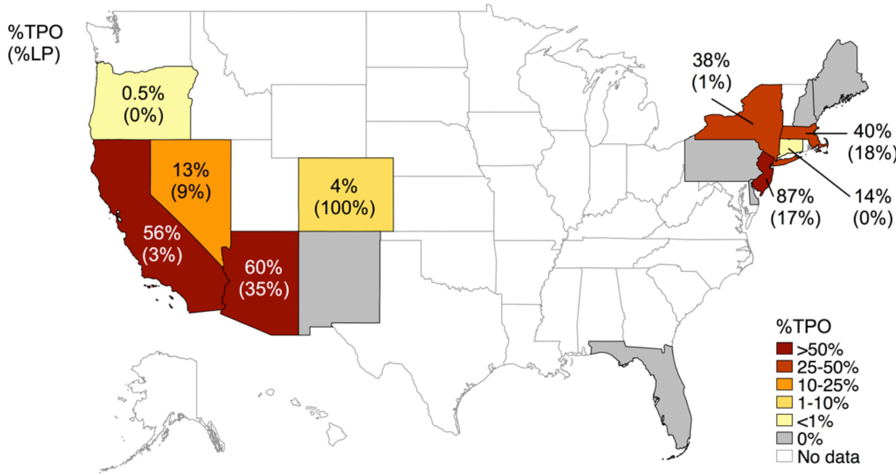

Figure 6. Percentage of TPO systems by state (percentage of TPO systems that are LP in parentheses).

1.5. Quantile regressions

Applying quantile regressions to equation 1 and our data, we obtain estimates for the effect of determinants of installed prices at several quantiles of the price distribution. We first compare the results across percentiles for our preferred model specification and then assess the robustness of these results to alternative specifications. For all of these results, the dependent variable is the installed price per watt. To address our research questions, we focus throughout on changes in the sizes and signs of the significant results in comparing LP systems to non-LP systems.

In addressing research question 1 (which factors are associated with lower prices among LP systems?), Figure 7 below summarizes the results for our preferred specification. On the left side are all variables for which the coefficients are significant at the 95% level using quantile regressions targeting the 10th percentile of the price distribution. The variables above the dashed line are continuous and those below are binary. The x-axis shows the effect on prices at the 10th percentile of the price distribution ($3.46/W) as blue bars and at the median ($4.68/W) as white bars. We use the median to represent other (non-LP) systems. The magnitudes on the x-axis are the effects on prices of moving from the 5th percentile to the 95th percentile for continuous variables. For example, at the 10th percentile, increasing system size from 3kW (the 5th percentile) to 10kW (the 95th percentile) reduces price by $0.27/W. The effect shown for system size combines both linear and quadratic terms for size. For the binary variables the values show the effect of shifting the variable from null to positive. For example, at the 10th percentile, third party ownership increases prices by $0.25/W compared to customer ownership. We include the coefficients for our preferred specifications at the 10th, 25th, 50th, 75th, and 90th percentiles in the SI. Among the continuous variables we see the largest effects on 10th percentiles prices from system size, value of solar, and share of value coming from solar renewable energy credits (SRECs), as well as inverter and module prices. We note that inverter prices were more dynamic than modules prices during 2013. For the binary variables, the largest factors increasing prices were tracking systems, building integrated PV, and being installed in Massachusetts. The largest price-reducing effects were from commercial, self-installations, and thin film, as well as being installed in Arizona, Nevada, and Florida.

For research question 2 (are the factors different for LP systems than for median priced systems?) we focus on results in which the blue bars and white bars diverge—as evidenced either by different signs or large (>50%) differences in magnitude. One can see in Figure 7 that two variables in particular stand out: consumer value of solar and new construction. For LP systems, moving from 5th percentile of value of solar ($3.39/W) to the 95th percentile ($8.32/W) reduces installed price by $0.27/W, approximately 8%. In contrast, value of solar has the opposite effect at the median; a higher value of solar increases the prices of systems by $0.23/W at the median. By separating the effects on LP vs. those on non-LP systems, this result reconciles two apparently conflicting results in previous work: previous work on mean priced systems found that value of solar is associated with increased prices (Gillingham et al. 2016) while work on LP systems found a statistically significant effect in the opposite direction (Nemet et al. 2016). Similarly, new construction has opposing effects for LP and non-LP systems. Installations on new homes make LP systems $0.18/W more expensive than installations on existing homes. For median priced systems, prices for installations on new construction are $0.68 less than on existing homes. Note that this is a large effect, reducing the price of median priced systems by 15%.

We also find results with a large change in the absolute value of the effect, without a change in direction. The following variables have effects that are at least $0.25/W larger for LP systems than median priced systems: Arizona, Florida, commercial, and thin film modules. These four variables are more important for the prices of LP systems than for non-LP systems and all four have negative effects on prices. Other variables are significant (with directions in parentheses) but are less important for LP systems than for median priced systems: tracking (+), self-installations (-), Massachusetts (+), system size (-), and installer experience (-). These five variables all have effects that are $0.25/W smaller for LP than for non-LP systems. They are thus more important for median priced systems than for LP systems.

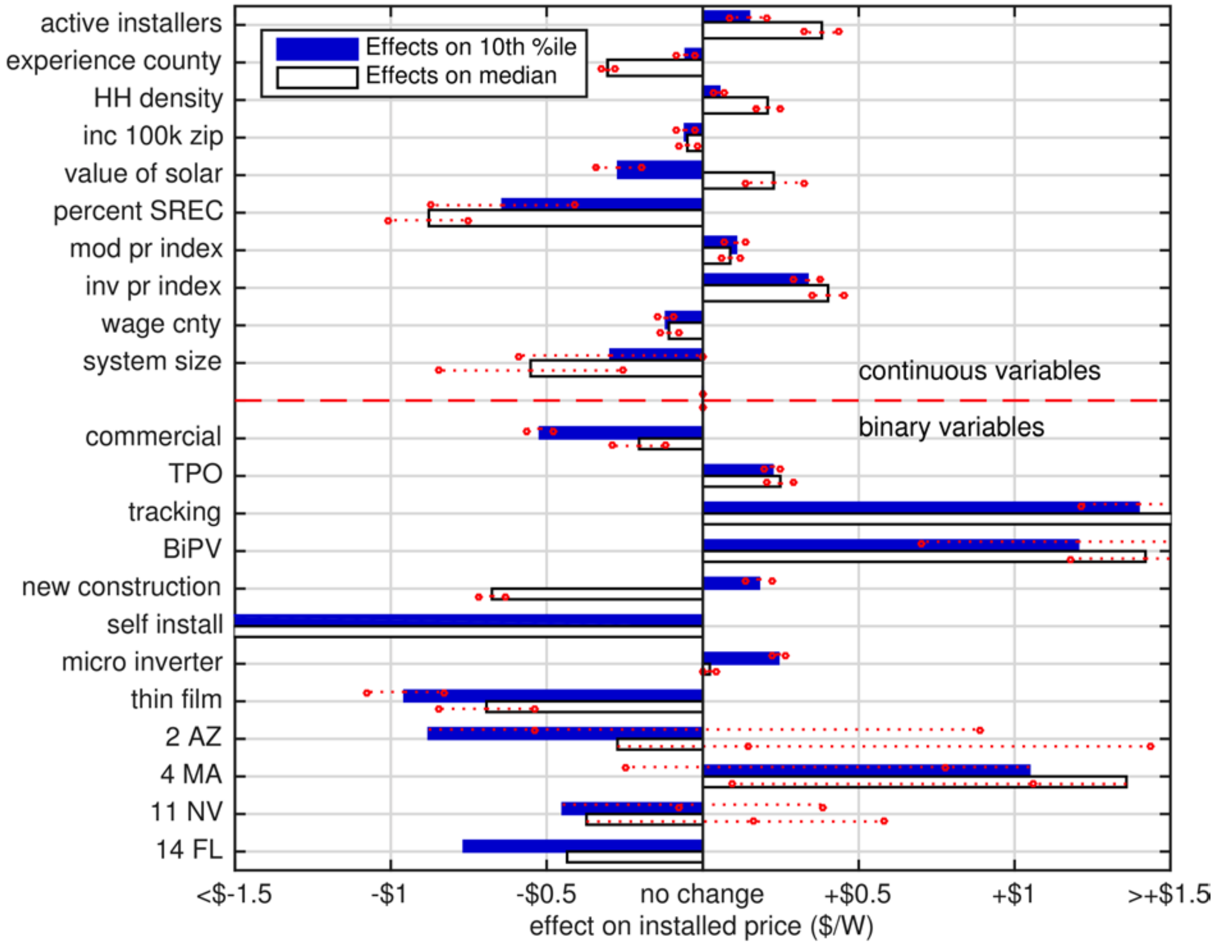

Figure 7. Sizes of effects for significant variables in base model. Values indicate change in price from moving from 5th percentile to 95th percentile for each variable.

In the SI we include robustness checks that employ alternative model specifications. We drop the state dummy variables, use other variables for competition and installer firm characteristics, add module characteristics (which are only available for a subset of the data), and include appraised value systems. We note that the directional change (from 10th to 50th percentile of all systems) in value of solar and new construction is robust to dropping the state dummies. The effects of those two variables are also robust to the other alternative specifications, with the exception of adding data on module characteristics (module efficiency and whether it was produced in China). Adding these additional data to the model, however, requires us to drop 9,500 observations (or 22% of all systems in the main model). With module data added to the models, new construction changes from positive to negative (for LP systems). This could result from the use of higher efficiency (and more expensive) modules in new construction, which we do see in the data. It could also result from a change in the mix of systems involved in dropping one quarter of the observations; these drops are not randomly distributed but involve dropping entire incentive programs that do not collect these data.

4. Summary and Discussion

We use quantile regression models to regress installed PV system prices on an array of characteristics of PV systems, markets, and the industry. Motivated by societal goals to reduce the costs of PV, our quantile regression approach allows us to look at differences in the effects between LP and non-LP systems. Both the consumer value of solar and the new construction variables have especially different effects; in fact, both have the opposite effect on prices for LP and for median-priced systems. These results have important implications for what can be expected from policy given that cost reductions are a goal. Our results imply that subsidies (the main way value of solar can be changed) reduce low-end prices but increase prices at the mid-range. Evaluating solar subsidy programs thus needs to take these differential effects into account. Subsidies may be effective at reducing low-end prices in the near term but one should not expect them to reduce median prices. Conversely, evaluations of programs to install solar on new homes need to consider that these programs are likely to be successful in reducing prices for average systems, but not for low priced systems. These results are generally very robust to alternative specifications. One minor exception is new construction. Specifically, one alternative model suggests that the higher efficiency modules that tend to be used in new construction may explain the result that new construction leads to higher prices for LP systems.

The robustness of the value of solar results is especially interesting in light of previous work showing that the signs of the value of solar coefficients are sensitive to the inclusion of state dummies (Gillingham et al. 2016, Nemet et al. 2016). But here, with quantile regressions, we find that even in models in which the state dummies are dropped, the results are the same: the value of solar coefficient is negative for LP systems and positive at the median (see SI). This may be due to the prevalence of LP systems at both ends of the VoS distribution, as illustrated below.

In particular, differences between California's two major utility service territories provide an explanation for the conflicting value of solar results. Mean utility bill savings in the Pacific Gas & Electric (PG&E) service territory (mostly northern California) are about $1.45/W higher than utility bill savings in the Southern California Edison (SCE) service territory due to PGE's steeper tiered rate structure, as of 2013. Further, average prices are about $0.06/W lower in PG&E than in SCE (t=4.5), and PG&E systems are 60% more likely to be LP (t=9.3). The contrast between the PG&E and SCE service territories establishes a strong positive VoS/LP relationship within California, which comprises 65% of the observations. To look at prices and VoS simultaneously we calculate net system cost (install price - VoS) for each system. PG&E systems are associated with lower net system costs while SCE systems are associated with higher net system costs (Figure 8).

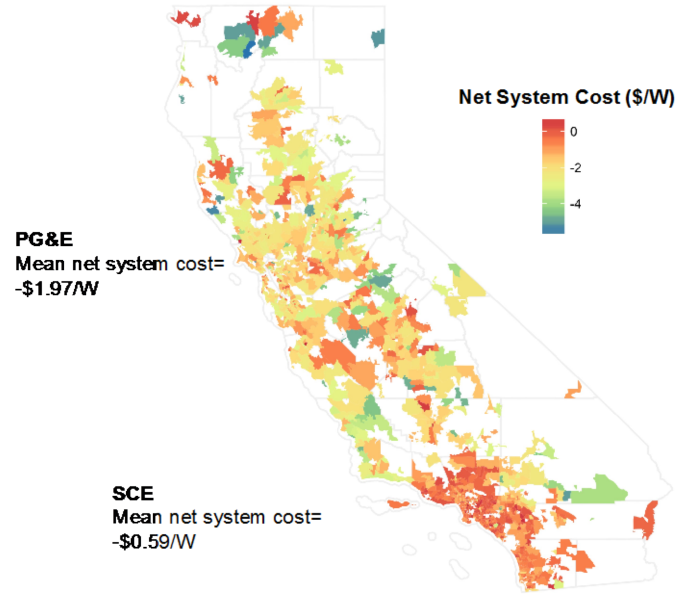

Figure 8. Net system cost (install price - VoS) for 25,073 systems in California. High net system costs in southern California, especially around Los Angeles, indicate higher prices and lower VoS relative to northern California. Lowest and highest 1% of net system costs excluded to enhance visual clarity

At the same time, high VoS is simultaneously associated with LP systems and high-priced systems in both California service territories. In California, systems with a VoS above $6.00/W (about 46% of systems) are about 87% more likely than lower VoS systems to fall into either extreme of the California system price distribution (t=26) (Figure 9). While the dynamics between northern and southern California explain the positive VoS/LP relationship observed in Nemet et al. (2016), the simultaneous relationship between VoS and LP and high-priced systems in California helps explain the VoS results of the current study. As posited in our previous work, high VoS environments may provide conditions that foster both LP and high-priced systems.

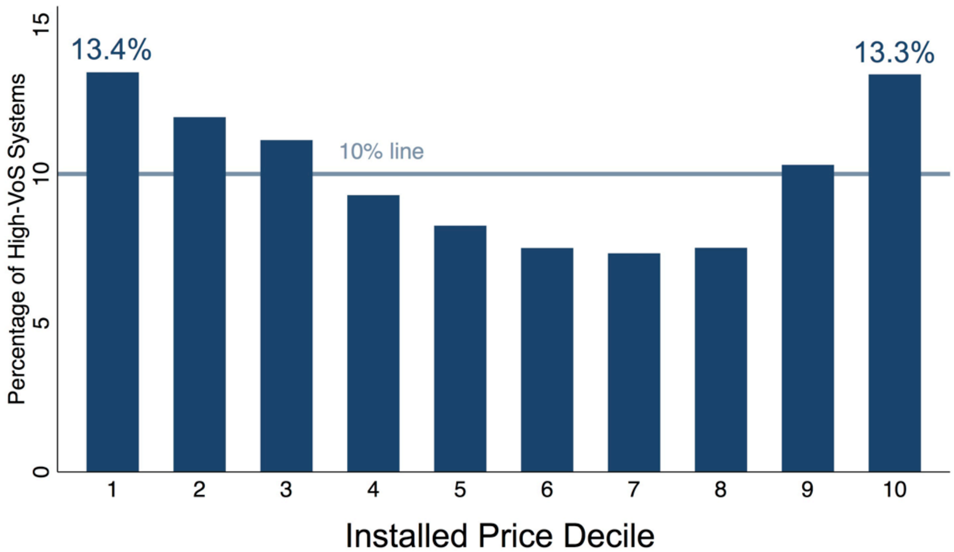

Figure 9. Installed price distribution of high value of solar systems (VoS>$6/W) in California. The uniform distribution should fall along the 10% line; however, the distribution shows clear clustering in both tails.

These results show that some of the factors affecting prices are different for low-priced systems than for other systems. Given that cost reductions are a stated policy goal by the federal government, as well as by some state incentive programs, this study elucidates the factors that might make low-priced systems even less expensive. This analysis has focused on the 12 months of installations in 2013, a period when prices were rather stable. Ultimately, it will be important to identify the effects of policy (e.g. via the value of solar) on the long term evolution of PV prices—with a special emphasis on the drivers of costs for systems at the low end of the price distribution. This will help enable improved assessments of the effects of policy on these longer-term goals and thus inform future polices on how most effectively to stimulate further costs reductions in PV.

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Appendix A. Data set descriptive statistics, variable definitions

A1. Variable definitions and summary statistics

The following tables show definitions and summary statistics for all variables.

Table A1. Variable Definitions.

Name	Definition
price per W	Install price per W (current $s)
price	Install price (current $s)
installers cnty	number of installers in county per HH (installs in past 6 months)
mkt duration	days since first install in the county, by any installer
hhi	HHI index (0-1) for county (last 12 months)
active instllrs	number of installers with >1 install in past 6 months in county
exp cnty	depr. installer experience in county, no exp from mergers
exp state	depr. installer experience in state, no exp from mergers
agg exp cnty	depr. experience in county, all installers
mkt share	market share in county in past 12 months, by installer
inst scale cnty	installs in past 3 months (incl current) in county by installer
inst scale st	installs in past 3 months (incl current) in state by installer
HH density	local market density (total number of owned-occ HHs within county/sq. mile)
edu college zip	percent completed Bachelor, in zip
inc 100k zip	pct HH income >100k, in zip
pct demo cnty	percent democratic in county (pres. election results)
value of solar	value of solar ($/W)
pct srec	SREC as pct of total incentive received, normalized by cost/W avg
interconnect	interconnection total score using statewide value from IREC scores
wage cnty	labor cost index: 2.5 (admin) to 2 (roof) to 1 (electr), by county
mod pr index	monthly module prices ($/W) at time of application
inv pr index	monthly inverter prices ($/W) at time of application
sys size	system size (W)
mod eff	module efficiency
commercial	Commercial dummy (1 if COM, NON-RES)
other cust	Other customer market, dummy (1 if GOV, NON-PROF, SCH, OTH)
TPO	dummy, 1 if TPO
self install	dummy, 1 if self-installed
china panel	dummy, 1 if panel made in China
thin film	dummy, 1 if thin Film
micro invrtr	dummy, 1 if micro-inverter
BiPV	dummy, 1 if BIPV
new constr	dummy, 1 if new construction
battery	dummy, 1 if battery
tracking	dummy, 1 if tracking

Table A2. Summary statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max	P50
price per W	42611	4.773	1.181	1.001	21.822	4.684
price	42611	29242.25	13561.91	2000.303	233505.8	27331.9
installers cnty	42611	0	0	0	.001	0
mkt duration	42611	4728.702	953.388	0	5712	5208
hhi	42611	.121	.084	.036	1	.096
active instllrs	42611	60.46	46.97	0	173	49
exp cnty	42611	118.967	221.022	0	1411.26	36.88
exp state	42611	572.63	915.824	0	3996.012	154.55
agg exp cnty	42611	3092.868	3129.044	0	10555.85	1929.958
mkt share	42611	.071	.11	0	1	.029
inst scale cnty	42611	33.252	65.759	0	475	8
inst scale st	42273	161.097	279.632	0	1267	35
HH density	42611	0	0	0	.003	0
edu college zip	42611	.345	.169	0	.877	.321
inc 100k zip	42611	.339	.153	0	.859	.333
pct demo cnty	41855	.548	.11	.209	.912	.516
value of solar	42611	5.51	1.541	2.274	10.723	5.015
pct srec	42611	.045	.111	0	.57	0
interconnect	42611	20.847	6.314	3	27.5	20
wage cnty	41995	57836.1	12309.29	19709.3	108658.8	54685.56
mod pr index	42611	.771	.019	.744	.804	.774
inv pr index	42611	.283	.018	.255	.312	.287
sys size	42611	6267.709	2766.159	1000	15000	5886
mod eff	36826	.165	.021	.058	.212	.155
commercial	42611	.034	.182	0	1	0
other cust	42611	.002	.041	0	1	0
TPO	42611	.537	.499	0	1	1
self install	42611	.008	.091	0	1	0
china panel	35683	.327	.469	0	1	0
thin film	42611	.002	.04	0	1	0
micro invrtr	42611	.286	.452	0	1	0
BiPV	42611	.003	.051	0	1	0
new constr	42611	.05	.217	0	1	0
battery	42611	0	.01	0	1	0
tracking	42611	.001	.024	0	1	0

A2. Policy Variables

A number of relevant policy variables can be inferred from the location of each PV system. We calculate a customer value of solar (VoS) variable reflecting the discounted value of all policy instruments and electricity bill savings. The VoS represents a rough estimation of the full economic value of the PV system to the customer and includes the following five components:

1. Tax credits. The federal government and a number of states offer investment tax credits (ITCs) for PV systems. Since 2009, the federal ITC has been 30% of system costs. For host-owned residential systems, the credit is based on the total system price net of any cash rebates (since the cash rebates are not taxable income). For commercial and TPO residential systems, the credit is assumed to be based on the total system price (since the cash rebates are taxable income for commercial entities). From the states for which we have PV system data, the following states have had ITCs over the 2000–2013 period (in addition to the federal ITC): California, Massachusetts, New Mexico, New York, North Carolina, Oregon, Texas, Utah, and Vermont. The ITC rules vary by state, with different rules for specific customer segments and periods as well as different ITC caps. The ITC calculations were based on the ITC descriptions in (DSIRE 2014) and correspondence with state programs.
2. Cash incentives and rebates, from state and local governments. In most cases, the exact amounts for the cash incentives and rebates were received directly from the incentive programs. In some cases, the incentive programs did not provide incentive data for all systems. For those systems, the cash incentive was estimated by using the average known incentive amount (in dollars per watt) from other PV systems in a similar size range that had applied for an incentive within 1 month from the same incentive program. Because cash incentives are taxable for commercial entities, we assumed that commercial and TPO systems were taxed at the appropriate corporate federal and state tax rate.

3. Performance-based incentives (PBIs) and feed-in tariffs (FiTs). PBIs and FiTs are tied to actual or estimated PV generation and in most cases disbursed annually for a fixed amount of time (5–20 years, depending on the incentive program). In order to calculate the annual PBI or FiT payment, we estimate the PV production using the National Renewable Energy Laboratory's PVWatts model (http://pvwatts.nrel.gov/), unless an estimated lifetime PBI amount is specified by the incentive program. In the latter case, we use those data directly, subject to discounting. Inputting system location (i.e., zip code) and system size and making a number of assumptions regarding system characteristics—such as south-facing panels with a 25-degree tilt and a derate factor of 0.77—the model returns the system's estimated annual generation. We then calculate the annual PBI or FiT payment (subject to applicable state and federal income taxes), assuming a system degradation rate of 0.5% per year (Jordan and Kurtz 2013) and a discount rate of 7%. The present value of the income stream is calculated and included in the customer VoS variable.

4. Solar renewable energy credit (SREC) payments. Seventeen states plus the District of Columbia have enacted renewable portfolio standards with solar or distributed generation set-asides, and in many of those states compliance with the set-aside is achieved through the purchase and retirement of tradable SRECs. Among the states in our sample, active SREC markets exist in the District of Columbia, Delaware, Massachusetts, Maryland, New Hampshire, New Jersey, Ohio, and Pennsylvania. Given the uncertainty in future SREC prices, we chose to extrapolate the 2-year rolling average price from the state's SREC market over 5 years, then assumed $100/MWh SREC payment for the following 10 years[3]. As with the PBI calculations, we use estimated PV system generation to calculate total SREC payments and sum the present value of all future SREC payments (again, with a discount rate of 7% and a system degradation rate of 0.5% per year).

5. Electricity bill savings. We estimate the present value of all electricity bill savings over the lifetime of the PV system. We use the National Renewable Energy Laboratory's OpenEI platform to determine each system's appropriate utility (assuming the default service provider in areas with retail competition). We then use the utility's average retail electricity rates for commercial and residential customers for 2013, extracted from the U.S. Energy Information Administration's Form 861, and the estimated annual PV system generation to calculate annual electricity bill savings for each PV system. To account for inclining block pricing in California investor-owned utilities, we multiply the utilities' average rate by a tiering factor. The tiering factor is based on how much higher the average rate is for net-metered customers (based on their gross consumption) than for average non-solar customers following work by the consulting company E3. Utilities with inclining block pricing in other states have much less steep price tiers, and hence tiered pricing is not modeled for utilities outside California. For commercial systems and TPO systems, the bill savings are taxed at the applicable state and federal corporate tax rate, to reflect the fact that the utility service costs are an expense that reduces taxable income. We assume that rates rise with inflation through the lifetime of the system (20 years) and calculate the present value of each year's bill savings from PV.

In addition, we construct a variable that reflects the percentage of the total customer VoS that comes from SRECs, which are more uncertain than other elements constituting the total customer VoS. We also include a state-level interconnection score, which evaluates the ease of interconnecting a PV system onto the grid (IREC 2013).

[3] For reference, the average SREC prices for 2013 were $290/MWh in DC, $53/MWh in DE, $310/MWh in MA, $170/MWh in MD, $50/MWh in NH, $170/MWh in NJ, $170/MWh in OH, and $30/MWh in PA.

Appendix B. Supplemental Analysis

B1. Appraised value systems

The dependent variable price in $/W is derived from installed system prices. Inaccurate system price reporting would therefore weaken the certainty of modeled relationships of the independent variables with prices. Appraised value systems (n=19,765) were excluded from the analysis because such systems do not convey meaningful price information. Unlike real value system installers that report the actual installed price of systems to incentive programs, appraised value system installers report prices based on appraised value formulae that do not correspond to specific system costs. Appraised value reporting results in system price binning, where large numbers of systems are reported with identical prices Figure B1. About 76% of appraised value systems fall into a bin of at least 100 identically-priced systems, compared to about 2% of real-value systems. This suggests that well over half of appraised values do not reflect a true system price.

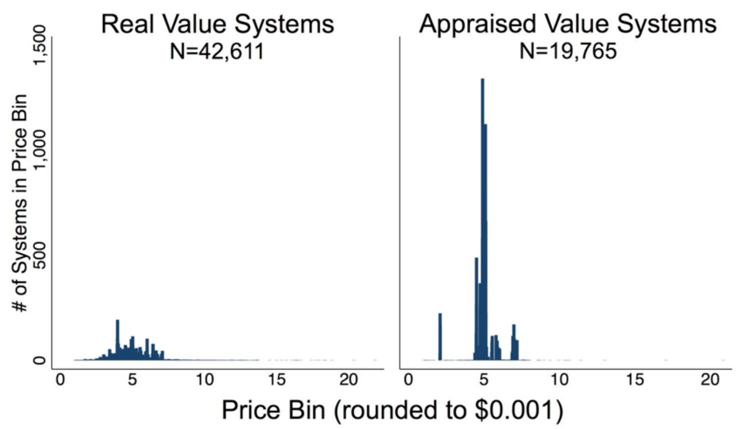

Figure B1. Comparison of appraised value and non-appraised value (real value) systems.

Table B1. Appraised value and non-appraised value systems by state.

state	non_apprais	appraised	Total	pct appraised
CA	27,564	10,701	38,265	28.0%
AZ	4,359	4,358	8,717	50.0%
NJ	3,523	2,228	5,751	38.7%
MA	2,459	1,619	4,078	39.7%
NY	1,619	682	2,301	29.6%
NM	878		878	0.0%
CT	733	1	734	0.1%
OR	600	175	775	22.6%
ME	272		272	0.0%
NH	254		254	0.0%
NV	178		178	0.0%
PA	127		127	0.0%
CO	24	1	25	4.0%
FL	16		16	0.0%
DE	5		5	0.0%
	42,611	19,765	62,376	

B2. Value of Solar

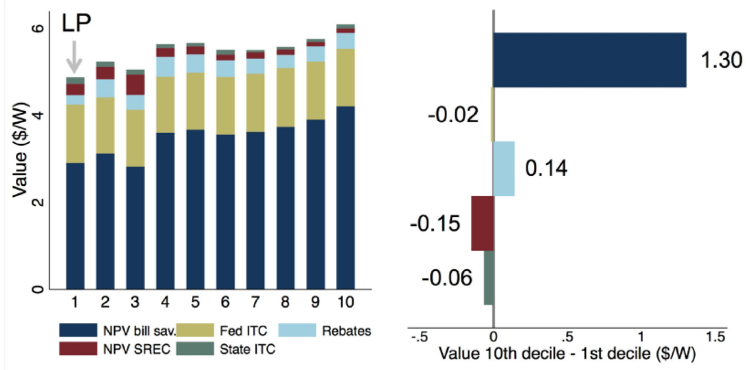

Figure B2. Components of value of solar, by decile.

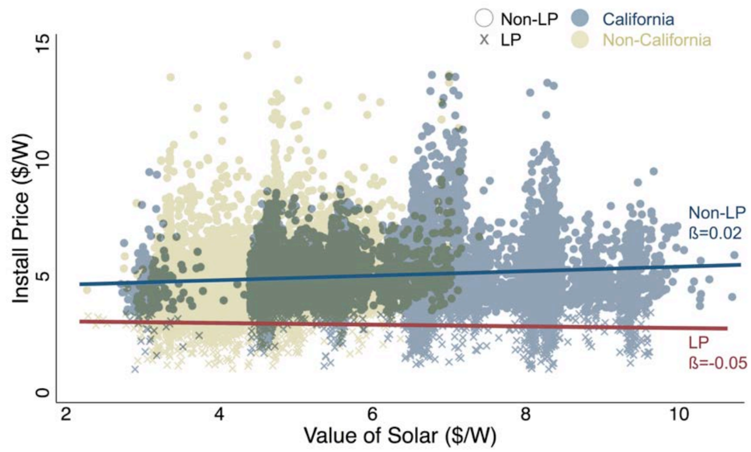

Figure B3. Scatterplot depicting relationship between install prices and VoS for LP and non-LP systems inside and outside of California. For illustrative purposes, the figure excludes systems priced above $15/W.

Value of solar and prices. The reason for this relationship remains unclear, however it is possible that high-VoS markets are fundamentally different. The data suggest that VoS has a positive effect on prices up to a VoS of about $6.82/W, and a negative effect on prices beyond $6.82/W. High VoS systems (>$6.82/W) are associated with more competitive markets. On average, high VoS systems are located in the same zip code as 76 other systems, compared to 60 other systems for low-VoS systems (t=19.3). Further, the average county-level HHI associated with high-VoS systems is about 15% lower than other systems (t=17.6). These data suggest that high-VoS markets may be fundamentally different from low-VoS markets in such a way that alters the relationship between VoS and system pricing. It is plausible that value-based pricing drives a positive relationship between VoS and system pricing in less competitive low-VoS markets, while opposing forces such as economies of scale and market competition drive a negative relationship between VoS and system pricing in more competitive high-VoS markets.

Appendix C. Detail on Regression Analyses

C1. Tables of regression results.

Table C1 provides coefficients and standard errors for quantile regressions discussed in the main text.

Table C1. Estimates from quantile regressions for base model. Columns indicate quantiles estimated.

mod pr index	1.775***	0.858**	1.465***	2.195***	1.141
	(0.294)	(0.293)	(0.264)	(0.358)	(0.599)
inv pr index	5.954***	5.565***	7.130***	10.66***	11.28***
	(0.407)	(0.459)	(0.471)	(0.525)	(0.962)
wage cnty	-0.372***	-0.333***	-0.343***	-0.332***	-0.220*
	(0.0433)	(0.0504)	(0.0487)	(0.0717)	(0.101)
sys size	-0.0491***	-0.136***	-0.185***	-0.293***	-0.326***
	(0.00856)	(0.00919)	(0.00845)	(0.00878)	(0.0169)
sys size sqrd	0.00123*	0.00651***	0.00907***	0.0138***	0.0146***
	(0.000560)	(0.000680)	(0.000561)	(0.000534)	(0.00118)
tracking	1.398***	1.657***	2.274***	4.344***	5.273***
	(0.0922)	(0.0821)	(0.117)	(0.0959)	(0.117)
BiPV	1.204***	1.882***	1.420***	1.508***	1.559***
	(0.258)	(0.133)	(0.121)	(0.0494)	(0.109)
new constr	0.180***	-0.256***	-0.676***	-1.187***	-1.157***
	(0.0228)	(0.0210)	(0.0237)	(0.0425)	(0.0508)
battery	0.837	4.304	7.875	6.977	11.16***
	(1.039)	(21.79)	(17.58)	(27.83)	(0.241)
self install	-1.737***	-2.019***	-2.300***	-2.205***	-2.053***
	(0.0260)	(0.0370)	(0.0580)	(0.0952)	(0.190)
micro invrtr	0.242***	0.118***	0.0222*	0.171***	0.211***
	(0.0125)	(0.0105)	(0.0105)	(0.0173)	(0.0198)
thin film	-0.956***	-0.906***	-0.693***	-0.108*	0.0638
	(0.0653)	(0.211)	(0.0756)	(0.0449)	(0.132)
1 CA	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)
2 AZ	-0.878***	-0.400	-0.275	-0.324	-0.650
	(0.239)	(0.234)	(0.225)	(0.190)	(0.342)
3 NJ	0.178	1.261***	0.787*	0.590	0.702
	(0.364)	(0.355)	(0.330)	(0.313)	(0.540)
4 MA	1.047**	1.863***	1.357***	1.271***	1.219*
	(0.369)	(0.360)	(0.332)	(0.321)	(0.555)
5 NY	0.265	0.845**	0.579*	0.404	-0.0738
	(0.262)	(0.258)	(0.247)	(0.209)	(0.372)
6 NM	-0.0965	0.722**	1.009***	0.705**	0.708
	(0.258)	(0.257)	(0.249)	(0.216)	(0.430)
7 CT	0.0592	0.838*	0.321	-0.258	-0.892
	(0.349)	(0.343)	(0.329)	(0.280)	(0.503)
8 OR	0.421	1.192***	0.607	-0.0350	-0.151
	(0.351)	(0.346)	(0.330)	(0.282)	(0.530)
10 NH	-0.192	0.826*	0.504	0.114	-0.255
	(0.359)	(0.360)	(0.335)	(0.305)	(0.542)
11 NV	-0.449***	-0.383***	-0.372***	-0.581***	-0.316
	(0.0741)	(0.0514)	(0.0833)	(0.0794)	(0.221)
12 PA	0.155	0.426**	0.373***	0.112	0.324
	(0.117)	(0.135)	(0.107)	(0.217)	(0.238)
14 FL	-0.766*	-0.00583	-0.436	-0.742	-1.566***
	(0.323)	(0.389)	(0.486)	(0.555)	(0.455)
Obs.	41995	41995	41995	41995	41995
Y at qtile(pr/W)	3.473	4.023	4.698	5.368	6.222

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C2. Figures of regression results

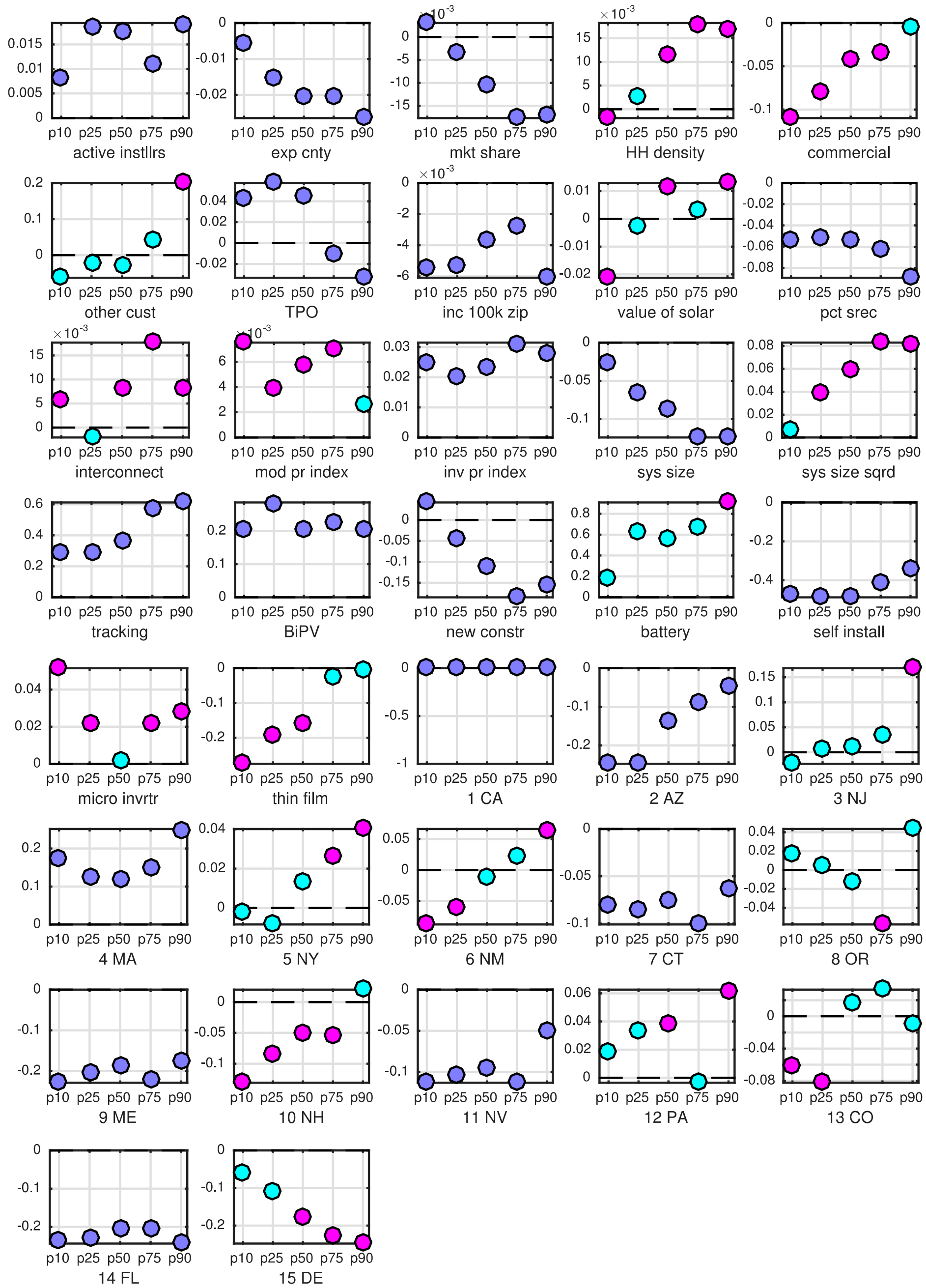

Figure C1. Coefficients from quantile regressions of base model at 5 quantiles. Blue indicates significance at 95% level.

C3. Alternative specifications

In Table C2 we show results for quantile regressions for model dropping state dummies. In Table C3, we show quantile regression estimates of y=price/W at 10th percentile for 2013 installs using five alternative specifications.

Table C2. Quantile regression estimates of y=price/W at multiple quantiles, for 2013 installs. Model dropping state dummies.

			0124)	(0.0175)	(0.0226)
pct srec	-0.0151	-0.0377***	-0.117***	-0.138***	-0.169***
	(0.00938)	(0.00908)	(0.00952)	(0.0156)	(0.0220)

interconnect	0.286***	0.267***	0.213***	0.217***	0.177***
	(0.0101)	(0.0101)	(0.00956)	(0.0135)	(0.0205)
sales tax	0.0933***	0.0842***	0.0654***	0.0470*	-0.0781*
	(0.0147)	(0.0153)	(0.0161)	(0.0237)	(0.0333)
mod pr index	0.0887***	0.0818***	0.0724***	0.0535***	0.0385***
	(0.00627)	(0.00538)	(0.00495)	(0.00716)	(0.00985)
inv pr index	0.191***	0.197***	0.180***	0.216***	0.225***
	(0.00747)	(0.00708)	(0.00667)	(0.00941)	(0.0138)
wage cnty	-0.0250***	-0.0334***	-0.0451***	-0.0432***	-0.0251*
	(0.00755)	(0.00627)	(0.00585)	(0.00934)	(0.0120)
sys size	-0.126***	-0.312***	-0.466***	-0.785***	-0.849***
	(0.0240)	(0.0240)	(0.0219)	(0.0303)	(0.0399)
sys size sqrd	0.0164	0.183***	0.307***	0.522***	0.541***
	(0.0217)	(0.0235)	(0.0202)	(0.0272)	(0.0370)
tracking	1.444***	1.743***	2.072***	3.941***	4.666***
	(0.0282)	(0.438)	(0.0691)	(0.294)	(0.134)
BiPV	1.353***	1.924***	1.460***	1.500***	1.682***
	(0.255)	(0.163)	(0.122)	(0.0852)	(0.193)
new constr	0.0888***	-0.339***	-0.758***	-1.276***	-1.169***
	(0.0246)	(0.0245)	(0.0216)	(0.0418)	(0.0449)
battery	1.028***	4.829	7.812	6.925	11.10***
	(0.240)	(24.04)	(15.70)	(27.64)	(0.251)
self install	-1.834***	-2.066***	-2.334***	-2.296***	-2.017***
	(0.0170)	(0.0475)	(0.0323)	(0.0930)	(0.217)
micro invrtr	0.225***	0.0750***	-0.0150	0.132***	0.187***
	(0.0134)	(0.0104)	(0.0105)	(0.0179)	(0.0190)
thin film	-1.029***	-0.917***	-0.801***	-0.0806	0.0348
	(0.0219)	(0.176)	(0.0992)	(0.212)	(0.443)
Obs.	41995	41995	41995	41995	41995
Y at qtile(pr/W)	3.473	4.023	4.698	5.368	6.222

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C3. Quantile regression estimates of y=price/W at 10th percentile for 2013 installs. Five alternative specifications.

	(1) base	(2) no states	(3) comp2	(4) firm2	(5) module	(6) appraised
active instllrs	0.0457***	0.0265**	0.0437***	0.0338***	0.0292***	-0.0800***
	(0.00937)	(0.00958)	(0.0103)	(0.00727)	(0.00828)	(0.00734)
hhi			-0.0338***			
			(0.00779)			
exp cnty	-0.0214***	-0.0626***	-0.0248***		-0.00782	0.240***
	(0.00579)	(0.00631)	(0.00599)		(0.00685)	(0.00458)
mkt share	-0.00185	0.0478***	0.00989		0.00202	0.0921***
	(0.00368)	(0.00646)	(0.00551)		(0.00565)	(0.00652)
inst scale st				-0.0165**		
				(0.00521)		
HH density	0.0235***	0.0292**	0.0287***	0.0327***	0.0423***	0.122***
	(0.00309)	(0.0107)	(0.00334)	(0.00429)	(0.00751)	(0.00491)
commercial	-0.522***	-0.0771***	-0.510***	-0.522***	-0.412***	-1.388***
	(0.0203)	(0.0162)	(0.0224)	(0.0186)	(0.0290)	(0.0317)
other cust	-0.243	-0.154*	-0.214	-0.226	0.0648	-0.772
	(0.335)	(0.0689)	(0.327)	(0.360)	(0.137)	(0.633)
TPO	0.223***	0.158***	0.236***	0.228***	0.320***	0.454***
	(0.0138)	(0.0152)	(0.0149)	(0.0139)	(0.0156)	(0.0167)
inc 100k zip	-0.0177***	-0.00320	-0.0211***	-0.0242***	0.00405	-0.00991**
	(0.00494)	(0.00551)	(0.00462)	(0.00384)	(0.00471)	(0.00368)
value of solar	-0.0853***	-0.0416***	-0.0779***	-0.0864***	0.0146	-0.0650***
	(0.0114)	(0.0102)	(0.0124)	(0.0111)	(0.0129)	(0.0108)
pct srec	-0.212***	-0.0151	-0.235***	-0.221***	-0.219***	1.497***
	(0.0392)	(0.00938)	(0.0416)	(0.0368)	(0.0466)	(0.0377)
interconnect	0.00826	0.286***	0.00569	0.00462	0.0564***	-0.0621***
	(0.0135)	(0.0101)	(0.0142)	(0.0109)	(0.0129)	(0.0143)
sales tax	0.137	0.0933***	0.223	0.168	0.481***	-0.210*
	(0.145)	(0.0147)	(0.147)	(0.115)	(0.146)	(0.102)
mod pr index	0.0334***	0.0887***	0.0321***	0.0351***	0.0388***	-0.0223***
	(0.00553)	(0.00627)	(0.00572)	(0.00488)	(0.00501)	(0.00411)
inv pr index	0.107***	0.191***	0.101***	0.109***	0.132***	0.0888***
	(0.00729)	(0.00747)	(0.00778)	(0.00616)	(0.00609)	(0.00641)
wage cnty	-0.0456***	-0.0250***	-0.0438***	-0.0449***	-0.0366***	-0.0973***
	(0.00531)	(0.00755)	(0.00484)	(0.00414)	(0.00709)	(0.00690)
sys size	-0.136***	-0.126***	-0.134***	-0.146***	-0.250***	-0.139***
	(0.0238)	(0.0240)	(0.0250)	(0.0217)	(0.0198)	(0.0150)
sys size sqrd	0.0500*	0.0164	0.0534*	0.0611**	0.119***	0.0214
	(0.0228)	(0.0217)	(0.0238)	(0.0204)	(0.0191)	(0.0137)
tracking	1.398***	1.444***	1.390***	1.402***	1.068	1.464***
	(0.0922)	(0.0282)	(0.0577)	(0.0857)	(1.872)	(0.0450)
BiPV	1.204***	1.353***	1.197***	1.174***	2.477***	1.151
	(0.258)	(0.255)	(0.273)	(0.293)	(0.457)	(0.946)
new constr	0.180***	0.0888***	0.175***	0.180***	-0.587***	0.102***

	(0.0228)	(0.0246)	(0.0242)	(0.0203)	(0.0257)	(0.0285)
battery	0.837	1.028***	0.889	0.866	0.938***	0.912
	(1.039)	(0.240)	(1.287)	(0.892)	(0.209)	(0.481)
self install	-1.737***	-1.834***	-1.742***	-1.429	-1.554***	-1.619***
	(0.0260)	(0.0170)	(0.0271)	(1.646)	(0.0737)	(0.0206)
micro invrtr	0.242***	0.225***	0.246***	0.245***	0.385***	0.317***
	(0.0125)	(0.0134)	(0.0136)	(0.0108)	(0.0161)	(0.0114)
thin film	-0.956***	-1.029***	-0.978***	-1.001*	-0.125*	-0.875***
	(0.0653)	(0.0219)	(0.113)	(0.460)	(0.0581)	(0.109)
china panel					-0.238***	
					(0.0156)	
mod eff					0.443***	
					(0.00669)	
1 CA	0		0	0	0	0
	(.)		(.)	(.)	(.)	(.)
2 AZ	-0.878***		-0.702**	-0.852***	0.0906	-1.473***
	(0.239)		(0.246)	(0.193)	(0.242)	(0.172)
3 NJ	0.178		0.446	0.239	1.301***	-5.819***
	(0.364)		(0.380)	(0.299)	(0.382)	(0.254)
4 MA	1.047**		1.324***	1.130***	2.100***	-4.678***
	(0.369)		(0.387)	(0.306)	(0.390)	(0.262)
5 NY	0.265		0.459	0.291	1.058***	-0.634***
	(0.262)		(0.269)	(0.211)	(0.266)	(0.184)
6 NM	-0.0965		0.114	-0.0715	1.062**	-0.954***
	(0.258)		(0.267)	(0.210)	(0.324)	(0.186)
7 OR	0.0592		0.299	0.107	1.158**	-0.425
	(0.349)		(0.357)	(0.280)	(0.355)	(0.251)
8 CT	0.421		0.645	0.478		-1.182***
	(0.351)		(0.359)	(0.283)		(0.248)
10 NH	-0.192		0.0868	-0.141	0.900*	-3.418***
	(0.359)		(0.370)	(0.299)	(0.407)	(0.252)
11 NV	-0.449***		-0.420***	-0.414***	-0.0948	-0.576***
	(0.0741)		(0.0535)	(0.0543)	(0.155)	(0.0643)
12 PA	0.155		0.257*	0.140	0.495**	-2.809***
	(0.117)		(0.124)	(0.106)	(0.179)	(0.100)
14 FL	-0.766*		-0.527	-0.739*	0.356	-1.901***
	(0.323)		(0.344)	(0.326)	(0.392)	(0.230)
Obs.	41995	41995	41995	41658	32486	61759
Y at qtile(pr/W)	3.473	3.473	3.473	3.497	3.532	3.657

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$