Characteristics of Low-Priced Solar PV Systems in the U.S.

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ABSTRACT

Despite impressive declines in average prices, there is wide dispersion in the prices of U.S. solar photovoltaic (PV) systems; prices span more than a factor of four. What are the characteristics of the systems with low-prices? Using detailed characteristics of 42,611 small-scale (< 15 kW) PV systems installed in 15 U.S. states during 2013, we identify the most important factors that make a system likely to be low-priced (LP). Comparing LP and non-LP systems, we find statistically significant differences in nearly all characteristics for which we have data. 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 states, such as Arizona, New Jersey, and New Mexico, and less likely in others, such as California. 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; PV; 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 additions increased by a factor of nineteen from 2009 through 2015 (GTM/SEIA 2016), driven in part by a more-than 50% decrease in average residential installed prices over the same period (Barbose and Darghouth 2016). In 2015, 29% of total new U.S. electric-generation capacity additions came from PV, with 29% of these PV additions as residential installations, 14% as commercial, and 47% as utility scale (GTM/SEIA 2016). 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 interacts with multiple potential market failures: it avoids the negative pollution externalities of its fossil fuel-based competitors (Wiser et al. 2016); its deployment generates positive learning externalities (Peters et al. 2012); adoption involves asymmetric information between consumers and installers (Zhu and Weyant 2003); and natural monopolies exist in the electricity distribution system (Borenstein and Bushnell 2015), to which it is connected. Of these, 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 (Bentham 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 adoption at the level of tens of US\$ billions per year (IEA 2014). 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). Though government policy clearly plays a large role in solar deployment (REN21 2016), understanding the details of that influence is 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, such as air pollution and energy security. Lower prices are consistently cited as a barrier for deployment (Denholm and Margolis 2007, Woodhouse et al. 2016), with survey respondents indicating that financial attractiveness is “very important” for adoption (Rai et al. 2016), and perceptions of high costs a key obstacle as well (Varun and Ariane 2015). Lower prices will also be important to help financially ameliorate the growing costs of grid integration of variable solar at higher penetrations (Mills and Wiser 2013, Hirth 2015, Deetjen et al. 2016, Denholm et al. 2016, Janko et al. 2016, Sivaram and Kann 2016). Given that price reduction is important to future deployment and that it is also an explicit policy goal (Mileva et al. 2013), we are especially interested in the characteristics of low-priced PV systems. This paper is the first to focus on low priced residential solar systems in the United States.

Though PV prices have declined worldwide, there is considerable heterogeneity within the price distribution (IEAPVPS 2016). This heterogeneity is very clear across countries: prices for smaller residential PV systems in the United States are on average considerably higher than 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 (Barbose and Darghouth 2016). In fact, the observed price (in dollars per watt) for small-scale U.S. systems installed in 2013, the year we study, spans more than a factor of four. 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 (2016). 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 the ease in obtaining local permits to install a system 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, Sawhney 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). All of this previous work has focused on understanding pricing trends for mean or median PV systems. 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. This follows the approach of previous work on the Tracking the Sun (TTS) database that has used similar data to assess price ranges, inter-state comparisons, and time trends (Barbose and Darghouth 2016). Second, we use t-tests of means between LP and non-LP systems for each variable individually. These tests provide a probabilistic assessment of whether the differences between the LP and non-LP groups are significant or random. The main advantage of this approach is the clarity of interpreting the results of a single variable. The main disadvantage is that it does not allow comparing effects among variables. For this reason, we use logit and probit models to assess each variable's significance in predicting whether a specific PV installation is in the LP group. Logit models are well suited to modeling a binary dependent variable. The results from these analyses allow us to look for significance of results as well as compare across variables the importance of the effects we find. 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 the Lawrence Berkeley National Laboratory's (LBNL's) *Tracking the Sun* (TTS) report series (Barbose and Darghouth 2016). 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 2016). This paper focuses on the (pre-incentive) 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. We were unable to collect installed price data for the remaining installations, primarily because they did not submit data to state subsidy programs.

Second, we focus our analysis on PV systems for which we observe the 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). 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 from the third party owner and 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 system prices differ from customer-owned system prices 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 US\$1/W, and systems with prices above US\$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. PV 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 expenses) 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 constant U.S. dollars. We define LP systems as at or below the 10th percentile (P10) of prices (US\$/W) for all systems installed in 2013. As a robustness check we also consider three alternative definitions and indicate when our results differ:

1. At or below the 5th percentile (P5) of prices (US\$/W) for all systems installed in 2013.
2. At or below the 20th percentile (P20) of prices (US\$/W) for all systems installed in 2013.
3. “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).

The motivation for the third alternative definition is that we know from previous work that system size and input costs have important effects on prices (Barbose and Darghouth 2016). All four definitions overlap. For example, 87% of observations that fall under our primary definition also fall under #3. To provide a sense of proportion, P5 is at 66% of the median price of US\$4.68/W, P10 is at 74%, and P20 is at 84%. Our primary definition, P10 is between P5 and P20 and simpler than P10r.

2.3. System Characteristics

One explanation for price dispersion is that apparently similar goods often have characteristics that distinguish them and affect their prices (Imbs et al. 2010). 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 are especially keen to include efficiency and country of manufacture as they are indicators of module ‘quality’ (Wang et al. 2011). 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

Another set of explanations for price dispersion has to do with producer heterogeneity (Davis et al. 2013) and market structure (Dai et al. 2014). We do see that those have been important factors affecting mean PV prices (Gillingham et al. 2016). The TTS data also include installer names. Throughout this paper we refer to “installers” as the name of the firm that installed the system. In the case of a “self-install” the installer is the homeowner. 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. To capture knowledge spillovers across firms, 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:

234

235 *1. Tax credits.* The federal government and a number of states offer investment tax credits (ITCs)

236 for PV systems. Since 2009, the federal ITC has been 30% of system costs. For host-owned

237 residential systems, the credit is based on the total system price net of any cash rebates (since the

238 cash rebates are not taxable income). For commercial and TPO residential systems, the credit is

239 based on the total system price (since the cash rebates are taxable income for commercial

240 entities). From the states for which we have PV system data, the following states have had ITCs

241 over the 2000–2013 period (in addition to the federal ITC): California, Massachusetts, New

242 Mexico, New York, North Carolina, Oregon, Texas, Utah, and Vermont. The ITC rules vary by

243 state, with different rules for specific customer segments and periods as well as different ITC

244 caps. The ITC calculations were based on the ITC descriptions in (DSIRE 2014) and

245 correspondence with state programs.

246

247 *2. Cash incentives and rebates,* from state and local governments. In most cases, the exact

248 amounts for the cash incentives and rebates were received directly from the incentive programs.

249 In some cases, the incentive programs did not provide incentive data for all systems. For those

250 systems, the cash incentive was estimated by using the average known incentive amount (in

251 dollars per watt) from other PV systems in a similar size range that had applied for an incentive

252 within 1 month from the same incentive program. Because cash incentives are taxable for

253 commercial entities, we assumed that commercial and TPO systems were taxed at the

254 appropriate corporate federal and state tax rate.

3. *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 US\$100/MWh SREC payment for the following 10 years¹. 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). We use these values to calculate the share of incentives coming from SREC payments (pct srec).

4. *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

¹ For reference, the average SREC prices for 2013 were US\$290/MWh in DC, US\$53/MWh in DE, US\$310/MWh in MA, US\$170/MWh in MD, US\$50/MWh in NH, US\$170/MWh in NJ, US\$170/MWh in OH, and US\$30/MWh in PA.

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 using the total annual estimated PV generation (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.

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 likely retail service provider (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).

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 4.1 includes pre-2013 data (also from TTS) to demonstrate underlying trends, and Section 4.2 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 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 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 US\$4.68/W, close to the mean of US\$4.77/W. Our key threshold for an LP system (P10) is US\$3.46/W. We include the 5th (US\$3.09/W) and 20th (US\$3.92/W) percentiles in the figure and in subsequent analyses as robustness checks on our definition of LP.

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 as calculated for all U.S. states above). 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. 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).

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.² 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.

PV system prices vary considerably among installation firms, and installers generally operate within a small price interval. Median price within each installer ranged from US\$3.70/W to US\$5.94/W at the 10th and 90th percentile for installers with at least 10 systems. Individual installers, however, priced their systems within US\$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 US\$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

² 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 (by number of systems installed) installed about 54% of all residential systems in the United States in 2014.

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 (<10 systems per 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.

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 in section 7.

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.³ The latter result is

³ In almost every case, the signs and significance of 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.

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.⁴ 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.

⁴ We include test results for the P10 definitions of LP (but, for legibility, not for P5, P10r, and P20).

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 factors affecting 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 derived from a similar one developed by Gillingham et al. (2016). The motivation for this specification come from previous work in the economic literature on price dispersion, specifically, the area of work that tries to explain why apparently homogenous goods do not follow the “law of one price” but instead are sold at different, sometimes radically different, prices (Dahlby and West 1986, Goldberg and Verboven 2005, Menzio and Trachter 2015). We set up our specification so that it includes vectors of variables that encompass the key explanations from the literature for why prices diverge from the law of one price. These include: the level of competition (COMP), firm heterogeneity (FIRM), consumer heterogeneity (MKT), policy conditions (POL), and attributes

of the good, in this case a PV system, that may affect its cost of production or value to the consumer (SYSTEM).

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

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 add 2 steps to our methodology. First, 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 SI. Other variables are dropped because they have the same value for all LP observations, e.g., no LP systems have batteries or tracking. Second, we run multiple specifications, with different sets of correlated variables, to see if our results are robust. We arrive at 6 regression models, which we describe in detail in the following section.

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.

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 (we drop the P05 definition due to too few observations). 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 1.⁵ The focus is on Model 1, which is represented by the bars. The circles refer to Models 2–6. The continuous variables are shown

⁵ 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.

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 installations in Arizona, New Jersey, New Mexico, Maine, and New Hampshire.⁶ TPO systems and systems with micro-inverters are less likely to be LP.⁷ 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

⁶ We include states with significant effects and at least 200 installations.

⁷ 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.

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.

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

The results for the competition and firm variables fit with economic theories of price dispersion (Carlson and McAfee 1983, Dahlby and West 1986, Baye et al. 2006) and with previous analyses of pricing in the U.S. PV market (Gillingham et al. 2016). Systems that are installed by a firm with more experience in installing previous system increases the likelihood of that system being LP. The explanation is straightforward: more experienced firms have learned from their previous installations and thus may have lower costs (Thompson 2012). Firms with higher county-level market share are less likely to install LP systems. Our interpretation is that this indicates some local market pricing power (Barron et al. 2004); firms with larger market shares are able to price higher and thus less likely to be LP. Similarly, 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 (high HHI). LP installers might tend to compete in markets where other, more dominant installers exist, and they might compete by offering especially low pricing (Menzio and Trachter 2015). 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. Fitting with other work (Barbose and Darghouth 2016), 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 US\$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 2016, Gillingham et al. 2016).

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 (Gillingham et al. 2016)—including broad ones, such as state effects. Further, a close look at the correlation matrices in the Supporting Information (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 (Gillingham et al. 2016). 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 = US\$6.93/W) than those in the south served by Southern California Edison (SCE) (mean = US\$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 a faster permitting process (from application to approval) in the PG&E area may enable a greater number of LP systems in Northern California (Burkhardt et al. 2015). 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 (Barbose and Darghouth 2016). 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 (Gillingham et al. 2016), 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 (Barbose and Darghouth 2016). 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.

673

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

684

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

696

697 Much still must be explained about PV pricing, including analysis of data on more specific
698 location characteristics, PV installers, roof characteristics, actual capacity factors, and prices for
699 TPO and unsubsidized installations. Codifying and measuring installation quality at the project
700 level would be helpful in expanding consideration of price reductions from a focus on installed
701 prices to the overall cost of producing electricity. Many of these data are becoming available for
702 increasingly large samples. Our results suggest that solar subsidies might be positively
703 influencing the generation of LP systems in some areas. Further work using new data will almost
704 certainly help in designing policies targeted toward generating LP systems, which provide
705 models for the mean-priced systems of the future.

706

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714

Figure Captions

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

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

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.

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.

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).

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.

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.

740 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 invtr	-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

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

743 **APPENDIX: DATA SET DESCRIPTIVE STATISTICS, VARIABLE DEFINITIONS**

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

Table A - 2).

Captions for Appendix Tables:

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

751 **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

752

753 *Abbreviations in Appendix Table A2:*

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

755 Council

Table A-3. List of Acronyms used in this paper:

BiPV:	building-integrated PV
DC:	direct current
FiT:	feed-in tariff
HHI:	Herfindahl-Hirschman index
ITC:	investment tax credit
LBNL:	Lawrence Berkeley National Laboratory
LP:	low priced
P5:	5th percentile
P10:	10th percentile
P10r:	residuals at or below the 10th percentile
P20:	20th percentile
PBI:	performance-based incentive
PG&E:	Pacific Gas & Electric
PV:	photovoltaic
SI:	Supporting Information
SCE:	Southern California Edison
SREC:	solar renewable energy credit
TPO:	third-party ownership
TTS:	Tracking the Sun
VoS:	value of solar

REFERENCES

- Baker, E., M. Fowlie, D. Lemoine and S. S. Reynolds (2013). "The economics of solar electricity." Annual Review of Resource Economics **5**(1).
- Barbose, G. L. and N. R. Darghouth (2015). Tracking the Sun VIII: The Installed Price of Residential and Non-Residential Photovoltaic Systems in the United States. Berkeley CA, Lawrence Berkeley National Laboratory.
- Barbose, G. L. and N. R. Darghouth (2016). Tracking the Sun IX: The Installed Price of Residential and Non-Residential Photovoltaic Systems in the United States.
- Barron, J. M., B. A. Taylor and J. R. Umbeck (2004). "Number of sellers, average prices, and price dispersion." International Journal of Industrial Organization **22**(8,Äi9): 1041-1066.
- Baye, M. R., J. Morgan and P. Scholten (2006). Information, search, and price dispersion. Handbook on economics and information systems. M. R. Baye. Amsterdam, Elsevier Press. **1**.
- Bentham, A. v., K. Gillingham and J. Sweeney (2008). " Learning-by-Doing and the Optimal Solar Policy in {California}." The Energy Journal **29**(3): 131.
- BLS (2014). Overview of BLS Wage Data by Area and Occupation 2014. Washington DC, U.S. Bureau of Labor Statistics (BLS).
- Borenstein, S. and J. Bushnell (2015). "The U.S. Electricity Industry After 20 Years of Restructuring." National Bureau of Economic Research Working Paper Series No. 21113.
- Burkhardt, J., R. Wiser, N. Darghouth, C. G. Dong and J. Huneycutt (2015). "Exploring the impact of permitting and local regulatory processes on residential solar prices in the United States." Energy Policy **78**(0): 102-112.
- Carlson, J. A. and R. P. McAfee (1983). "Discrete Equilibrium Price Dispersion." Journal of Political Economy **91**(3): 480-493.
- Census (2014). 2010 U.S. Census. Washington DC, U.S. Census Bureau.
- Dahlby, B. and D. S. West (1986). "Price Dispersion in an Automobile Insurance Market." Journal of Political Economy **94**(2): 418-438.
- Dai, M., Q. Liu and K. Serfes (2014). "Is the effect of competition on price dispersion nonmonotonic? evidence from the us airline industry." Review of Economics and Statistics **96**(1): 161-170.
- Davidson, C. and D. Steinberg (2013). "Evaluating the impact of third-party price reporting and other drivers on residential photovoltaic price estimates." Energy Policy **62**(0): 752-761.

809 Davidson, C., D. Steinberg and R. Margolis (2015). "Exploring the market for third-party-owned
810 residential photovoltaic systems: insights from lease and power-purchase agreement contract
811 structures and costs in California." Environmental Research Letters **10**(2): 024006.

812 Davis, S. J., C. Grim, J. Haltiwanger and M. Streitwieser (2013). "Electricity Unit Value Prices
813 and Purchase Quantities: US Manufacturing Plants, 1963–2000." Review of Economics and
814 Statistics **95**(4): 1150-1165.

815 Deetjen, T. A., J. B. Garrison, J. D. Rhodes and M. E. Webber (2016). "Solar PV integration cost
816 variation due to array orientation and geographic location in the Electric Reliability Council of
817 Texas." Applied Energy **180**: 607-616.

818 Denholm, P., K. Clark and M. O'Connell (2016). On the Path to SunShot: Emerging Issues and
819 Challenges in Integrating High Levels of Solar into the Electrical Generation and Transmission
820 System, NREL (National Renewable Energy Laboratory (NREL), Golden, CO (United States)).

821 Denholm, P. and R. M. Margolis (2007). "Evaluating the limits of solar photovoltaics (PV) in
822 traditional electric power systems." Energy Policy **35**(5): 2852–2861.

823 Dong, C. and R. Wiser (2014). "The impact of city-level permitting processes on residential
824 photovoltaic installation prices and development times: An empirical analysis of solar systems in
825 California cities." Energy Policy **63**: 531-542.

826 Dong, C., R. Wiser and V. Rai (2014). Incentive Pass-through for Residential Solar Systems in
827 California. Berkeley, CA, Lawrence Berkeley National Laboratory.

828 DSIRE. (2014). "Database of State Incentives for Renewables and Efficiency." Retrieved
829 October 11, 2014, from <http://www.dsireusa.org/solar/>.

830 Gillingham, K., H. Deng, R. H. Wiser, N. Darghouth, G. Nemet, G. L. Barbose, V. Rai and C.
831 Dong (2016). "Deconstructing Solar Photovoltaic Pricing: The Role of Market Structure,
832 Technology, and Policy." The Energy Journal **37**(3): 231-250.

833 Goldberg, P. K. and F. Verboven (2005). "Market integration and convergence to the Law of
834 One Price: evidence from the European car market." Journal of International Economics **65**(1):
835 49-73.

836 GTM/SEIA (2016). U.S. Solar Market Insight Report 2015 Q4. Washington DC, Solar Energy
837 Industries Association.

838 Hirth, L. (2015). "The Optimal Share of Variable Renewables: How the Variability of Wind and
839 Solar Power affects their Welfare-optimal Deployment." The Energy Journal **Volume 36**(1).

840 Hughes, J. E. and M. Podolefsky (2015). "Getting Green with Solar Subsidies: Evidence from
841 the California Solar Initiative." Journal of the Association of Environmental and Resource
842 Economists **2**(2): 235-275.

843 IEA (2014). World Energy Outlook 2014.

844 IEA (2015). World Energy Outlook 2015 Special Report on Energy and Climate Change. Paris,
845 International Energy Agency.

846 IEAPVPS (2016). National survey reports of PV power applications for 2015. Paris,
847 International Energy Agency – Photovoltaic Power Systems Programme.

848 Imbs, J. M., H. Mumtaz, M. O. Ravn and H. Rey (2010). "One TV, One Price?" The
849 Scandinavian Journal of Economics **112**(4): 753-781.

850 IREC (2013). Freeing the Grid 2013. Latham, NY and San Francisco, CA, Interstate Renewable
851 Energy Council and The Vote Solar Initiative.

852 Janko, S. A., M. R. Arnold and N. G. Johnson (2016). "Implications of high-penetration
853 renewables for ratepayers and utilities in the residential solar photovoltaic (PV) market." Applied
854 Energy **180**: 37-51.

855 Jordan, D. and S. Kurtz (2013). "Photovoltaic Degredation Rates-An Analytical Review."
856 Progress in Photovoltaics **21**(1): 12-29.

857 Menzio, G. and N. Trachter (2015). "Equilibrium price dispersion with sequential search."
858 Journal of Economic Theory **160**: 188-215.

859 Mileva, A., J. H. Nelson, J. Johnston and D. M. Kammen (2013). "SunShot Solar Power Reduces
860 Costs and Uncertainty in Future Low-Carbon Electricity Systems." Environmental Science \&
861 Technology **47**(16): 9053-9060.

862 Mills, A. D. and R. H. Wiser (2013). "Changes in the economic value of photovoltaic generation
863 at high penetration levels: a pilot case study of California." Photovoltaics, IEEE Journal of **3**(4):
864 1394-1402.

865 Nemet, G. F. (2012). "Subsidies for New Technologies and Knowledge Spillovers from Learning
866 by Doing." Journal of Policy Analysis and Management **31**(3): 601-622.

867 Peters, M., M. Schneider, T. Griesshaber and V. H. Hoffmann (2012). "The impact of
868 technology-push and demand-pull policies on technical change ,À Does the locus of policies
869 matter?" Research Policy **41**(8): 1296-1308.

870 Rai, V., D. C. Reeves and R. Margolis (2016). "Overcoming barriers and uncertainties in the
871 adoption of residential solar PV." Renewable Energy **89**: 498-505.

872 Rai, V. and B. Sigrin (2013). "Diffusion of environmentally-friendly energy technologies: buy
873 versus lease differences in residential PV markets." Environmental Research Letters **8**(1):
874 014022.

875 REN21 (2016). Renewables 2016: Global Status Report. Paris, REN21 Secretariat.

876 Sawhney, R., K. Thakur, B. Venkatesan, S. Ji, G. Upreti and J. Sanseverino (2014). "Empirical
877 analysis of the solar incentive policy for Tennessee solar value chain." Applied Energy **131**: 368-
878 376.

879 Seel, J., G. L. Barbose and R. H. Wiser (2014). "An analysis of residential PV system price
880 differences between the United States and Germany." Energy Policy **69**: 216-226.

881 SEIA/GTM (2014). U.S. Solar Market Insight 2013: Year in Review. Washington, Solar Energy
882 Industries Association/GTM Research.

883 Shrimali, G. and S. Jenner (2013). "The impact of state policy on deployment and cost of solar
884 photovoltaic technology in the U.S.: A sector-specific empirical analysis." Renewable Energy
885 **60**(0): 679-690.

886 Sigrin, B., J. Pless and E. Drury (2015). "Diffusion into new markets: evolving customer
887 segments in the solar photovoltaics market." Environmental Research Letters **10**(8): 084001.

888 Sivaram, V. and S. Kann (2016). "Solar power needs a more ambitious cost target." Nature
889 Energy **1**: 16036.

890 Tang, T. and D. Popp (2016). "The Learning Process and Technological Change in Wind Power:
891 Evidence from China's CDM Wind Projects." Journal of Policy Analysis and Management **35**(1):
892 195-222.

893 Thompson, P. (2012). "The Relationship between Unit Cost and Cumulative Quantity and the
894 Evidence for Organizational Learning-by-Doing." Journal of Economic Perspectives **26**(3): 203-
895 224.

896 Varun, R. and L. B. Ariane (2015). "Public perceptions and information gaps in solar energy in
897 Texas." Environmental Research Letters **10**(7): 074011.

898 Wang, X., L. Kurdgelashvili, J. Byrne and A. Barnett (2011). "The value of module efficiency in
899 lowering the leveled cost of energy of photovoltaic systems." Renewable and Sustainable
900 Energy Reviews **15**(9): 4248-4254.

901 Wiser, R., D. Millstein, T. Mai, J. Macknick, A. Carpenter, S. Cohen, W. Cole, B. Frew and G.
902 Heath (2016). "The environmental and public health benefits of achieving high penetrations of
903 solar energy in the United States." Energy **113**: 472-486.

904 Woodhouse, M., R. Jones-Albertus, D. Feldman, R. Fu, K. Horowitz, D. Chung, D. Jordan and
905 S. Kurtz (2016). On the Path to SunShot: The Role of Advancements in Solar Photovoltaic
906 Efficiency, Reliability, and Costs, NREL (National Renewable Energy Laboratory (NREL),
907 Golden, CO (United States)).

908 Zhu, K. and J. P. Weyant (2003). "Strategic decisions of new technology adoption under
909 asymmetric information: A game-theoretic model." Decision Sciences **34**(4): 643-675.
910

Percentage of systems that are LP