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Authors
Nemet, Gregory F
O'Shaughnessy, Eric
Wiser, Ryan
et al.

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**Gregory F. Nemet [1], Eric O'Shaughnessy [2], Ryan Wiser [3], Naïm Darghouth [3], Galen Barbose [3], Ken Gillingham [4], and Varun Rai [5]**

[1] University of Wisconsin—Madison, La Follette School of Public Affairs
[2] National Renewable Energy Laboratory
[3] Lawrence Berkeley National Laboratory
[4] Yale University, School of Forestry & Environmental Studies
[5] University of Texas—Austin, LBJ School of Public Affairs

## Energy Analysis and Environmental Impacts Division
## Lawrence Berkeley National Laboratory

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[3] Lawrence Berkeley National Laboratory
[4] Yale University, School of Forestry & Environmental Studies
[5] University of Texas—Austin, LBJ School of Public Affairs
[*] corresponding author: nemet@wisc.edu. 1225 Observatory Drive, Madison WI 53705 USA

## ABSTRACT

Despite impressive recent price declines, there is wide dispersion in the prices of U.S. solar photovoltaic (PV) systems. We identify the most important factors that make a system likely to be low priced (LP). Our sample consists of detailed characteristics for 42,611 small-scale (< 15 kW) PV systems installed in 15 U.S. states during 2013. Using four definitions of LP systems, we compare LP and non-LP systems and find statistically significant differences in nearly all factors explored, including competition, installer scale, markets, demographics, ownership, policy, and system components. Logit and probit model results robustly indicate that LP systems are associated with markets with few active installers; experienced installers; customer ownership; large systems; retrofits; and thin-film, low-efficiency, and Chinese modules. We also find significant differences across states, with LP systems much more likely to occur in some than in others. Our focus on the left tail of the price distribution provides implications for policy that are distinct from recent studies of mean prices. While those studies find that PV subsidies increase mean prices, we find that subsidies also generate LP systems. PV subsidies appear to simultaneously shift and broaden the price distribution. Much of this broadening occurs in a particular location, northern California.

Keywords: subsidies, solar, price dispersion, technological change

# 1. INTRODUCTION

The substantial drop in prices of solar photovoltaic (PV) systems in the last decade has been a principal driver of the expanding global PV market. In the United States, cumulative residential PV capacity increased by a factor of eight from 2009 through 2014 (GTM/SEIA 2015), driven in part by a 50% decrease in average residential installed prices over the same period (Barbose and Darghouth 2015). In 2014, 32% of total new U.S. electric-generation capacity additions came from PV, with 20% of these PV additions as residential installations, 17% as commercial, and 63% as utility scale (GTM/SEIA 2015). Renewable energy, and solar in particular, is viewed by many as a key strategy for meeting long-term electricity supply needs, especially within the context of global climate change mitigation (Baker et al. 2013, IEA 2015).

Governments play a central role in renewable energy because the technology involves multiple potential market failures: it avoids the negative pollution externalities of its competitors; its deployment generates positive learning externalities; adoption involves asymmetric information between consumers and installers; and natural monopolies exist in the electricity distribution system, to which it is connected. Perhaps the strongest justification for government support of demand rests on knowledge spillovers—the notion that adoption creates opportunities for learning by doing that can spillover across firms (Benthem et al. 2008, Nemet 2012, Tang and Popp 2016). Although many of the social costs and benefits of PV remain non-priced, governments are subsidizing PV demand at the level of tens of billions per year. Those amounts are small compared to the possible future levels of combined public and private investment in PV over the next 15 years, which are on the order of a trillion dollars (IEA 2015). Understanding the influence of policy is thus central to enabling further PV price reductions, which will be necessary to sustain PV capacity growth and enable PV to contribute meaningfully to addressing climate change and other energy-related problems. Given that price reduction is a policy goal, we are especially interested in the characteristics of low-priced PV systems.

Though PV prices have declined worldwide, there is considerable heterogeneity within the price distribution. This heterogeneity is very clear across countries: prices for smaller residential PV systems in the United States are on average considerably higher than (sometimes up to twice as high as) prices in other mature markets (Seel et al. 2014). Even within the United States there is significant variation across states, among different installers, and within those groups. In fact, the observed price (in dollars per watt) for small-scale U.S. systems installed in the past 3 years spans more than a factor of five. As such, some U.S. systems are priced on par with systems in other lower-priced international markets. In this paper we address the questions: what is different about systems at the low end of the PV price distribution? The results speak to important policy-relevant questions: What factors increase the likelihood of a system being a low-priced (LP) system? And, ultimately, what can be done to reproduce or facilitate those conditions more broadly, to drive down U.S. PV system prices?

We explore the characteristics of LP systems to help identify practices and policies that might reduce future PV prices and further stimulate the market. This research complements a number of studies exploring the nature of small-scale PV system pricing in the U.S. market. The dramatic heterogeneity in prices is quantified in Barbose and Darghouth (2015). Gillingham et al. (2016) examine how various factors influence PV system price differences, including variables related to market competition, PV installer experience and market share, market characteristics, solar policy design, and PV system characteristics. Using a subset of those data, Burkhardt et al. (2015) and Dong and Wiser (2014) establish a link between local permitting and regulatory processes and PV system prices. Other work has investigated the impact of solar incentives and policies on PV system prices (Shrimali and Jenner 2013, Dong et al. 2014, Hughes and Podolefsky 2015) and the influence of third-party ownership (TPO) on reported PV prices (Davidson and Steinberg 2013, Rai and Sigrin 2013, Sigrin et al. 2015). Our focus on LP systems makes a unique contribution to this literature by analyzing what is needed to achieve the lowest PV prices.

The remainder of the paper is structured as follows. The next two sections provide an overview of our methods, data, and variables. Section 4 provides descriptive comparisons of the data. Section 5 compares the means of LP and non-LP systems, and Section 6 uses estimates from logit regressions to identify predictors of LP systems. We discuss the results in Section 7 and include conclusions and policy implications in Section 8.

## 2. METHODS AND DATA

This paper relies on a rich data set of recent small-scale U.S. residential and commercial PV installations and develops in-depth descriptive and statistical analyses of LP PV systems. Our approach has three parts. First, we examine descriptive characteristics of the trends and patterns in the entire data set. Second, we use t-tests of means to assess the significance of the differences between LP and non-LP systems for each variable individually. Finally, we use logit and probit models to assess each variable's significance in predicting whether a specific PV installation is in the LP group. Definitions for all variables are included in the Appendix.

### 2.1. Installation Data

We use installed PV system data from 59 PV incentive programs in 34 U.S. states, collected as part of LBNL's *Tracking the Sun* (TTS) report series. The full TTS data set accounts for about two thirds of U.S. PV installations since 2000 and is described in detail in the annual TTS report (Barbose and Darghouth 2015). This paper focuses on the prices paid for PV systems and considers a wide variety of possible explanatory variables. We take several steps to restrict and clean the data, ensuring that our final data set is as free of measurement error as possible, has all variables of interest defined, accurately represents the U.S. residential PV market, and is capable of addressing our research questions. First, because we are most interested in the determinants of the most recent LP systems, we analyze 71,861 systems installed during 2013, the most recent year for which comprehensive data were available when the analysis was performed. This accounts for about half of the 140,000 U.S. PV systems installed in 2013.[1]

Second, we focus our analysis on PV systems for which we observe the (pre-incentive) transaction prices paid—that is, transactions between the PV system owner and the system installer. Transaction prices represent a real flow of funds between the two parties, and they are often used to calculate rebates and other government incentives. A dramatic change in the U.S. PV market in the past 5 years has been the increase in TPO arrangements, under which homeowners lease a PV system from a company or enter into a power purchase agreement with a company for the electricity the PV system on their property produces (Davidson et al. 2015).

[1] We were unable to collect installed price data for the remaining installations, primarily because they did not submit data to state subsidy programs.

More than half of the 2013 installations in our data set are TPO systems, while the remaining systems are customer owned. These TPO systems come in two basic varieties. In some cases, the third-party owner contracts with a separate entity to install the system, and the purchase price reported represents the payment to the installation contractor. In other cases, however, the third-party owner conducts the installation itself, in which case no transaction occurs from which a purchase price can be identified. In these cases, system prices reported to incentive programs and other entities are typically "appraised values." Previous work shows that appraised-value prices are not reliable and not generally comparable to prices involving transactions between different parties (Davidson and Steinberg 2013). We thus drop the 21,000 appraised-value systems from our data set, but we retain other TPO systems for which reported prices are based on a transaction between a third-party owner and an installation contractor. We also investigate how the retained TPO systems differ from customer-owned systems in our results.

Third, our focus is on "small-scale" systems, up to 15 kW direct current (DC) in size, and therefore excludes 3,600 larger systems from the data. The remaining systems of 15 $kW_{DC}$ or smaller include residential and commercial systems. To account for the possibility of reporting errors or extreme outliers (e.g., misplaced decimal points), we exclude systems smaller than 1 kW, systems with prices below $1/W, and systems with prices above $25/W. Together these account for less than 100 systems.

Finally, we remove from our regression analysis 4,000 systems that are missing location information, the name of the installing firm, or a component used to calculate the customer value of solar (VoS). The final data set includes 42,611 installations in 15 states, representing roughly 30% of all U.S. installations during 2013.

### 2.2. System Prices

The transaction price is the total pre-incentive installed price of the PV system. It includes hardware costs (modules, inverter, wiring, support structure, and meters) as well as "soft costs" (labor, marketing, insurance, permitting, and other overhead) and installer profit. The price excludes government subsidies, such as rebates, tax credits, and renewable energy certificates. It also excludes the social costs of grid intermittency and associated need for backup power and grid maintenance as well as the social benefits from avoided air pollution. All prices are in nominal dollars. We use these prices to define LP systems in 4 ways:

1. At or below the 5th percentile (P5) of prices ($/W) for all systems installed in 2013.
2. At or below the 10th percentile (P10) of prices ($/W) for all systems installed in 2013.
3. At or below the 20th percentile (P20) of prices ($/W) for all systems installed in 2013.
4. "Conditional LP systems": After regressing price per watt on system size, system size squared, and the sum of module and inverter price indices, we count those systems as LP if their residuals are at or below the 10th percentile (P10r).

All four definitions overlap. For example, 87% of observations that fall under #2 also fall under #4. We use #2 as our primary definition because it is between #1 and #3 and simpler than #4. The others we treat as robustness checks, and we indicate when our results differ.

### 2.3. System Characteristics

The TTS data provide detailed characteristics of each system, including system size (in watts DC) and an array of binary variables, including whether the system has a sun-tracking mechanism, is integrated into roof materials (i.e., is building-integrated PV or BiPV), is installed on a newly constructed home, has been self-installed by the PV system host (installer ="owner"), or has a battery backup system. The TTS data set also includes data on the panels and inverters, including their efficiency, whether the panels were manufactured in China, whether the cells are thin film or crystalline silicon, and whether the system uses micro-inverters attached to each panel rather than the more typical string inverter. We also know whether the system is residential (97% of the systems), commercial, or other (e.g., on a school).

### 2.4. PV Installer and Market Structure Characteristics

The TTS data also include installer names. We standardize the names to account for issues such as variant spellings and typographical errors, and we account for any mergers among installers. We then use the installer names to construct variables that characterize installers and market structure. We construct stocks of experience for each installer based on the number of previous installations (using the original data back to 2000) and depreciated at 20% per quarter to account for loss through employee turnover and technological obsolescence of the acquired knowledge

(Nemet 2012). These installer experience stocks are estimated at the county, state, and national levels. We also create aggregate experience stocks, shared by all firms, at the county, state, and national levels. We create a firm-scale variable using the number of installations by a specific installer in the past 3 months at the county, state, and national levels. We create a variable for the installer market share based on the number of installations by each installer in each county in the 12 months prior to the installation date, and we use these market shares to create a Herfindahl-Hirschman index (HHI) for each county to measure market concentration. We also create variables for how many installers have installed a system in the past 12 months in each county as well as the number of months since the first installation in a county.

### 2.5. Other Data Sources

We complement the TTS data with other sources. We use data on monthly module and inverter prices from the Solar Energy Industries Association and GTM Research to account for the slight increase (+2%) in hardware costs during 2013 (SEIA/GTM 2014). We add Census zip-code-level data on the number of households, education levels, household income, labor costs, and political party affiliation (BLS 2014, Census 2014). We also construct a measure of population density at the zip code and county levels from the Census data.

## 3. 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 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 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[2]. 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 2010, 2011, 2012, and 2013, as appropriate, 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 environmental 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).

[2] 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.

## 4. DESCRIPTIVE COMPARISONS

In this section, we provide a descriptive overview of recent price dynamics in the PV market and evidence of where and when LP systems tend to be found. Section 3.1 includes pre-2013 data to demonstrate underlying trends, and Section 3.2 includes installations for which we have incomplete data to put the subsequent results in context. All other analyses refer to the data set of 42,611 observations, which is summarized in the Appendix.

### 4.1. Price Dynamics

The most salient long-term trend in installed U.S. PV prices for residential-scale installations is their steady decline over the 14 years from 2000 to 2013 (Figure 1). Annual average prices paid (in real dollars per watt) declined nearly threefold over that period, with much of the decline occurring since 2009. Taking the difference between 2000 and 2013 prices, hardware costs (module and inverter) and "other costs" each account for about half the decline. Another trend over this period has been the steady increase in the size of installed systems, from an average of 3 kW in 2000 to over 6 kW in 2013.

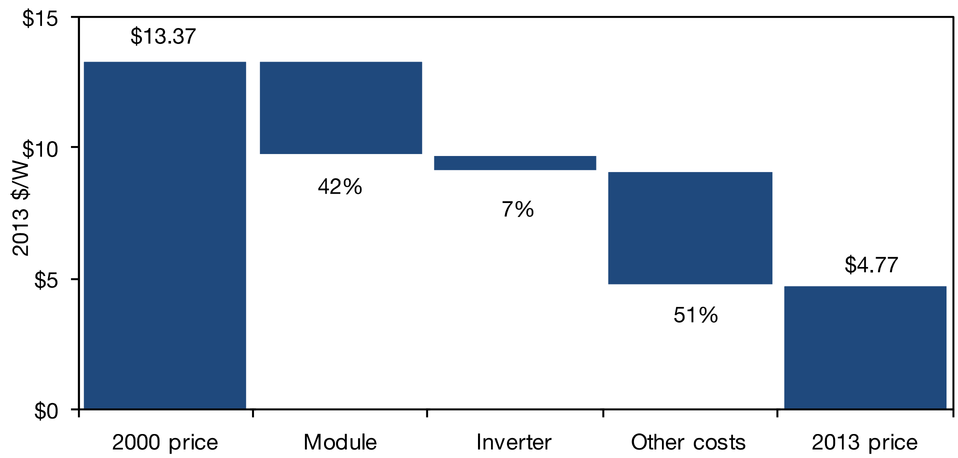


**Figure 1. Average installed prices of U.S. PV systems in 2000 and 2013, in real $/W.**

Figure **2** shows the distribution of unit prices of systems installed in 2013. The distribution is approximately normal, with a slight positive skew—the median is $4.68/W, close to the mean of $4.77/W. Our key threshold for an LP system (P10) is $3.46/W. We include the 5th ($3.09/W) and 20th ($3.92/W) percentiles in the figure and in subsequent analyses as robustness checks on our definition of LP.

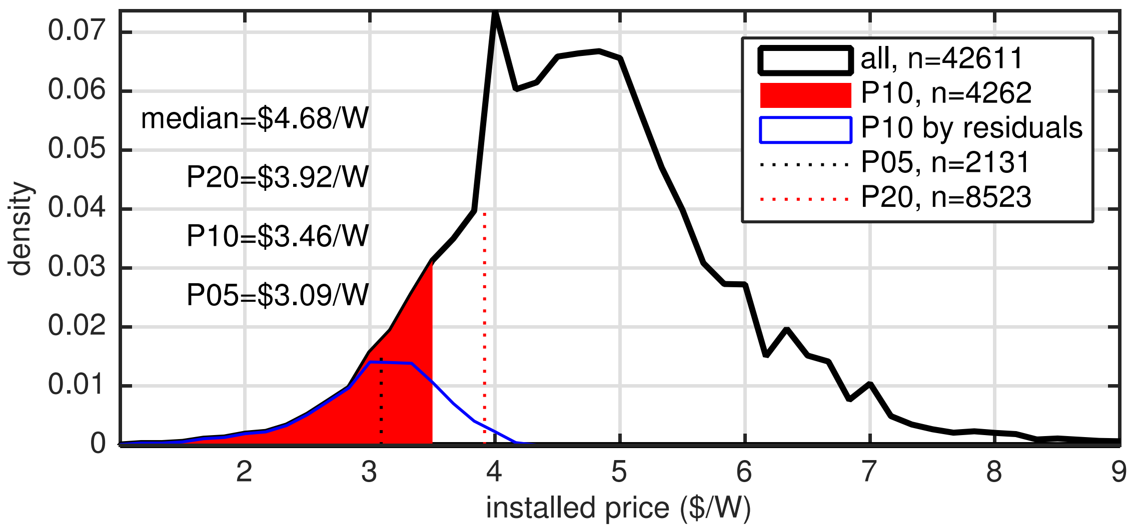


**Figure 2. Distribution of installed prices for systems installed in 2013.**

### 4.2. Geographic Distribution of LP Systems

Figure **3** shows the share of installations in each U.S. state that is LP (at or below the 10th percentile). The figure includes states for which we have price data but are missing county and installer information: Washington DC, Illinois, Maryland, North Carolina, Rhode Island, Texas, Utah, Vermont, and Wisconsin. We drop these nine states in the subsequent analyses owing to their incomplete data.

A perfectly even distribution of LP systems across states would imply that each state in the figure would show 10%. The actual distribution is dramatically uneven. Of the states with more than 200 PV systems in our data sample, some—including California and New York—have relatively few LP systems as a proportion of their statewide totals, while others—such as Arizona, Maine, Texas, and New Hampshire—have relatively high shares of LP systems. The states with the largest number of LP systems are Arizona, California, New Jersey, and Massachusetts, driven by LP markets in some cases (e.g., Arizona) or simply by the overall size of the market in others (e.g., California). The uneven distribution of LP systems is consistent with price variability across states, which has been attributed to differences in market size, local incentives, and system characteristics (Barbose and Darghouth 2015).

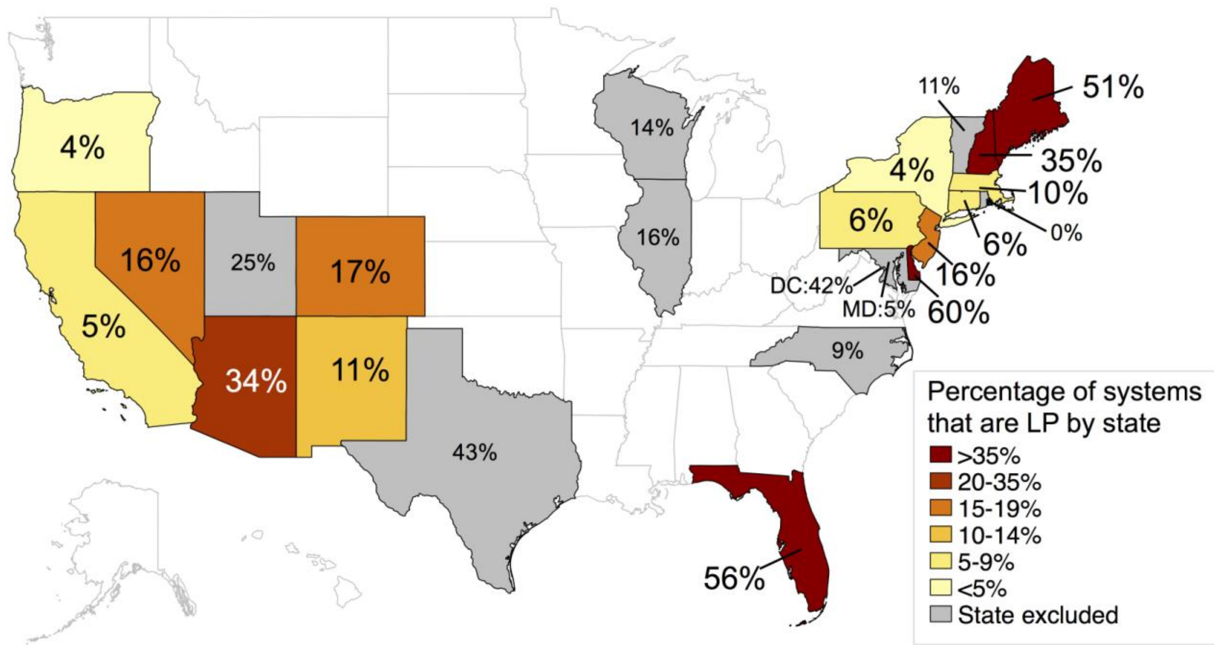


**Figure 3. Share of systems in each state that is P10. Gray states have price data but are missing data on other characteristics, so they are dropped from all other analyses.**

### 4.3. Installer Firms

With the exception of a few hundred systems that homeowners installed themselves, 1,901 firms installed the systems included in our data set. These installers differ considerably from one another in the number of systems installed in 2013 and in their experience installing systems before 2013. Nationally, the industry is concentrated: the largest 1% of installers accounted for 38% of 2013 installations.[3] The vast majority of installers are small. About 74% of installers installed fewer than 10 systems in 2013, and two thirds installed five or less. Small solar installers were predominantly localized businesses in 2013. About 55% of installers installed all of their systems in a single county, and about 96% installed all of their systems in a single state. A few large installers were highly geographically dispersed. About 3% of installers were active in more than 10 counties. Of these installers, only 16% installed more than half of their systems in any single county.

[3] Our data set may understate the true level of concentration owing to our exclusion of appraised-value TPO systems. When appraised-value TPO systems are included, the largest five installers installed about 54% of all residential systems in the United States in 2014.

PV system prices vary considerably across installers, and installers generally operate within a small price interval. Installer-level median prices ranged from \$3.70/W to \$5.94/W at the 10$^{th}$ and 90$^{th}$ percentile for installers with at least 10 systems. Individual installers, however, priced their systems within \$1/W of their median system price for 84% of installations; this contrasts with the 67% of all systems in the full sample that are within \$1/W of the median system price. Equipment preferences (including module efficiency) help explain intra-installer price consistency. On average, installers that installed more than 10 systems (large installers) used the same module brand in 68% of their installations, while 33% of installers used the same module brand in more than 90% of their installations. In some cases, high-priced installers represent companies that specialize in premium systems (Barbose and Darghouth 2015). Compared with large-installer systems, small-installer systems are lower priced, larger in capacity, use less efficient modules, and are much less likely to be TPO.

TPO systems account for roughly half (54%) of all installations in the data sample and a slightly smaller proportion (49%) of LP systems. About 29% of installers installed at least one TPO system, 15% used TPO in more than half of their systems, and about 4% used TPO for all systems installed. TPO systems are less prevalent among small installers: only 15% of small installers used TPO, compared to 68% of larger installers. Depending on the state, TPO systems may be more or less likely to be LP than customer-owned systems, as shown in Figure **4**. For example, in Massachusetts, LP systems are more highly concentrated among TPO systems than among customer-owned systems, while the opposite is true in California, Nevada, and New York.

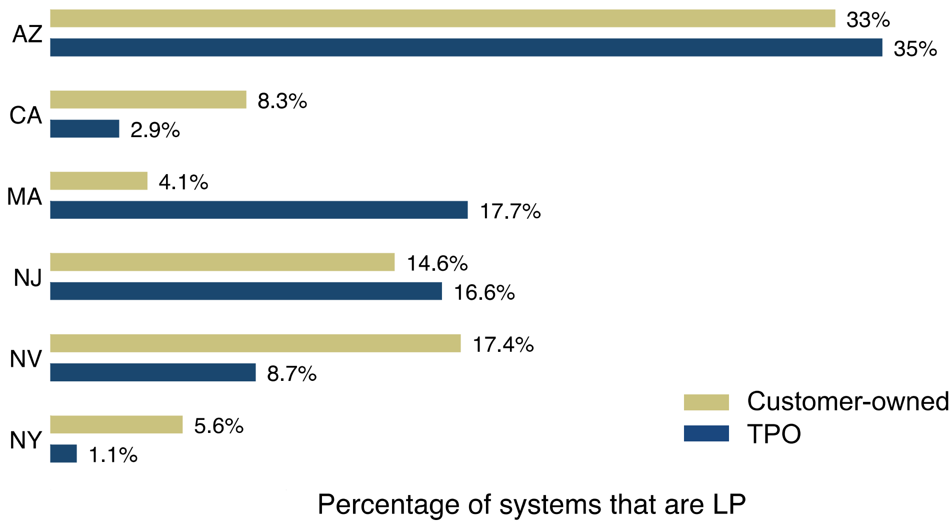


**Figure 4. Percentage of customer-owned and TPO systems that are LP by state for states with TPO systems constituting greater than 10% of all systems, in 2013.**

## 5. COMPARISONS OF MEANS: LP AND NON-LP SYSTEMS

A first step in understanding what makes LP systems different is to evaluate a number of PV system and market variables for LP systems and non-LP systems. We do this by comparing the mean of each relevant variable for our four definitions of LP systems to the mean for the remaining (non-LP) systems. As with the rest of our analysis, our main focus is on the P10 comparisons.

In Figure 5, we normalize means for each group of LP systems by the mean for the remaining non-LP systems. Bars pointing left (less than 1) indicate that the mean value for LP systems is below that of non-LP systems. For example, the variable "price per W" for P10 systems is 60% of the non-LP mean; for the same variable, P5 systems average 54% of the non-LP mean. Variables "price per W" through "mod eff" are continuous; "commercial" through "tracking" are binary.

The continuous variables for which the P10 mean values most exceed the non-P10 mean include HHI, pct srec, and system size. The continuous variables for which the P10 means are substantially lower include state-level installer experience, state- and county-level installer scale, household density, and interconnection score. An interpretation—from looking at each variable independently—is that LP systems are more likely to be installed in markets with fewer active installers, by installers with fewer previous installations in the state, in geographies with lower household density, and in utility jurisdictions with less-favorable interconnection procedures. Some of these results are counterintuitive, and we return to them after the multivariate analysis.

PV system characteristics also differ substantially between LP and non-LP systems. LP systems are more likely to be larger and self-installed and to have Chinese-brand panels and thin-film panels. They are less likely to use micro-inverters, battery backup, and tracking mechanisms as well as to be building integrated and installed in new construction.[4] The latter result is counterintuitive in that previous studies have found new construction systems, which often consist of groups of identical systems installed throughout large housing developments, to be less expensive owing to standardized designs and lower labor requirements. This difference is likely due to our focus on the left tail rather than the central tendency of the distribution; we revisit this at the end of the paper.

We apply t-tests to the continuous variables and tests of proportions to the binary variables to determine whether the difference in means between LP and non-LP systems is statistically significant. Asterisks in Figure 5 indicate that the resulting t- or z-statistics are significant at the 95% level.[5] The mean difference is significant for almost all variables. The lack of significance for some variables is due to small differences in the means (module prices), while for others it is due to few LP systems having this characteristic (other customer type, battery, and tracking). Finally, we conducted similar means comparisons for TPO and customer-owned systems and found that the means ratios for TPO and customer owned are similar to each other. Some differences that do emerge from the analysis are that TPO LP systems have relatively higher values for experience, scale, SRECs, and commercial systems compared with customer-owned LP systems. These are small differences, however, and so we pool TPO and non-TPO systems in our analysis in the next section, despite the differences in those transactions noted in Section 2.

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[4] In almost every case, these results are robust to alternative definitions of LP. A general, and expected, pattern is that the P5 means have bigger differences, and the P20 (and P10r) means have smaller differences.

[5] We include test results for the P10 definitions of LP (but, for legibility, not for P5, P10r, and P20).

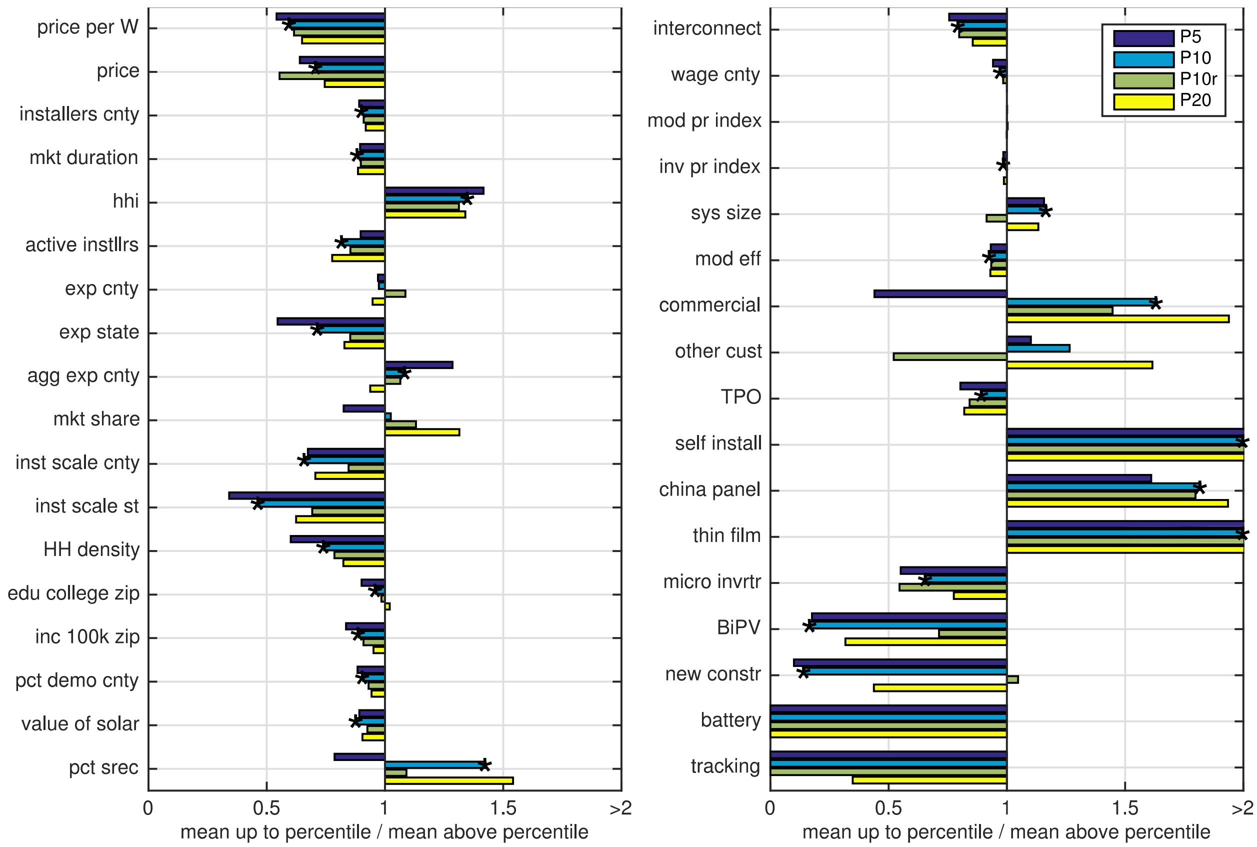


**Figure 5. Comparisons of means for LP systems (for four LP definitions) to mean for non-LP systems (mean for non-LP = 1). Asterisks indicate difference is significant with 95% confidence (t- and z-tests only for P10).**

## 6. PREDICTORS OF LP SYSTEMS

Next we examine the effects of each of the explanatory variables simultaneously rather than one at a time. Because our primary interest is to understand what factors differentiate LP systems from non-LP systems, we focus our analysis on understanding the factors that predict membership in the LP group. Our strategy is thus to define our dependent variable as a binary indicator for whether an installed system is an LP system or not. Using a binary variable provides less statistical power than using a continuous variable such as price. However, using a binary dependent variable more directly addresses our research questions, and any significant results we find are likely to be robust. While quantile regressions are appealing in that they use the full distribution of prices, they estimate marginal effects at a quantile; this does not address our research question, which is about the likelihood of any system being LP. Discarding the price distribution, however, does require that we take caution to avoid false negatives (i.e., a type II error). We use logit regression models for our primary results and run robustness checks using probit models. Our empirical specification is given by Gillingham et al. (2016):

$$LP_{ijst} = \beta_0 + \beta_1 COMP_{ist} + \beta_2 FIRM_{jst} + \beta_3 MKT_{ist} + \beta_4 POL_{ist} + \beta_5 SYSTEM_{ist} + \mathrm{B} + \mathrm{e}_{ijst}$$

for each installation *i*, installer firm *j*, state *s*, and date *t*. COMP is a vector of competition variables: county-level HHI, number of active installers, and how long since the first system was installed in the county. FIRM includes county-level experience, market share, and scale. MKT includes whether the customer is residential, commercial, or other; whether the system is third-party or customer owned; household density; as well as income and percent Democrat for the zip code. POL includes three policy variables: customer VoS, percent SREC, and interconnection score. We drop sales tax because it is time invariant during 2013. SYSTEM is a vector of installation characteristics including system size (and size squared), average module and inverter hardware costs, and module efficiency. It also includes binary variables for tracking, BiPV, new construction, battery, self-installation, micro-inverters, Chinese panels, and thin-film panels. We also add binary variables, B, for the state, the month of application for the installation, the installer firm, and the manufacturer of the panel. Because several of these variables co-vary, we arrange our specifications to avoid including highly collinear pairs (e.g., installer scale and experience; zip-code-level education, income, and wages). The correlations are included in the Supporting Information (SI) document. Other variables are dropped because they have the same value for all LP observations, e.g., no LP systems have batteries or tracking.

### 6.1. Main Results

Table 1 provides the results for six models. Model 1 is our preferred (base) specification. Model 2 uses the same regressors but fits the data to a probit rather than logit function. Model 3 drops the state binary variables. Model 4 adds HHI as a competition variable. Model 5 uses firm scale instead of experience and market share, with which scale is collinear. Model 6 uses a subset of the data for which we have module efficiency and manufacturer information. The state effects are all relative to the base state, which is California, because it accounts for 65% of the installations.

**Table 1. Coefficient estimates from logit regressions of Y = P10 on Xs for 2013 installations.**

| | (1) base | (2) probit | (3) no states | (4) comp2 | (5) firm2 | (6) module |
|---|---|---|---|---|---|---|
| Y=1 if P10 | | | | | | |
| active instllrs | -0.159*** | -0.0798*** | -0.0675* | -0.154*** | -0.0398 | -0.141*** |
| hhi | | | | 0.0436 | | |
| exp cnty | 0.263*** | 0.114*** | 0.230*** | 0.263*** | | 0.169*** |
| mkt share | -0.0622** | -0.0376** | -0.0459* | -0.0706** | | 0.0245 |
| inst scale st | | | | | -0.0477* | |
| HH density | 0.00549 | 0.00654 | -0.119*** | 0.00114 | 0.00973 | 0.0462* |
| commercial | 1.230*** | 0.665*** | 0.303*** | 1.229*** | 1.168*** | 1.407*** |
| other cust | 0.219 | 0.207 | -0.0674 | 0.213 | 0.146 | -0.0862 |
| TPO | -0.193** | -0.122*** | -0.431*** | -0.195*** | -0.120* | -0.280*** |
| inc 100k zip | 0.00648 | 0.00152 | -0.0688*** | 0.00923 | 0.00902 | 0.00206 |
| value of solar | 0.425*** | 0.188*** | -0.0607 | 0.421*** | 0.395*** | 0.358*** |
| pct srec | 0.237* | 0.139* | 0.156*** | 0.234* | 0.188 | 0.0824 |
| interconnect | 0.0746 | 0.0161 | -0.701*** | 0.0893 | 0.0963 | 0.0539 |
| mod pr index | -0.0342 | -0.0248* | -0.165*** | -0.0319 | -0.0488* | -0.0386 |
| inv pr index | -0.196*** | -0.111*** | -0.373*** | -0.182*** | -0.197*** | -0.235*** |
| sys size | 0.765*** | 0.377*** | 0.529*** | 0.765*** | 0.719*** | 0.799*** |
| sys size sqrd | -0.435*** | -0.208*** | -0.238** | -0.435*** | -0.402*** | -0.397*** |
| BiPV | -0.661 | -0.337 | -0.618 | -0.676 | -0.902 | -2.850** |
| new constr | -1.382*** | -0.595*** | -1.072*** | -1.375*** | -1.058*** | -0.333 |
| self install | 3.929*** | 2.213*** | 4.165*** | 3.926*** | 2.911*** | 3.820*** |
| micro invrtr | -0.290*** | -0.166*** | -0.324*** | -0.292*** | -0.339*** | -0.806*** |
| thin film | 1.935*** | 0.980*** | 1.845*** | 1.937*** | 2.233*** | 0.116 |
| china panel | | | | | | 0.615*** |
| mod eff | | | | | | -0.970*** |
| 2 AZ | 3.125*** | 1.547*** | | 3.108*** | 3.127*** | 3.190*** |
| 3 NJ | 1.240*** | 0.518** | | 1.252*** | 1.370*** | 1.171** |
| 4 MA | -0.410 | -0.359 | | -0.395 | -0.274 | 0.0228 |
| 5 NY | -0.0928 | -0.112 | | -0.119 | -0.131 | -0.551** |
| 6 NM | 1.403*** | 0.639*** | | 1.329*** | 1.344*** | 1.154* |
| 7 CT | 0.593** | 0.227* | | 0.568** | 0.569** | -0.0199 |
| 8 OR | 0.438 | 0.132 | | 0.420 | 0.422 | |
| 9 ME | 3.930*** | 2.063*** | | 3.790*** | 3.726*** | |
| 10 NH | 2.294*** | 1.089*** | | 2.283*** | 2.336*** | 2.099*** |
| 11 NV | 1.715*** | 0.800*** | | 1.730*** | 1.721*** | 1.348*** |
| 12 PA | 0.396 | 0.0588 | | 0.373 | 0.509 | 0.259 |
| 13 CO | 1.690** | 0.769* | | 1.635** | 1.600* | 1.961* |
| 14 FL | 3.680*** | 1.917*** | | 3.624*** | 3.647*** | 2.966** |
| 15 DE | 2.894*** | 1.554** | | 2.798*** | 2.979*** | |
| N | 42582 | 42582 | 42582 | 42582 | 42244 | 32503 |
| ll | -11051 | -11052 | -11671 | -11049 | -10920 | -6868 |
| r2_p | 0.202 | 0.202 | 0.157 | 0.202 | 0.174 | 0.273 |

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

### 6.2. Robustness Checks

As a further robustness check, we run our preferred specification (Model 1 from Table 1) using alternative definitions for the binary dependent variable: LP = P10r and LP = P20. The coefficients are shown in the SI. As a further check, we ran additional models in which we include dummy variables for each installer, each panel manufacturer, and each installation month. These additional models do not generally change the signs or significance of the main results.

### 6.3. Sizes of Effects

To provide a sense of how important these effects are, Figure 6 provides odds ratios for each variable using the significant coefficients (*b*) in Table 1.[6] The focus is on Model 1, which is represented by the bars. The circles refer to Models 2–6. The continuous variables are shown above the dashed line and the binary values below. Because each of the continuous variables has been transformed to have a standard deviation of 1, the interpretation for these values is as follows: each odds ratio indicates the change in the likelihood of a system being LP due to a 1 standard deviation increase in that variable, compared to a system with the mean value for that variable. For example, increasing installer experience by 1 standard deviation would increase the likelihood of an installation being LP by 30%. For the binary variables, the comparison is to the null case, e.g., self-installed systems vs. systems installed by installer firms. For states, the base case is California, so the chances of an installation located in Arizona being LP are 23 times higher than one in California. For negative values, like TPO, the interpretation is that a customer-owned system is 18% more likely to be LP than a TPO system is.

Based on these results, the continuous variables for which a 1 standard deviation increase increases the likelihood of LP the most are system size, customer VoS, county-level installer experience, and percent of value from SRECs. For the binary variables, the biggest increases in chances of LP are commercial systems, self-installations, thin films, existing homes, and

[6] The odds ratio is the unlogged value of each coefficient, *b*, in Table 1. Here we show $e^b$ -1 to show the percentage change in the odds of a system being LP.

installations in Arizona, New Jersey, New Mexico, Maine, and New Hampshire.[7] TPO systems and systems with micro-inverters are less likely to be LP.[8] Variables for tracking and battery were dropped from the estimation because no LP systems have those characteristics. While this precludes estimating sizes of those effects, avoiding batteries and avoiding tracking are certainly important predictors of LP. Finally, while the bars represent sizes from Model 1, the circles provide a sense of robustness of these effects. In particular, the coefficient for customer VoS loses its significance and reverses sign when the state dummies are removed in Model 3. We propose explanations for this finding in the next section.

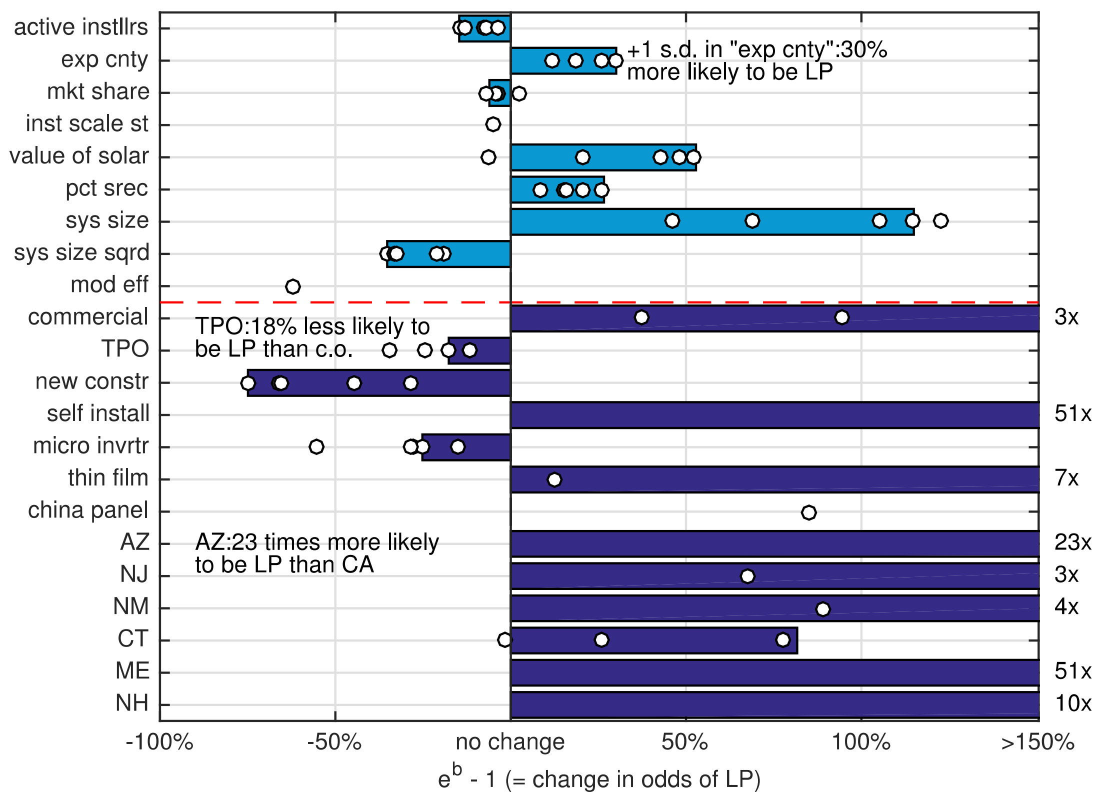


**Figure 6. Size of effect of each significant variable on odds of an installation being LP. Bars refer to Model 1 in Table 1. Circle markers refer to Models 2–6 in Table 1. Variables above dashed line are ratio; those below are binary.**

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[7] We include states with significant effects and at least 200 installations.

[8] This result is especially notable since the TPO prices in our sample may not generally include customer acquisition costs, and so we might otherwise expect those prices to be lower than for customer-owned systems.

# 7. SUMMARY AND DISCUSSION

Taking the results altogether—including the means tests in Section 5, the main logit regression results, and all robustness checks—several conclusions emerge. Looking at each vector of regressors, systems are more likely to be LP under the following conditions:

1. *Competition*: in markets with fewer installers, and to some extent in more concentrated markets.
2. *Firm*: installed by firms with more county-level installation experience but with less county-level market share, or by smaller firms.
3. *Markets*: for commercial installations and for customer-owned (rather than TPO) installations.
4. *Policy*: systems with a high customer VoS (although with caveats) and a higher portion of those incentives from SRECs.
5. *System*: for larger systems; systems excluding tracking, BiPV, micro-inverters, and batteries; systems installed on existing homes and self-installed; and systems using thin films, less efficient modules, and modules from China.
6. *States*: After controlling for all of the above, Arizona, Connecticut, New Jersey, New Mexico, Maine, and New Hampshire are large markets that are more likely to have LP systems; the base state, California has about half as many LP systems compared to its overall share of U.S. systems. Systems in the smaller markets (<200 installations)—Nevada, Colorado, Florida, and Delaware—are also more likely to be LP.

The largest predictors of LP are system size, customer VoS, county-level installer experience, and percent of value from SRECs. Among binary variables, the largest predictors are commercial systems, self-installations, thin films, existing homes, and installations in Arizona, Maine, and New Hampshire.

## 7.1. Installer Competition and Firm Variables

For the most part, results for the competition and firm variables either fit with theory or with previous analyses of the U.S. PV market. Installer experience, as might be expected, increases the likelihood of a system being LP: more experienced firms may have lower costs, on average. Similarly, firms with lower county-level market share tend to have a higher proportion of LP systems, perhaps indicating a lack of local market pricing power. A model that uses installer scale rather than experience and market share produces a significant negative result, indicating that LP systems are more common among small installers. On the other hand, LP systems appear to be more prevalent in markets with fewer installers and maybe in more concentrated markets. LP installers might tend to compete in markets where other, more dominant installers exist, and they might compete by offering especially low pricing. We also looked at several other measures of experience, scale, and industry structure, but we generally found weak and mainly insignificant results. Because we are using a logit model, we cannot entirely dismiss the potential importance of these factors, but in our results they are less important determinants of LP systems.

### 7.2. Market and State Variables

We also find robust results among the market variables. Notably, customer-owned systems are 18% more likely to be LP than are TPO systems. Commercial systems are more likely to be LP than are residential systems—after controlling for size and considering our system size range of 1–15 kW.  Zip codes with fewer registered Democrats are more likely to host LP systems. Note that these zip-code-level data are collinear with income, labor costs, and education, so those could also play a role in these location-based effects.  Once other variables are controlled for, location in several states significantly increases the likelihood of a system being LP (compared to California). These state-level effects are robust across specifications and even when controlling for other variables that operate in large part at the state level—such as customer VoS, percent of value from SRECs, and interconnection score. Other variables that might be attributed to state difference, such as household income and labor costs (which we drop), are not significant and not correlated with state dummies. California, meanwhile, has about half as many LP systems compared to its overall share of U.S. systems. Further research may be warranted to understand the drivers for LP systems in these states as well as the lack of LP in parts of California.

### 7.3. The Effects of Policy

In contrast to some of the other results, the main policy result—the effect of customer VoS—requires a more nuanced interpretation. The effect of customer VoS on LP changes sign from negative in the univariate means tests (Figure 5) to positive in most of the multivariate models (Table 1). The means test results are obvious when looking at the western states, where LP systems are more prevalent in low VoS counties (Figure 7). Including all 15 states, the mean customer VoS of an LP system is \$0.67/W lower than the mean value for non-LP systems (t = 24). On the other hand, the positive effect on LP likelihood is a particularly robust result in the regressions; it is positive and significant in almost every model. This latter result also apparently contrasts with previous work finding a positive relationship between customer VoS and PV prices (Seel et al. 2014, Barbose and Darghouth 2015, Gillingham et al. 2016).

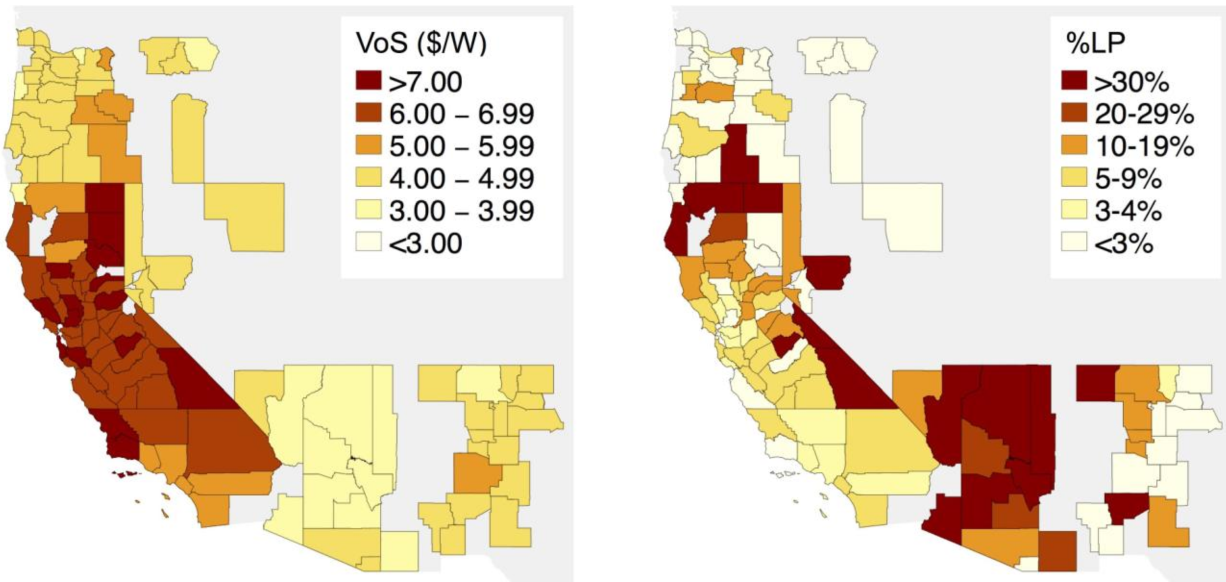


**Figure 7. Customer value of solar in dollars per watt (left) and percent of systems that are LP (right), by county for California, Arizona, New Mexico, and Nevada.**

We offer three possible explanations to reconcile these results. A first possibility is that the more recent data, from 2013, are different than the 2010–2012 data used in previous studies. Perhaps the local economies of scale and learning by doing that subsidies stimulate are finally offsetting the increase in willingness to pay that subsidies also create.

A second possibility is that customer VoS is correlated with other characteristics, either observed or unobserved, and that we are spuriously attributing effects to VoS when they are actually driven by something else. Our substantial data-collection effort was intended to minimize the chances of endogeneity due to omitted variables; we control for a large number of variables—at least as many as in other studies—including broad ones, such as state effects. Further, a close look at the correlation matrices (in the SI) reveals little concern for collinearity with customer

VoS and other variables. The state dummies seem of highest potential for this problem. In Model 3 of Table 1, the VoS coefficient becomes insignificant once the state dummies are dropped. An interpretation is that customer VoS only has a positive effect on LP systems in countering statewide effects.

A third possibility is that the effects of subsidies are fundamentally different at the left tail of the distribution, where we are focused, than they are at the mean, where previous studies have focused. Perhaps the set of activities that generate LP systems are more likely to occur when customer VoS is high. As such, high VoS may be inflating prices overall, but it is stimulating LP systems at the same time. Customer VoS may both shift the mean of the price distribution higher and broaden the distribution. For example, high customer VoS may stimulate installer entry into new markets, and we see some descriptive evidence that installers underprice systems in new markets.

Of the above possibilities, this third explanation—a distinct effect at the tail—is the most promising. A careful look at the coefficients for models in which we change the LP definition (SI), shows a clear slope in the coefficient for customer VoS; it falls by a factor of four from Y = P10 to Y = P20. The effect of customer VoS is largest at the base definition of LP (P10) and shrinks as the LP definition is expanded to include systems with prices closer to the mean. While not conclusive, these results raise the possibility that a higher customer VoS increases both the mean and the distribution of price outcomes—increasing average prices but also generating more LP systems.

Finally, California plays a large role across the analyses, because it accounts for two thirds of the observations, and its effect is particularly important for customer VoS. When rerunning Model 1 without California installations, the effect of VoS becomes negative. As Figure 7 shows, California has a generally high customer VoS. Within California, however, systems in the northern part of the state, primarily the Pacific Gas & Electric (PG&E) service area, have a higher customer VoS (mean = $6.93/W) than those in the south served by Southern California Edison (SCE) (mean = $5.61/W). Likewise, PG&E systems are 65% more likely to be LP than are SCE systems. PG&E system prices have a larger range, a larger coefficient of variation, and a lower minimum price compared with SCE system prices. Taking these items together, an interesting hypothesis to explore in future research is whether solar subsidies are stimulating a wider distribution of system prices in northern California. More specifically, are there characteristics of the PV adoption environment in that area that make LP systems more likely than in other places? One hypothesis is that faster permitting in the PG&E area may enable a greater number of LP systems in Northern California. Because we use a statewide (rather than utility-specific) interconnection score variable, this effect may be captured in the customer VoS variable.

### 7.4. System Characteristics

The effects of system characteristics are mostly straightforward. Economies of scale in installation size are strong and robust. The mean LP system is about 1 kW larger than the mean non-LP system. Negative coefficients on system size squared indicate that the gains in system size become smaller at large sizes. Although we have incomplete coverage (76%) on module information, those characteristics are also important predictors. LP systems are more likely to use low-efficiency, Chinese, and thin-film modules. The mean efficiency of LP modules is 1.2 percentage points lower than the non-LP mean of 17%. Solar panels using micro-inverters, as opposed to a central inverter for the whole system, are also less likely to be LP. Variation in roof type (material, pitch, and height) is not included in our data and likely accounts for some of our unexplained residual.

Self-installations are also strong predictors of LP. However, we interpret this as a control rather than an important result, because self-installations do not count the homeowner's labor in the installed price. Other system configuration variables all make systems less likely to be LP: tracking systems, battery backup systems, and BiPV. These latter three variables might, however, offer benefits that our dependent variable—which is based on installed price per watt—does not count. For example, tracking systems have higher capacity factors, battery systems provide independence, and BiPV may avoid roofing materials costs. Future work using actual electricity production data would be helpful here.

Finally, in contrast to previous studies of the effects at the mean, we find a robust result that installations on existing homes are more likely to be LP than are those on new construction. Almost all of the new construction is in California, but the results for new construction are similar with and without the state effects. Despite the opportunities for cost savings—for typical, or average installations—in new construction, systems on new construction are less likely to be LP, perhaps owing to the typically larger firms that install them and the tendency to use higher-quality modules. Note that in Model 6, with module information, the new construction effect loses significance.

## 8. CONCLUSIONS AND POLICY IMPLICATIONS

The goal of this analysis was to identify the characteristics of recently installed small-scale LP PV systems. We looked at differences in the means for characteristics of LP and non-LP systems using four different definitions of LP. We also looked at the effects of these characteristics simultaneously using logit and probit regressions with several model specifications. These analyses indicate the significance and size of the effects of each variable on the likelihood of a system being LP. We found results that were robust across several of these tests. We found particularly strong effects for policy, market, and system characteristics as well as for several states, which represent a bundle of unobservable effects.

Several of our results—in particular the effects of new construction and customer VoS—run counter to results in other studies (Barbose and Darghouth 2015, Gillingham et al. 2016). Our primary interpretation of these differences is that they arise from a focus on central tendency in other studies and a focus on the left tail in ours. The effects of price determinants differ at various points on the price distribution. If a primary social objective of solar subsidies is to stimulate cost reductions, then we need a research focus on both the central tendency as well as the lowest-priced systems available. The LP results are interesting because they presage what average systems may look like in the future; for example, a system priced at the P10 threshold in 2011 would lie at the mean in 2013.

More specifically, the factors we identify may be amenable to influence by policy. These results raise questions about which LP predictors are controllable and which are likely to be exogenous, or at least driven mainly by consumer preferences. Policy makers will diverge about the extent to which government should influence consumer purchasing decisions. Another consideration is to what extent policy makers should target cost reductions at the mean price versus at the low end. We have identified effects important for LP systems that differ from effects in previous studies of mean prices. If a policy goal is to reduce the social cost of a given PV deployment level, then attention to determinants at the mean is likely the most appropriate. If a goal of policy is to generate—and learn from—new system configurations, financing models, and adoption dynamics, then policy makers should examine these results and consider which LP predictors are appropriate to influence via public incentives.

Much still must be explained about PV pricing, including analysis of data on more specific location characteristics, PV installers, roof characteristics, actual capacity factors, and prices for TPO and unsubsidized installations. Many of these data are becoming available for increasingly large samples. Our results suggest that solar subsidies might be positively influencing the generation of LP systems in some areas. Further work using new data will almost certainly help in designing policies targeted toward generating LP systems, which provide models for the mean-priced systems of the future.

## Acknowledgements

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# APPENDIX: DATA SET DESCRIPTIVE STATISTICS, VARIABLE DEFINITIONS

This appendix provides descriptive statistics for the study data set (Table A - 1) and definitions of the variables used (Table A - 2).

**Table A - 1. Descriptive statistics for all observations used.**

| 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 | 5.491 | 1.551 | 2.274 | 10.723 | 4.963 |
| 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 |

**Table A - 2. 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 |

depr. = depreciated; exp = experience; HH = household; IREC = Interstate Renewable Energy Council

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Supplementary Material

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Highlights

- We estimate factors predicting low-priced (LP) US PV systems in 2013
- Focus on LP reveals differences from studies of mean prices
- System characteristics (e.g. size, module type) are important predictors
- Experienced installers associated with LP
- Solar subsidies appear to broaden distribution of system prices