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What factors affect the prices of low-priced U.S. solar PV systems?

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A B S T R A C T

The price of solar PV systems has declined rapidly, yet there are some much lower-priced systems than others. This study explores the factors that determine prices in these low-priced (LP) systems. 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 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 price-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.

1. Introduction

The global deployment of solar photovoltaics (PV) is on the rise, motivated by a variety of policy interventions and falling solar prices [1–3]. But the degree to which solar continues its rapid pace of deployment and its resulting role in climate mitigation depends on future price reductions [4–7]. Increasingly lower installed prices will be important to help overcome the inherent grid-integration limitations to time-variable PV output and to counteract declining incentives and compensation rates [8–11]. As such, a key goal for the solar industry, policymakers, and other decision makers is to foster continued, dramatic declines in solar installed prices to ensure a sizable future role for this technology in meeting energy supply needs under carbon constraints.

A surprising feature of the PV 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 [12–16]. Researchers have begun exploring some of the reasons for this heterogeneity in PV pricing, 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. Other work investigates the impact of local permitting processes [17,18], solar incentives [19–21], market concentration [22], customer acquisition costs [12], and the influence of third-party ownership (TPO) [23]. All of this previous work has focused on understanding trends for mean or median PV systems.

The existence of a subset of low-priced (LP) systems in the left tail of the installed price distribution generates two policy-relevant research questions. First, what distinguishes LP systems from higher-priced systems, and how can policymakers increase the availability of LP systems? Second, what factors drive prices within

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LP systems, and how can policymakers make LP systems even lower priced? Nemet et al. (2017) [16] address the first question, finding that system characteristics, location, and policies have significant effects on whether systems are priced below the 10th percentile of the price distribution. Our study builds on the past literature by addressing the second question. We statistically evaluate what drives LP systems to be *even lower* priced. An improved understanding of the factors that drive prices in LP systems will help policymakers identify further opportunities for installed price reductions and deployment expansion.

Consistent with previous studies, we find that local PV policies and incentives affect installed prices [15–21]. Our contribution with this study is that policy appears to have differential effects on LP systems. Previous work suggests that more generous local PV incentives increase installed prices at the median [15]. Our study finds that this relationship flips at the low end of the price distribution: more favorable PV policy environments result in lower prices for LP systems. Our findings indicate that PV policies have complex influences on installed prices and that these effects vary at different points in the price distribution.

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. Material and methods

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

2.1. Data sources

We begin with data from LBNL's *Tracking the Sun* (TTS) report series [24]. 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. Ref. [24] 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 Ref. [25]; 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 [26], and the U.S. Bureau of Labor Statistics [27]. We include variable definitions in the Supporting Information (SI).

2.2. Variables and restrictions

We restrict this data set by including only systems with the following characteristics: installed in 2013 (for the most recent data), between 1 and 15 kW_{DC} (for residential scale), and with installed prices between \$1 and \$25/W (to eliminate outliers). The limitation to 2013 data was based on the lengthy data collection and cleaning process involved for the large and complex TTS dataset. The U.S. PV market has grown since 2013 but has not undergone significant changes that would undermine the validity of our findings based on the dates of the data. 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. Fig. 1 shows the probability distribution of installed prices for these systems. We include summary statistics for all variables in the SI.

2.3. 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 [28]. 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. (2017)[16], which uses regressors for competition variables (COMP), firm (FIRM) and market

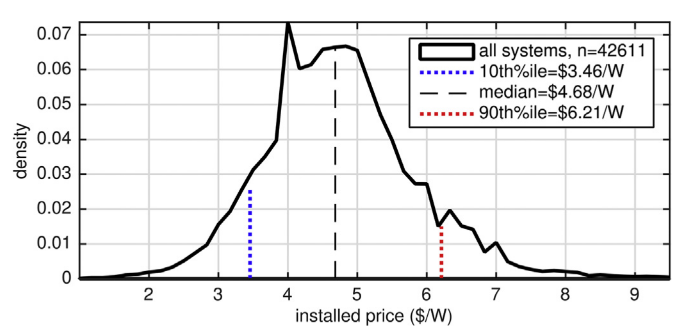

Fig. 1. Probability distribution of installed PV prices 2013.

[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.

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

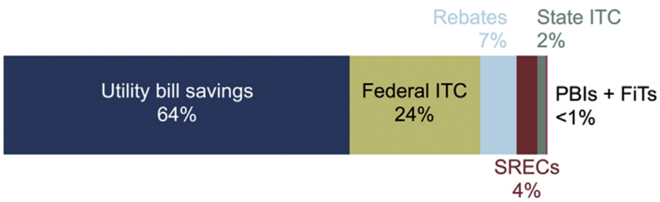

Fig. 2. Components of the consumer value of solar for all systems.

(MKT) characteristics, policies (POL), PV system attributes (SYSTEM), and binary variables (B):

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

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

We first provide descriptive comparisons in Section 3.1 to contextualize the evaluative results. The results of the quantile regressions are presented in Section 3.2.

3.1. 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.

3.1.1. Consumer value of solar

Consumer *value of solar* 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

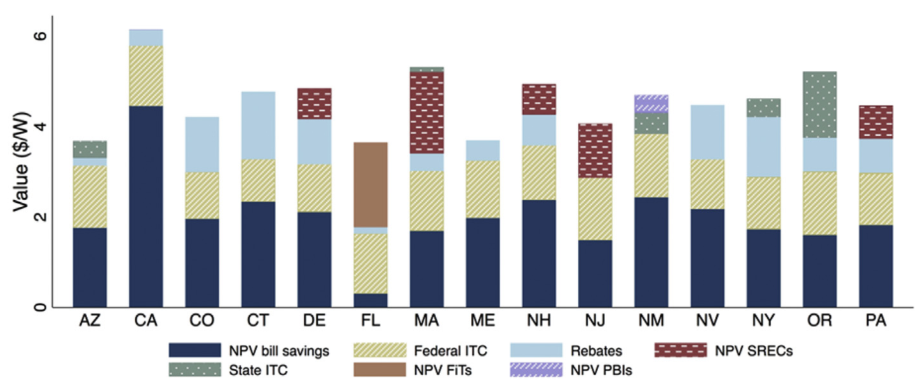

Fig. 3. Disaggregation of value of solar components by state.

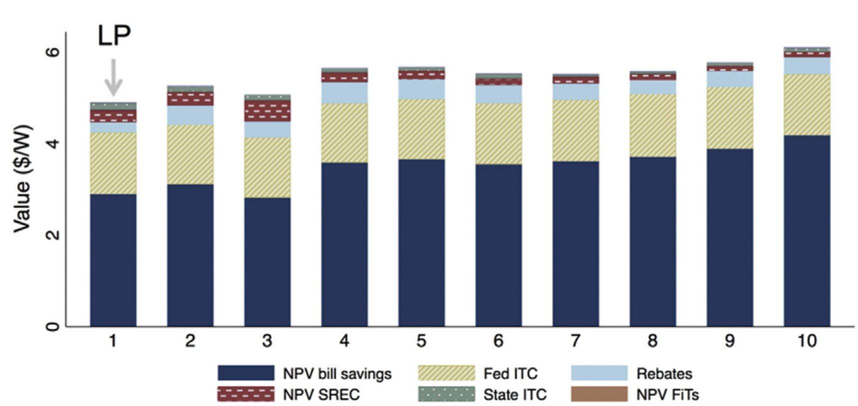

Fig. 4. Value of solar disaggregation by system price decile.

(Fig. 2).

Value of solar varies geographically according to incentive availability, local retail rates, and local solar resources (Fig. 3). Utility bill savings are the primary contributor to value of solar in most states, comprising about 64% of the value of solar of an average system—highest in California, lowest in Florida (utility bill savings in Florida are replaced by feed-in tariff revenue).

The mean value of solar 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) (Fig. 4). However, previous work has found that LP systems are associated with higher value of solar when controlling for state fixed effects and other covariates [16]. 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 (Fig. 3). California's disproportionate representation among non-LP systems (about 68% of non-LP systems compared to 34% of LP systems) drives a negative value/LP relationship without state fixed effects [16], indicating that higher value of solar PV systems 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 value/LP relationship when including state fixed effects. In the quantile regressions, we assess the value/LP relationship further, and in the discussion consider differences between northern and southern California.

Spatially variable factors, such as value of solar, 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 (Fig. 5). Low prices in Arizona and New Jersey, which also happen to be relatively low value of solar states, further drive a negative value/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 value of solar and installed prices. The most prominent state-level value/price relationship is in California, a relationship we discuss in the concluding section.

3.1.2. 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 (Fig. 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.

3.2. 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?), Fig. 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 3 kW (the 5th percentile) to 10 kW (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

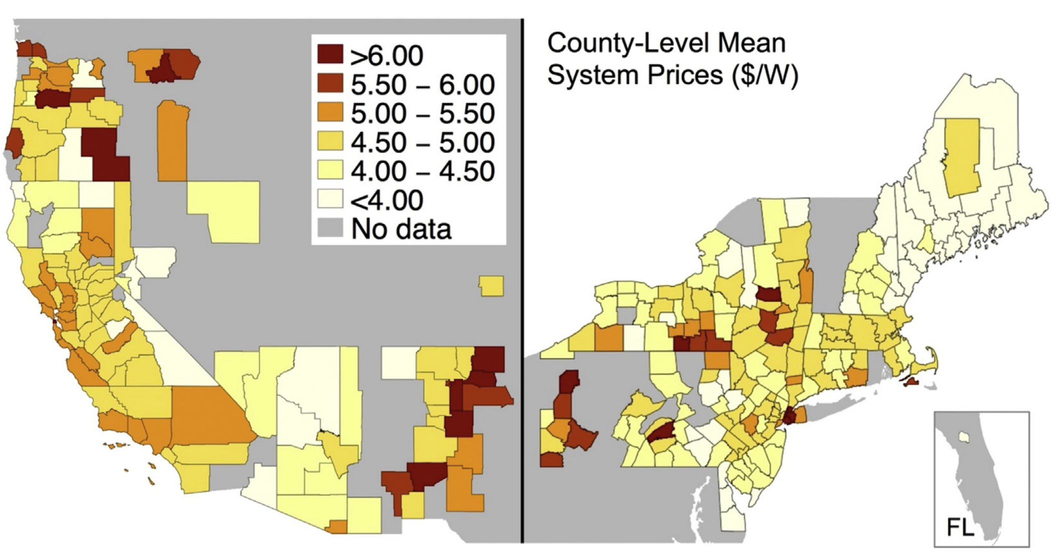

Fig. 5. County-level mean system prices ($/W). Left panel shows 5 western states and right panel shows 8 eastern states.

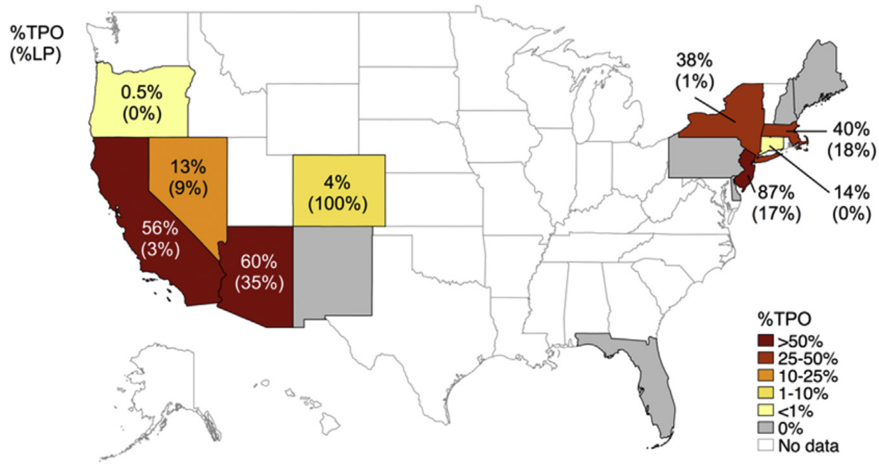

Fig. 6. Percentage of TPO systems by state (percentage of TPO systems that are LP in parentheses).

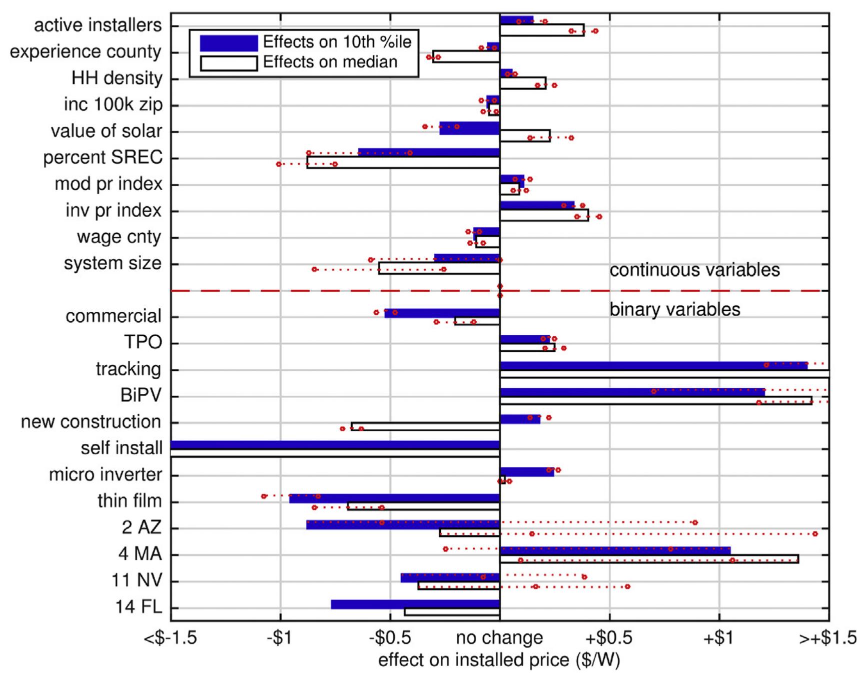

Fig. 7. Sizes of effects for significant variables in base model. Values indicate change in price from moving from 5th percentile to 95th percentile for each variable.

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 Fig. 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 [15] while work on LP systems found a statistically significant effect in the opposite direction [16]. 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.

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 9500 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. 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 policy and societal goals to reduce the installed PV prices, 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 installed price reductions are a goal. Previous findings indicated that more favorable solar policy environments increase customer value of solar and installed prices at the median [15]. In contrast, we find that the effect flips for LP systems: higher incentive levels reduce prices at the low end of the installed price distribution. Together, these 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 LP 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 [15,16]. 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 value of solar distribution, as illustrated below.

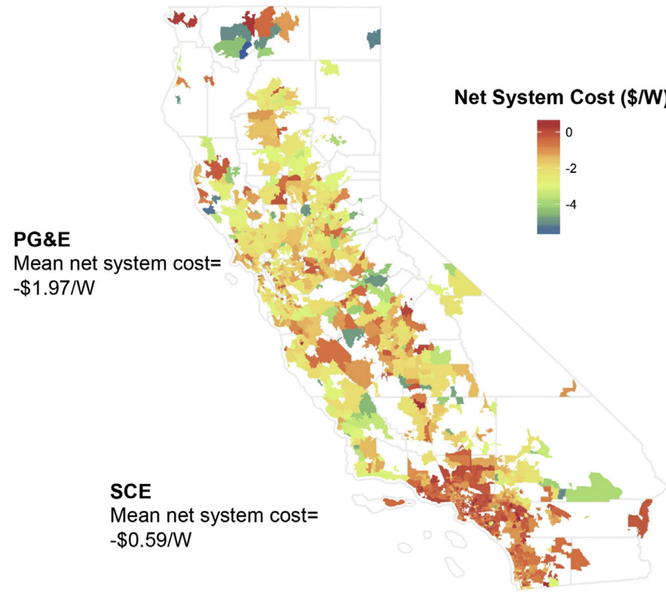

Fig. 8. Net system cost (install price − value of solar) for 25,073 systems in California. High net system costs in southern California, especially around Los Angeles, indicate higher prices and lower value of solar relative to northern California. Lowest and highest 1% of net system costs excluded to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

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 value/LP relationship within California, which comprises 65% of the observations. To look at prices and value of solar simultaneously we calculate net system cost (install price − value of solar) for each system. PG&E systems are associated with lower net system costs while SCE systems are associated with higher net system costs (Fig. 8).

At the same time, high value of solar is simultaneously associated with LP systems and high-priced systems in both California service territories. In California, systems with a value of solar above $6.00/W (about 46% of systems) are about 87% more likely than lower value of solar systems to fall into either extreme of the California system price distribution ($t = 26$) (Fig. 9). While the dynamics between northern and southern California explain the positive value/LP relationship observed in Nemet et al. (2017)[16], the simultaneous relationship between value of solar and LP and high-priced systems in California helps explain the results of the current study. As posited in our previous work, high value of solar environments may provide conditions that foster both LP and high-priced systems.

5. Conclusion

Many factors, including local policy environments, affect the installed prices of residential solar PV systems. We find that some of these factors affect prices in different ways at different points in the

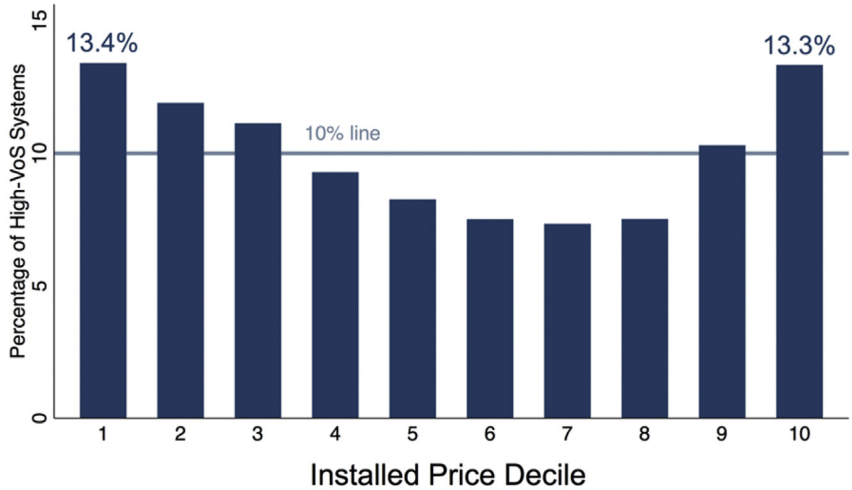

Fig. 9. Installed price distribution of high value of solar systems (value of solar > $6/W) in California. The uniform distribution should fall along the 10% line; however, the distribution shows clear clustering in both tails.

price distribution. Specifically, though previous studies have found that the consumer value of solar increases prices at the median, through a quantile regression we find that more favorable PV policies and incentive reduce prices at the low end of the price distribution. Given that price 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 prices 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 PV price reductions.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.renene.2017.08.018.

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