How Much Do Local Regulations Matter?

Exploring the Impact of Permitting and Local Regulatory Processes on PV Prices in the United States

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Abstract

Solar photovoltaics (PV) are providing an ever increasing proportion of U.S. energy supply. In part, this is because the costs of PV modules and other hardware have declined rapidly over the last decade, primarily due to technology improvements and manufacturing scale. Non-hardware "soft" costs, on the other hand, including permitting and other local regulatory processes, have not been falling as rapidly, and now comprise the majority of total costs for residential PV systems. This paper statistically isolates the impacts of city-level permitting and other local regulatory processes on residential PV prices in the U.S. by combining data from two "scoring" mechanisms that independently capture local regulatory process efficiency with the largest dataset of installed PV prices in the United States. Our dataset also utilizes a rich set of installation level control variables that allows us to better explain PV price variations in general. Based on regression analysis, we find that variations among and improvements in local regulatory processes can meaningfully affect residential PV installation prices. More specifically, we find that variations in local permitting procedures can lead to differences in average residential PV prices of approximately \$0.18/W between the jurisdictions with the most-onerous and most-favorable permitting procedures. For a typical 5-kW residential PV installation, this equates to a \$700 (2.2%) difference in system costs between jurisdictions with scores in the middle 90 percent of the range (i.e., 5^{th} percentile to 95^{th} percentile). Moreover, when considering variations not only in permitting practices, but also in other local regulatory procedures, price differences grow to \$0.64-0.93/W between the most-onerous and most-favorable jurisdictions. For a typical 5-kW residential PV installation, these results correspond to a price impact of at least \$2500 (8%) between jurisdictions with scores in the middle 90 percent of the range. These results highlight the magnitude of cost reduction that might be expected from streamlining local regulatory regimes.

Introduction

Though still a minor share of total electricity supply, solar photovoltaics (PV) have deployed at a rapid pace in recent years. In 2013, 38 GW of PV was installed globally, up from just 1.1 GW installed ten years earlier in 2004 (EPIA 2014). The United States, as the world's third largest market in 2013, installed 4.8 GW, with significant new capacity in smaller household and larger commercial systems as well as in utility-scale applications (SEIA/GTM 2014). This growth has been spurred by both government policy and system cost reductions (Shrimali and Jenner 2013), with continued growth expected over the near- and longer-term, especially within the context of combatting global climate change (Baker et al. 2013, Edenhofer et al. 2011, IPCC 2014).

For this growth to continue, given recent changes in the cost structure of PV systems, heightened emphasis is now being placed on reducing non-hardware "soft" costs. In particular, overall system-level PV cost reductions have been substantial in recent years (Barbose et al. 2014, Bolinger and Weaver 2013, Bazilian el al. 2013, Branker et al. 2011, Candelise et al. 2013, Hernandez-Moro and Martinez-Duart 2013). But, in the United States at least, these reductions have been largely driven by hardware—specifically, a steep decline in the price of PV modules. Though learning-based reductions in non-hardware soft costs are apparent on a longer term basis (Schaeffer et al. 2004), soft costs have been somewhat stagnant in the United States, at least through 2012 (Barbose et al. 2014). As a result, for typical residential systems, soft costs represented 64% of total system costs in the United States in 2012 (Friedman et al. 2013). Moreover, these high soft costs are at least somewhat unique, as average residential PV prices in the United States remain well above those witnessed in many other major global PV markets (Barbose et al. 2013). Significant additional reductions in total installed costs, likely a pre-condition for continued rapid market growth, will therefore necessitate substantial progress in reducing soft costs.

This paper focuses on one soft-cost element that has received a considerable amount of recent attention in the United States as being partly responsible for the persistently high PV prices: local regulatory processes, including permitting, inspection, and interconnection. A typical local regulatory process for PV may involve multiple local government departmental reviews (e.g., building, electrical, mechanical, plumbing, fire, structural, zoning, and esthetic), a permitting fee and a site inspection, as well as interconnection-based reviews by the local utility. These processes are partially directed by state policies, but local governments and utilities are typically given wide latitude in how they are administered. Though the resulting procedures can help protect against unscrupulous or unskilled PV installers, the diversity of documentation requirements, application procedures, inspection processes, and fees complicates the PV market: approximately 18,000 different local "authorities having jurisdiction" exist in the United States, many of which have unique requirements.[1]

A variety of efforts are underway to not only document the procedures required in various jurisdictions, but also to streamline those procedures in order to reduce PV costs, especially in jurisdictions where procedures are particularly onerous. The DOE's Rooftop Solar Challenge (RSC), for example, has funded teams of local and state governments along with utilities, installers, nongovernmental organizations, and others to work to reduce local administrative barriers to PV.[2] As part of this effort, the DOE has developed a scoring protocol for cities, and applied that system on two occasions. Vote Solar, meanwhile, created "Project Permit," which includes an online summary of city-level permitting requirements and scores cities based on those processes.[3] The Solar America Board for Codes and Standards has developed an expedited permit process for PV (Brooks 2012), while Clean Power Finance has created an online database that compiles permitting requirements from around the nation and that is used as the data source

[1] Also worth noting is that these 18,000 authorities oversee roughly 42,000 unincorporated communities, some of which have their own requirements.
[2] See: http://www.eere.energy.gov/solarchallenge/
[3] See: http://projectpermit.org/

for Vote Solar's Project Permit.[4] Partly in response to these myriad efforts, a number of states have sought to streamline their local procedures (Stanfield et al. 2012).

In this paper we statistically analyze the impact of these local, often city-level[5] processes on the reported prices of residential PV systems. We utilize two unique city-level "scores" of these processes—one created by the U.S. Department of Energy (DOE) through its RSC program and one by the non-profit organization Vote Solar through its Project Permit initiative. Our work leverages the sizable dataset of system-level PV prices managed by Lawrence Berkeley National Laboratory, and is part of a larger body of research conducted by LBNL, Yale University, University of Wisconsin, and University of Texas at Austin that is exploring, more broadly, the drivers for PV price variability in the United States.

Our analysis helps to answer two key questions. First, to what degree are local regulatory processes in the United States impacting residential PV prices? Second, do the two different scoring mechanisms capture the idiosyncrasies of these local processes? Answers to these questions can highlight the magnitude of cost reduction that might be expected from streamlining local regulatory regimes and, secondarily, may help refine city-level scoring methods.

We build on existing literature that has assessed these costs, and seek to inform efforts that have sought to reduce them. Friedman et al. (2013) find that the national average cost of permitting, inspection and interconnection (PII) in the United States for residential systems in 2012 was $0.19/W ($0.10/W for labor and $0.09/W for the permit fee). Seel et al. (2014) compare average PII costs in Germany and the United States for 2011, finding that German costs (at just $0.03/W) were substantially lower than in the United States, on average. Ardani et al. (2014) identify a roadmap by which U.S. PII costs might approach German levels by 2020. Earlier, SunRun (2011) found that local permitting and inspection could cost $0.50/W in total for a typical residential installation. Tong (2012) estimated that the labor costs association with permitting averaged $0.11/W, with 36% of installers limiting or avoiding certain jurisdictions due to cumbersome processes. Dong and Wiser (2013) evaluate the heterogeneity in city-level permitting practices, finding that cities in California with the most-favorable permitting practices had PV prices that were $0.27–$0.77/W lower than cities with the most-onerous practices.

Overall, this previous work suggests that local regulatory processes can impact PV prices, both directly through administrative labor and fees imposed on PV installers, as well as indirectly in the form of economic rents that accrue to installers as a result of barriers to entry into local markets created by onerous processes. It is also evident that the impact of local regulatory procedures on the PV market exceeds the impact on PV prices alone, as these procedures may

[4] See: http://solarpermit.org/

[5] Though we colloquially refer to "city-level" processes throughout much of this paper, in fact local procedures impacting PV are sometimes set by the county or by unincorporated jurisdictions.

cause delays in the completion of PV projects (Dong and Wiser 2013) and can also limit participation in the market by both installers and potential PV customers (Tong 2012). At the same time, there remains some uncertainty on the size of the *average* price impact and, more significantly, on the *heterogeneity* of those price effects across jurisdictions.

Our work seeks to tackle this latter uncertainty. In so doing, it builds on Dong and Wiser (2013), which conducted an econometric analysis of residential PV systems in California to explore the relationship between DOE RSC residential permitting scores and PV prices. We extend that work in several respects. First, we evaluate the impact of local processes using two third-party jurisdiction-level scoring systems from the RSC and Vote Solar. Second, we extend the work both geographically and temporally. Whereas Dong and Wiser (2013) focus on RSC scores and PV installations in California in 2011 (44 cities, 3,000 PV installations), the present analysis uses RSC scores and PV installations for both 2011 and 2012, and we evaluate the impact of those scores across 13,904 PV systems within 73 cities and 6 states. The Vote Solar scores allow us to assess a much larger number of PV systems (43,551), cities (603) and states (11), adding to the richness of our dataset. Third, Dong and Wiser (2013) focus solely on the "residential permitting score" from the RSC, which is just one aspect of the total score that the DOE assigns to participating cities. In the present analysis, in order to capture local procedures that go beyond permitting, we use the city-level "total score" from the RSC. In so doing, we capture local variations in interconnection procedures, planning and zoning, financing options, and net metering rules, in addition to permitting. Fourth, and related, we are then able to loosely contrast the RSC results with those that focus on the Vote Solar scores, which only cover permitting. Because the Vote Solar scoring mechanism emphasizes a smaller subset of the issues covered by the RSC scores, an analysis of both programs can lead to better understanding of how local procedures impact PV prices. Finally, while Dong and Wiser (2013) statistically controlled for a variety of other potential drivers of PV prices, the present analysis includes an even greater number of diverse control variables, reducing the chance of statistical bias and improving estimates of the impact of local regulatory procedures.

The remainder of the paper is structured as follows. In section 2, we discuss the data used to conduct our analysis. In section 3, we then summarize the statistical models used. Section 4 provides the key results of our analysis, while section 5 offers conclusions.

Data

This paper combines data from two independent city-level scores of local regulatory processes for PV with data on PV prices, systems and market characteristics from the largest dataset of PV installations in the United States. Below we first discuss the PV price and other data used in our analysis, and then we turn to a discussion of the two scoring methods.

PV System Prices and Other Data

This work leverages the largest dataset of PV system prices worldwide, used in Lawrence Berkeley National Laboratory's annual Tracking the Sun (TTS) report series (e.g., TTS VI: Barbose et al. 2013). The TTS VI data includes reported PV system prices for over 200,000 PV installations, representing 72% of cumulative grid-connected PV capacity in the United States as of year-end 2012. The data were collected from 47 PV incentive programs in 29 states, and were subsequently cleaned and standardized to remove potential errors in the data.[6] In addition to system prices, the data also contain a variety of information about the PV installations—including date of installation; system size; geographical location; whether the system is residential, commercial, or other; and its technology type (module and inverter manufacturer and model, ground mounted vs. roof-mounted systems, new construction vs. retrofit systems). After cleaning the module and inverter data, additional information on the technology used in each PV installation was inferred, including whether the module is building integrated PV (vs. rack-mounted), thin-film PV (vs. crystalline), Chinese made (vs. non-Chinese made), and whether the PV system uses micro-inverters (vs. central or string inverters). To maximize sample size, certain assumptions were made for some PV system characteristic variables when their value was unknown for specific PV systems. Namely, when the variables are unknown, systems are assumed to be retrofit (rather than new construction), crystalline silicon (rather than thin film), or rack mounted (rather than building integrated PV).

Various screens were applied to select the data used for the analysis presented in this paper. A key step was to isolate PV systems with locations and installation dates that coincided with the Vote Solar and RSC scores, as described in this section below. As with the underlying TTS VI dataset, outliers were removed by only keeping data for systems with installed prices between \$1.5/W and \$20/W,[7] as well as excluding PV systems that are ground mounted, self-installed, or with battery backup. As the focus of this study is on residential systems, we restricted the sample to PV systems between 1 and 10 kW that were identified as either "residential" or "unknown" for customer segment. Customer-owned PV systems are included in our analysis. However, a large fraction of the residential PV systems installed in the United States in recent years are owned by third parties, with the host customer either leasing or purchasing power from such systems. In these cases, as with the underlying TTS VI dataset, PV systems with reported prices identified as likely to represent an "appraised value" rather than a transaction price paid to the installer were removed from the sample. These are third-party owned (TPO) systems installed by integrated companies that provide both system financing as well as PV system installation, and the reported appraised-value pricing in these instances does not reasonably approximate the actual cost of individual installations. On the other hand, systems that are TPO but not installed by integrated

[6] For details on the standardization and cleaning process, refer to Barbose et al. (2013).
[7] All price data (in \$/W) were converted to real 2012 dollars, and are presented in terms of rated module power output under standard test conditions (DC-STC).

companies were retained in the dataset, as the reported price in these instances reflect the transaction price between the third-party company and the local installer.[8]

In addition to the existing data within the TTS VI dataset, we constructed additional data fields to be used as control variables in the analysis, leveraging the larger LBNL project mentioned earlier.[9] Using the zip code data for each PV system installation and data from the U.S. Census Bureau (2014), a number of demographic and socioeconomic characteristics were associated with each PV installation, including household education level, average income and average housing prices in the given zip code, and average household density in the given county. We derived a county-level composite labor-cost index from average administrative, electrician, and roofing wages using data from the Bureau of Labor Statistics. Cleaning the installer names for each PV installation in our dataset also enabled us to calculate a number of variables that reflect installer experience and competition within counties. These include a discounted county-level installer experience variable, a discounted county-level aggregate experience variable, a county-level installer density variable, a county-level installer market share variable, and a county-level Herfindahl–Hirschman Index (HHI) that measures the degree of concentration of installers in each local PV market (see also Table 5). Finally, we constructed a variable reflecting the net present value of the economic benefits of each PV system, including utility bill savings, based on electricity rates and insolation levels (for net-metered systems) as well as the expected present value of any performance-based incentives, feed-in tariffs, solar renewable energy certificate (SREC) payments, federal and state investment tax credits, and cash rebates.

Figure 1 shows the resulting distribution of PV system prices, focusing just on the data used for the Vote Solar and the RSC analysis; the figure therefore contains data on PV systems installed in 2011 and 2012 in a subset of states and cities, as described further below. The figure illustrates the significant variation in residential solar PV prices: within our analysis dataset, average prices are roughly $6/W, but the overall distribution of prices is wide. The degree to which some of this variation may be attributed to differences in permitting practices and other local regulations is the central question addressed by the present study.

[8] See Barbose et al. (2013) for additional details on price reporting for TPO systems.
[9] Further details on these variables and their precise construction, beyond what is provided below and in Table 5, can be found in a forthcoming LBNL report that explores, more broadly, the drivers for PV price variability.

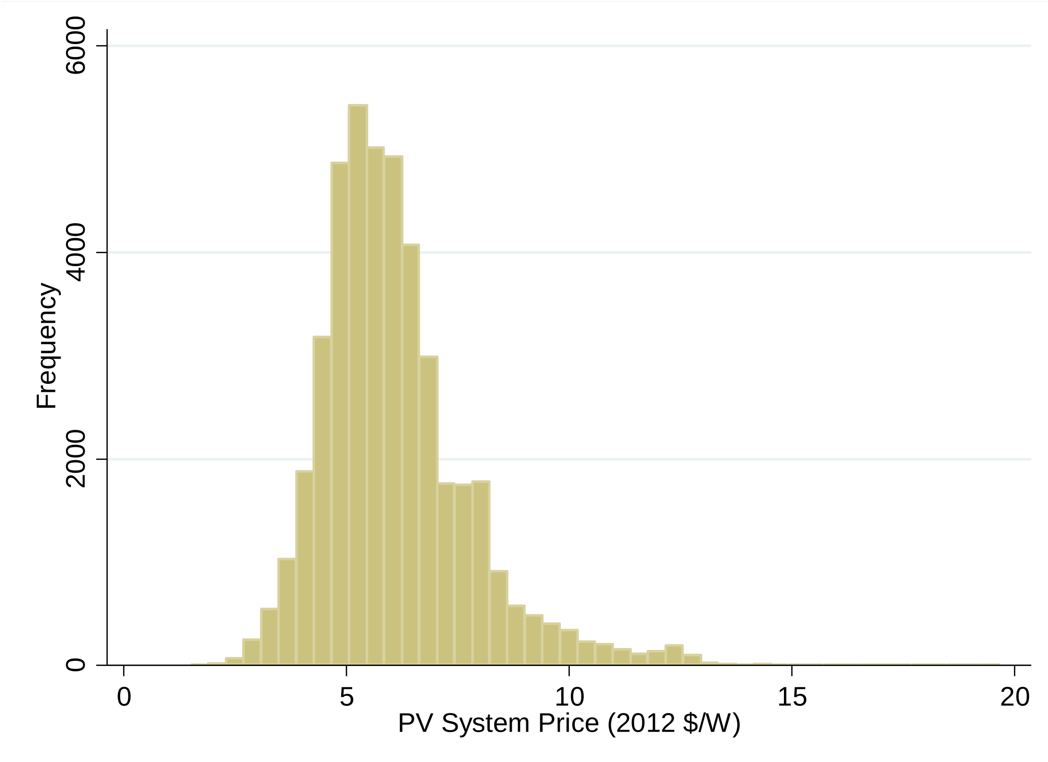


Figure 1. Distribution of PV System Prices in the Final Dataset for the Vote Solar and RSC Analysis

Scores of Local Regulatory Processes

Our analysis relies on two different sets of scores for local regulatory processes applied to PV installations: one by the non-profit organization Vote Solar (VS) Initiative and one by the U.S. Department of Energy through its RSC program.

The Vote Solar Initiative's Project Permit campaign provided the first set of regulatory process scores. Vote Solar worked with the Interstate Renewable Energy Council to develop a set of best practices for municipal permitting to be used for scoring local jurisdictions. As indicated in Table 1, seven of these best practices were scored and weighted to determine jurisdictional performance in solar permitting [Best (7-10), Good (2.5-7), Worst (0-2.5)]. A total of 915 jurisdictions in the United States have been scored. The data used by Vote Solar to determine scores was obtained from Clean Power Finance's National Permitting Database (SolarPermit.org), which is funded by the DOE and uses a crowdsourcing methodology to populate and verify information on municipal permitting practices and is continuously updated by a community of over 1,300 users.

Table 1. Vote Solar Project Permit Best Practices and Scoring Methodology

#	SolarPermit.org Question	Scoring Metric	Score = Best Practice	Score = Not Best Practice	Weight	Final Score
1	Is there a solar permitting checklist	Posts requirements online?	yes	no	0.05	0.5
2	Online permit applications	Allows online processing?	available	no	0.05	0.5
3	Is there an over-the-counter permit option	Fast turn-around time?	yes	no	0.25	2.5
3	Average turn-around time for residential permit	Fast turn-around time?	< 3 days	> 3 days	0.15	1.5
4	Permit Fee = "Flat Rate" PLUS "$400 or less"	Reasonable permitting fees?	≤ $400	no	0.25	2.5
5	Licensing for solar contractors	No community specific licenses needed?	Additional licensing not required	Additional licensing required	0.05	0.5
6	Time window for a scheduled inspection	Offers a narrow inspection appointment window?	≤ 2 hours	> 2 hours	0.1	1
7	Number of inspections required	Eliminates excessive inspections?	1 inspection	> 1 inspection	0.1	1
				Total Points:		10

Source: http://projectpermit.org/2013/02/06/best-practices/; accessed July 2014

The DOE's Rooftop Solar Challenge program supplied the second set of local regulatory process scores. The RSC is a competitively-awarded funding opportunity created by the U.S. Department of Energy in 2011 with the goal of eliminating market barriers and reducing soft costs via local and state-level initiatives. The RSC included a quantitative tracking of participants' progress across a variety of "action areas" that define the local regulatory environment for PV, including local permitting and interconnection processes, interconnection and net metering standards, financing options, and planning and zoning (see Table 2). In particular, the 22 participating teams in the RSC program, representing approximately 50 million people and 154 jurisdictions, provided DOE with responses to a multiple-choice questionnaire regarding the status of the local regulatory environment for PV in each participating jurisdiction. These responses were converted to numerical scores and weighted within each action area, according to the impact that local jurisdictions were likely to have in the context of the award funding (see Table 2).[10] Participants were then given one year to enact their strategies for enhancing local solar markets. At the end of the year, participants were once again scored using the same questionnaire to obtain a comparison against initial baseline scores and measure local solar market improvements.

[10] Participants were not made aware of the particular weighting for each response in order to avoid potential score manipulation.

Table 2. RSC Solar Market Maturity Model and Scoring Methodology

ACTION AREA	POINTS
Permitting Process	**460**
Application	110
Information Access	60
Process Time	110
Fee	30
Model Process	30
Inspection	80
Communication w/ Utility	40
Interconnection Process	**110**
Application	40
Information Access	20
Process Time	20
Inspection	30
Interconnection Standard	**100**
Net Metering Standard	**100**
Financing Options	**150**
Third Party Ownership (or equivalent)	90
Direct Finance Options	25
Community Solar	15
Other	20
Planning and Zoning	**80**
Solar Rights and Access	54
Zoning	20
New Construction	6
TOTAL POINTS POSSIBLE	**1000**

As indicated earlier and as suggested by the discussion above, these two sets of scores differ in their scope. In particular, the RSC scores encompass a substantially larger array of indicators, including those pertaining to state-level policies and financing options, whereas the Vote Solar scores are narrowly focused on a core set of municipal solar permitting best practices.

Final Dataset for Analysis

Though Vote Solar scored 915 cities, because of limited coverage in the TTS dataset, 603 cities remain within 11 states after matching the Vote Solar data to the TTS data. The Vote Solar scores used here reflect permitting processes in 2013. To best match Vote Solar scores with TTS data, which only extends through 2012, we assume that PV installations in 2012 are reasonably reflective of permitting procedures that existed in 2013.[11] In total, 43,551 residential PV (≤ 10 kW) installations match to the Vote Solar data—representing more than 50% of the residential PV systems installed in the United States in 2012 (SEIA/GTM 2013). Vote Solar scores range from 0 (onerous permitting processes) to 8.5 (efficient permitting processes), with an average of 3.1 (Figure 2). Table 3 shows state-level summary statistics for the Vote Solar scores and matched TTS PV prices. The full dataset is dominated by systems and cities in California, but also has a significant number of observations in a geographically diverse set of additional states.

Table 3. Vote Solar Matched Summary Statistics

State	City Score (mean)	Average Price ($/watt)	Number of Matched VS Cities	Number of Installations
AR	0.0	7.07	1	3
AZ	3.2	5.24	40	5654
CA	3.4	6.32	318	32472
CT	2.9	6.53	8	52
MA	1.5	5.78	37	533
NJ	1.5	5.61	72	1662
NM	0.8	6.01	3	171
NY	2.5	6.33	54	542
OR	4.0	5.82	13	963
PA	1.5	5.89	45	550
TX	0.8	4.71	12	949
Total			**603**	**43551**

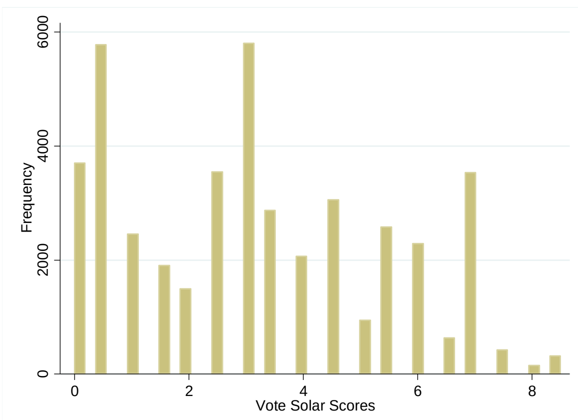
The DOE's RSC program scored 154 jurisdictions; after matching with the TTS installation data, however, 73 cities in six states remain for analysis. Two sets of scores are available: the baseline scores from early 2011 and the final scores from late 2012. To best match these scoring time frames, we match PV installations in 2011 with the 2011 baseline RSC scores, and we match PV installations from May through December of 2012 with the 2012 final RSC scores. In total, 13,904 residential PV (≤ 10 kW) installations match the RSC scoring data. RSC scores range from 228 (more-onerous local procedures) to 914 (more-favorable local procedures), with an average of 615 in 2011 and 751 in 2012 (see Figure 2, which collectively summarizes the scores

[11] There may be some limited bias in this temporal match as some jurisdictions will have streamlined their permitting procedures between 2012 and 2013.

from both time periods). Table 4 shows state-level summary statistics for the RSC scores and matched TTS PV prices. The RSC dataset is also dominated by California, but with significant numbers of systems in Arizona and Texas.

Table 4. Rooftop Solar Challenge Matched Summary Statistics

State	Jurisdiction Score (mean)	Average Price ($/watt)	Number of Matched RSC Jurisdictions	Number of Installations
AZ	580	5.11	8	1543
CA	711	6.39	47	11487
MA	657	5.45	5	95
NY	557	9.07	1	5
PA	393	6.14	11	53
TX	669	4.28	1	721
Total			**73**	**13904**



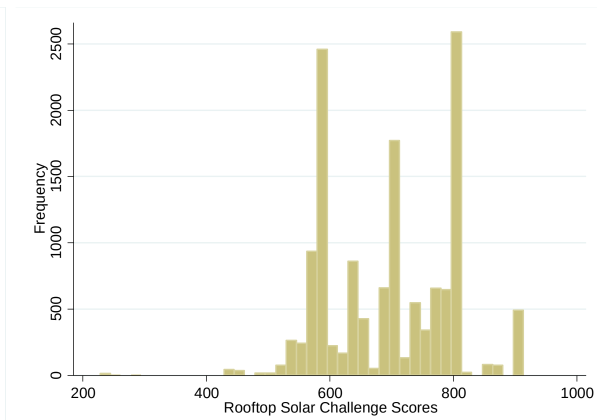


Figure 2. Distribution of Vote Solar and RSC Scores by PV Systems in the Matched Datasets

Methodology

We seek to evaluate the influence of local permitting and regulatory processes on installed residential solar PV prices ($/W). The main identifying assumption is that the scoring mechanism—whether RSC or Vote Solar—captures the exogenous variation in local regulatory processes. Our primary regression specification is captured by equation (1) below.

$$P_{ijt} = \alpha + \beta_1 S^k{}_{jt} + \beta_2 X_{ijt} + \beta_3 Z_{jt} + \beta_4 D_{ijt} + \gamma m_t + \theta_j + \varepsilon_{it} \quad (1)$$

This primary specification regresses the installation price per watt for PV system i, in jurisdiction j, at time t (P_{ijt}) on jurisdiction j*'s* score at time t (S_{jt}^k for k in (VS, RSC)). Vote Solar scored each jurisdiction once while the RSC program scored each jurisdiction twice. Thus, we have a single cross section of data from the Vote Solar program while we have a two-year panel dataset for the RSC program. A large number of control variables are also included.

- First, a set of variables comprising system-level characteristics (D_{ijt}) are included: PV system size; PV system size squared; and dummy variables indicating whether the system was installed as part of a new home, uses building-integrated PV (BIPV), uses thin film modules, uses modules manufactured in China, employs micro-inverters, and is third party owned (TPO).

- Second, a set of demographic and socio-economic controls (Z_{jt}) are included: local average education levels; housing prices; and household income.

- Third, a set of market characteristics (X_{ijs}) are included: household density; a labor cost index; individual installer experience at the county level; aggregate installer experience; measures of installer competition and market power; and an estimate of the present value of economic benefits of PV to the customer.

- Fourth, a linear time trend in months (m_t) is employed to control for the overall decrease in PV prices over the study period (2011-2012).

- Fifth, jurisdiction- or state-level fixed effects (θ_j) are included in a subset of the models.

A mean zero i.i.d. normally distributed error term (ε_{it}) is included. Huber-White robust standard errors are reported to limit the impacts of heteroskedasticity. Our primary regression outputs do not report clustered standard errors, but the results of clustering at the jurisdiction and state level are discussed later.

Each of the control variables is described in Table 5, with the expected signs listed. Summary statistics for these control variables, as well as for PV prices and RSC and Vote Solar scores, are provided in Appendix A.

Table 5. Control Variable Definitions and Expected Direction of Impacts

Variable	Definition	Expected Sign
system size	PV system size in watts	Negative
system size squared	Square term of system size	Positive
new construction	PV installed in new home construction (vs. retrofit on existing home)	Negative
BIPV	Building-integrated PV system (vs. not)	Positive
thin-film	Thin-film PV module (vs. crystalline silicon)	Either
China	China-made PV module (vs. not)	Negative
micro-inverter	PV system uses micro-inverter (vs. not)	Positive
TPO	Third-party owned PV system (vs. not)	Either
education level	Percent of individuals in zip code with bachelor's education or more	Negative
mean house value	Mean home value by zip code	Positive
mean income	Mean household income by zip code	Positive
household density	Total number of owner-occupied households per square mile within county	Negative
labor cost index	Composite labor cost index in county	Positive
installer experience	County-level installation experience by installer, measured as the discounted cumulative number of PV systems installed	Negative
aggregate experience	County-level aggregate installation experience by all installers, measured as the discounted cumulative number of PV systems installed	Negative
installer density	Total number of installers within county in last six month per household	Negative
installer market share	Market share by installer at county-level within last year	Either
HHI	Herfindahl - Hirschman Index for county-level PV market (installer concentration indicator)	Positive
value of solar	Present value of customer-economic benefits of a PV system	Positive
time	Linear time trend (also tested other specifications, see below)	Negative

Ultimately, we present five regression specifications for the RSC program and three for the Vote Solar program. Our primary specifications use ordinary least squares with jurisdiction-level (RSC) and state-level (VS and RSC) fixed effects to assess the impact of local permitting and other regulatory processes on PV prices.[12] We also include specifications that include no fixed effects for both scoring programs. Additionally, considering that the panel data is highly unbalanced, with far greater numbers of PV installations in some jurisdictions than in others, we show some regression results with sample weighting (i.e., pweight). The purpose of sample

[12] Because the Vote Solar program scored each jurisdiction only once, we do not have jurisdiction level variation in the Vote Solar score and cannot include jurisdiction fixed effects in our Vote Solar estimates.

weighting is to ensure that all jurisdictions are weighted equally, regardless of the number of PV systems installed; as a result, each observation in jurisdiction *j* is weighted by the inverse of the number of installations within jurisdiction *j*.

We performed a number of other tests to help check the robustness of our results. Each control variable was independently removed to determine whether any individual controls had a disproportionate effect on the outcomes. Though the regression results are not presented in the present study, the coefficient estimates for Vote Solar and RSC scores were robust to the removal of all of the control variables. We also tested the possible inclusion of additional control variables (including registered voter affiliation, land area and population density), but found that the efficiency gains from including these extra controls was outweighed by the cost of lost observations due to limitations in the underlying data set. We experimented with adding non-linear time trends (including various polynomial functions, and functions that might be associated with “learning-by-doing”) and time-based fixed effects, but neither had a significant impact on the variables of interest. Finally, we ran the regressions with the removal of both large- and small-sample jurisdictions and with standard errors clustered at the jurisdiction and state level. The results of these last two robustness checks are summarized in the next section.

Results and Interpretation

The results provide evidence that local regulatory and permitting processes can have meaningful impacts on installed PV prices. Our preferred regression specifications for the Vote Solar and RSC scores include state fixed effects and jurisdiction fixed effects, to control for potential time-invariant and unobservable PV price drivers at the state or jurisdiction level. These preferred specifications are presented in column (2) in Table 6 and in columns (2) and (4) in Table 7. Our results suggest that a 1 point increase in the Vote Solar score is associated with an average $0.021/W reduction in residential PV prices, while a 1 point increase in the RSC score is associated with a $0.00093/W – $0.00135/W reduction in residential PV prices.

The results for Vote Solar—using a larger dataset—are more robust. In particular, the exclusion of state-level fixed effects (column 1, Table 6) and the application of sample weighting (column 3, Table 6) do not meaningfully impact the size or statistical significance of the Vote Solar score variable, with a range of just $0.021/W to $0.023/W. The results for the DOE’s Rooftop Solar Challenge, on the other hand, are significantly impacted by model specification. The exclusion of state- and jurisdiction-level fixed effects (column 1, Table 7), for example, reduces the size of the estimated impact to $0.0004/W, whereas sample weighting (columns 3 and 5, Table 7) leads the RSC score variable to lose statistical significance; the sample weighting results are discussed in further detail later in this section.

Table 6. Regression Results: Vote Solar

	(1) Price/W	(2) Price/W	(3) Price/W
VS score	-0.0208^{***} (0.003)	-0.0209^{***} (0.003)	-0.0231^{**} (0.008)
system size	-0.560^{***} (0.020)	-0.564^{***} (0.020)	-0.606^{***} (0.053)
system size squared	0.0343^{***} (0.002)	0.0353^{***} (0.002)	0.0378^{***} (0.004)
new construction	-0.548^{***} (0.046)	-0.517^{***} (0.047)	-0.517^{***} (0.097)
BIPV	0.758^{***} (0.070)	0.840^{***} (0.071)	1.033^{***} (0.214)
thin film	0.340 (0.178)	0.397^{*} (0.174)	0.275 (0.210)
China	-0.405^{***} (0.015)	-0.429^{***} (0.015)	-0.522^{***} (0.035)
micro-inverter	0.627^{***} (0.019)	0.597^{***} (0.019)	0.326^{***} (0.041)
TPO	0.330^{***} (0.021)	-0.0203 (0.025)	-0.189^{***} (0.053)
education level	-0.989^{***} (0.068)	-0.0879 (0.070)	-0.0461 (0.171)
mean house value	0.00109^{***} (0.000)	0.00000867 (0.000)	-0.000266 (0.000)
mean income	-0.000258 (0.000)	0.000669 (0.000)	0.00154 (0.001)
household density	1.148^{***} (0.053)	1.169^{***} (0.053)	1.317^{***} (0.173)
labor cost index	-0.0130^{***} (0.001)	-0.0125^{***} (0.001)	-0.00178 (0.002)
installer experience	-0.000212^{***} (0.000)	-0.000295^{***} (0.000)	-0.0000303 (0.000)
aggregate experience	-91.67^{***} (6.357)	-63.15^{***} (6.848)	-3.028 (15.274)
installer density	-1.034^{***} (0.098)	-1.494^{***} (0.101)	-0.609^{**} (0.201)
installer market share	-0.0938 (0.083)	-0.129 (0.079)	-0.415^{*} (0.190)
HHI	-1.001^{***} (0.099)	-0.292^{*} (0.122)	-0.219 (0.281)
value of solar	0.204^{***} (0.009)	0.0421^{***} (0.011)	-0.0297 (0.022)
time	-0.0743^{***} (0.002)	-0.0882^{***} (0.002)	-0.102^{***} (0.004)
pweight			yes
state fixed effect		yes	yes
R2	0.316	0.340	0.313
N	43551	43551	43551

Robust standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7. Regression Results: Rooftop Solar Challenge

	(1)	(2)	(3)	(4)	(5)
	Price/W	Price/W	Price/W	Price/W	Price/W
RSC score	-0.000406^{**}	-0.000930^{***}	-0.000370	-0.00135^{***}	0.000553
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
system size	-0.682^{***}	-0.717^{***}	-0.545^{***}	-0.676^{***}	-0.274^{*}
	(0.034)	(0.036)	(0.069)	(0.035)	(0.110)
system size squared	0.0451^{***}	0.0476^{***}	0.0364^{***}	0.0449^{***}	0.0119
	(0.003)	(0.003)	(0.006)	(0.003)	(0.010)
new construction	-1.081^{***}	-1.171^{***}	-0.458^{***}	-0.979^{***}	-0.190
	(0.083)	(0.092)	(0.137)	(0.085)	(0.148)
BIPV	1.253^{***}	1.330^{***}	0.771^{***}	1.374^{***}	0.917^{***}
	(0.145)	(0.149)	(0.162)	(0.152)	(0.186)
thin film	0.529	0.562	-0.324	0.537	-0.537^{*}
	(0.508)	(0.495)	(0.258)	(0.506)	(0.219)
China	-0.342^{***}	-0.359^{***}	-0.263^{***}	-0.356^{***}	-0.218^{*}
	(0.028)	(0.028)	(0.065)	(0.028)	(0.086)
micro-inverter	0.496^{***}	0.487^{***}	0.298^{***}	0.507^{***}	0.405^{***}
	(0.034)	(0.033)	(0.059)	(0.034)	(0.077)
TPO	0.328^{***}	0.0518	0.304^{*}	-0.0480	-0.0431
	(0.042)	(0.062)	(0.125)	(0.052)	(0.100)
education level	-1.905^{***}	-0.422^{**}	-0.666	-0.721^{***}	0.358
	(0.126)	(0.163)	(0.440)	(0.138)	(0.389)
mean house value	0.00190^{***}	0.000462^{*}	0.000768	0.000474^{**}	-0.000219
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
mean income	-0.000786	0.000314	0.00236	0.000533	-0.000957
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
household density	1.655^{***}	11.25^{**}	1.065	0.655^{***}	1.244^{**}
	(0.145)	(4.132)	(4.414)	(0.155)	(0.393)
labor cost index	-0.0254^{***}	-0.0969^{***}	-0.0465^{*}	-0.00670^{*}	-0.00555
	(0.003)	(0.011)	(0.020)	(0.003)	(0.006)
installer experience	-0.0000918^{*}	-0.000413^{***}	-0.0000494	-0.000287^{***}	-0.000358
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
aggregate experience	-221.6^{***}	-181.0^{***}	-165.3^{*}	-154.6^{***}	-39.56
	(13.281)	(40.052)	(69.419)	(14.657)	(35.726)
installer density	-0.486^{**}	0.978	-0.729	-0.727^{***}	-1.406^{**}
	(0.187)	(0.503)	(0.902)	(0.182)	(0.515)
installer market share	-1.355^{***}	-0.287	-2.748^{***}	-0.635^{**}	-0.121
	(0.193)	(0.207)	(0.662)	(0.206)	(0.960)
HHI	-5.982^{***}	-0.769	-1.316	-1.713^{***}	0.101
	(0.451)	(0.916)	(1.631)	(0.452)	(1.322)
value of solar	0.189^{***}	0.108^{***}	0.211^{***}	0.0187	0.0743
	(0.018)	(0.030)	(0.059)	(0.024)	(0.046)
time	-0.0524^{***}	-0.0469^{***}	-0.0495^{***}	-0.0684^{***}	-0.0706^{***}
	(0.003)	(0.004)	(0.010)	(0.003)	(0.008)
pweight			yes		yes
state fixed effect				yes	yes
Jurisdiction fixed effect		yes	yes		
R2	0.382	0.422	0.475	0.398	0.371
N	13904	13904	13904	13904	13904

Robust standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Focusing for the moment on the more-preferred specifications, Figures 3 and 4 summarize the impact of marginal changes in Vote Solar and RSC scores on average residential PV prices, across the full set of jurisdictions (and scores) in the data. We predict marginal changes in PV prices by multiplying the coefficient on score from model (2) and models (2) and (4) for the Vote Solar and RSC programs, respectively, by the observed difference in scores between each jurisdiction, while holding all other control variables constant at their average values.

These predictions indicate that the average price of residential PV systems in the highest scoring Vote Solar jurisdiction, all else being equal, would be approximately \$0.18/W lower than the average price in the lowest-scoring jurisdiction (Figure 3). This variation across jurisdictions equates to roughly 3% of average residential PV prices in 2012. When focusing on the inner 90 percent of jurisdiction scores (to remove outlier jurisdictions), the impact range drops to \$0.14/W (2.2%). The size of the predicted impact from the DOE's Rooftop Solar Challenge is larger, with PV prices from the highest- to lowest-scoring jurisdictions (across both scoring time periods) varying by \$0.64/W or \$0.93/W, depending on model specification (Figure 4). This variation equates to 10-15% of average PV prices in 2012, but is impacted by the lowest- and highest-scoring jurisdictions as indicated in Figure 4. When focusing on the inner 90 percent of jurisdiction scores (to remove outlier jurisdictions), the impact range drops to \$0.50/W or \$0.73/W (8-12%), depending on model specification.

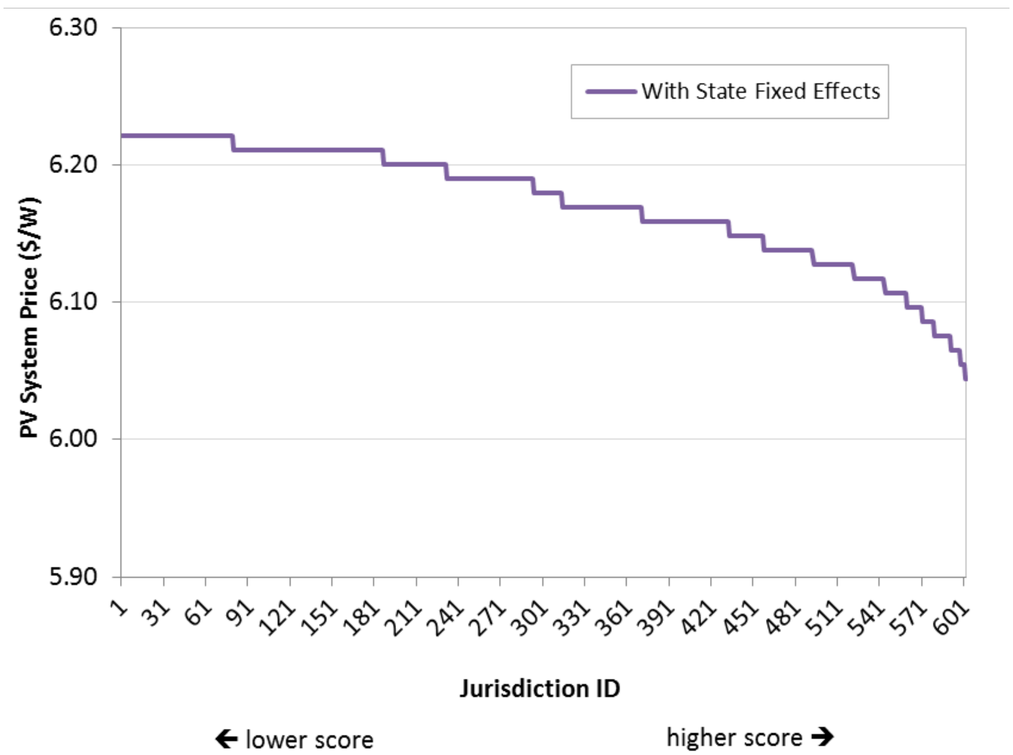


Figure 3. Predicted Relationship between Vote Solar Scores and PV Prices

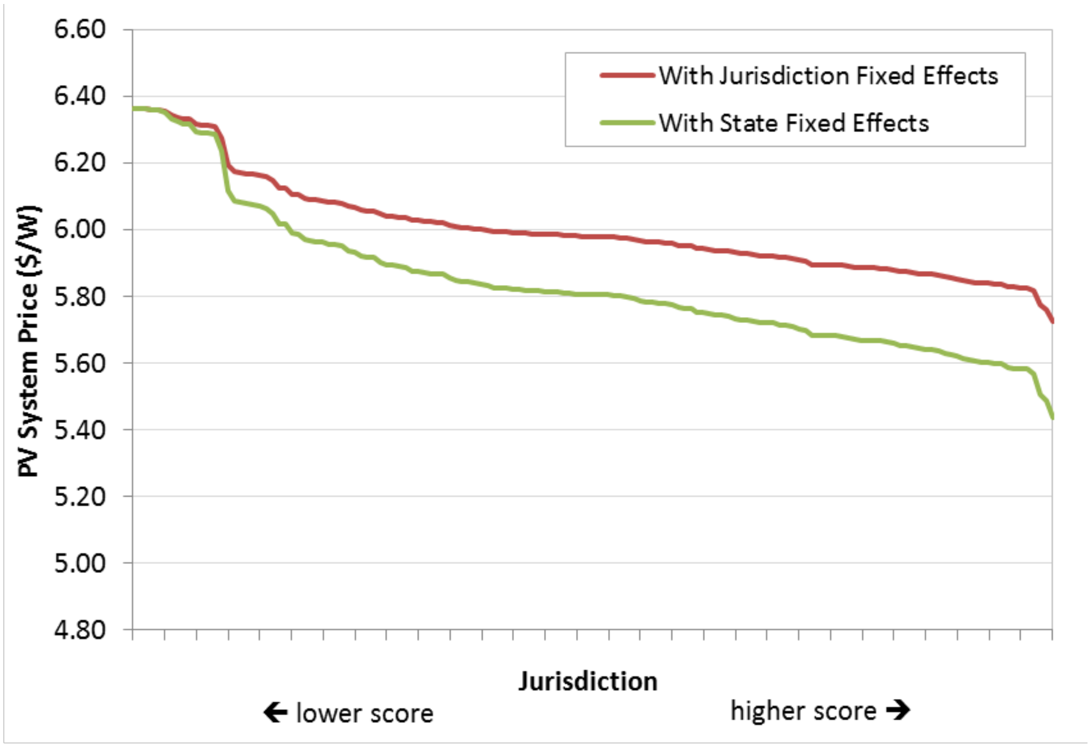


Figure 4. Predicted Relationship between Rooftop Solar Challenge Scores and PV Prices

As another intuitive measure of the impact of local permitting and other regulatory processes on PV prices, the average RSC score improved by 163 points in our sample from the baseline score to the final score. This average score increase translates to a predicted decline in PV prices of $0.15-$0.22/W (2.5-3.6%). The *total* decline in average PV prices from 2011 to 2012 was approximately $1.16/W in our sample dataset. Our results therefore suggest that, on average, 13-19% of the total price change might be attributed to improvements in permitting and other local regulatory processes in participating RSC jurisdictions, equating to $700–1100 for an average sized residential PV system.

As expected, the results show that RSC scores appear to drive larger local price variations ($0.64-0.93/W; as much as $3200-4700 for a typically sized residential system, but $2500-3700 when focusing on the inner 90 percent of jurisdiction scores) than Vote Solar scores ($0.18/W; as much as $900 for a typically sized residential system, but $700 when focusing on the inner 90 percent of scores). Though the two datasets cover different geographies and the scoring methods are not perfectly comparable, presumably these results are driven, in part, by the fact that the RSC scores embed not only variations in local permitting requirements, but also variations in interconnection procedures, planning and zoning, financing options, and net metering rules; Vote Solar scores, on the other hand, narrowly focus on local permitting procedures. These results suggest that local permitting practices do play a strong role in explaining PV price differences, but that other local regulatory procedures also play important roles.

The validity of these models is supported by the results for many of the control variables, most of which have coefficients with the expected sign. Specifically, the coefficients on PV system size and size squared consistently show that PV prices decrease as system sizes increase but with diminishing margin returns. Other system-level characteristics also have the predicted impacts on PV prices: systems installed in new construction or with Chinese-manufactured modules have lower prices, whereas BIPV systems and those using micro-inverters have higher prices. Results for thin-film modules and third-party owned systems are mixed, with some specification suggesting a small price premium, but with other models finding insignificant or even the opposite effect. As for the demographic and socio-economic variables, an increase in average education levels tends to result in lower PV prices, perhaps suggesting that competitive bidding is more common for these customers. Increased average housing values, in many specifications, leads to higher PV prices, whereas household income is found to have inconsistent or statistically insignificant effects, but collinearity among these and other variables is of some concern. The coefficients for the labor cost index and household density variables are in opposition to our expectations, but may similarly be impacted by collinearity with other variables that proxy for the cost of living, as found in Dong and Wiser (2013). Among the other market-level characteristics, increases in aggregate- and installer-level experience as well as installer density lead to lower PV prices, as expected. Installer market share tends to have a negative coefficient, further suggesting some economies of scale at the local level. These installer-level results also suggest that reductions in soft costs are passed on to the consumer in the form of lower prices. The HHI variable has an unexpected sign, perhaps suggesting that the impact of local installer scale in reducing prices outweighs market-power considerations. The value of solar coefficient tends to have a positive sign, indicating that installers are able to raise PV prices in those markets that provide higher financial incentives for solar installations. Finally, prices decline with time.[13]

Notwithstanding these findings, other regression specifications suggest a certain level of nuance in these results. In particular, the weighted regressions suggest that a small number of large jurisdictions drive the statistical significance of the coefficient of interest for the RSC results. In particular, as shown in columns (3) and (5) in Table 7, the score coefficients in the RSC regressions lose significance when all jurisdictions are weighted equally, i.e., increasing the influence of small-sample jurisdictions and decreasing the influence of large-sample jurisdictions.[14] On the other hand, as shown in column (3) in Table 6, the Vote Solar results are not impacted by weighting, and so are not unduly influenced by large-sample jurisdictions. The impact of large-sample jurisdictions on the RSC results, but not the Vote Solar results, may simply be a consequence of the larger number of jurisdictions in the Vote Solar sample.

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[13] Forthcoming work by LBNL will provide a deeper analysis of how these and other variables influence PV prices and price variability.

[14] This was verified by removing the largest jurisdictions (without weighting), with results similar to the weighting method; removing the smallest jurisdictions did not produce similar results.

Alternatively, these results may be an indication of an unexplained geographically heterogeneous impact of permitting and local regulatory processes on residential PV prices.

Finally, we also ran the same regressions with standard errors clustered at the jurisdiction or state level to control for the potential correlation of unobservables below the jurisdiction or state level.[15] Though not presented here, controlling for potential correlation within jurisdictions (clustering) reduces the statistical power of the results in all but one of our specifications for each scoring program, suggesting that installations within jurisdictions are affected by unobserved characteristics unique to each jurisdiction.

Conclusion

As PV module and other hardware costs have declined in recent years, the relative importance of non-hardware soft costs has grown. Understanding these soft costs – not just PII but also installation labor, customer acquisition, financing, etc. – and developing pathways for their reduction may be central to continued solar market expansion in the United States.

This paper has statistically isolated the impacts of a portion of these soft costs, namely city-level permitting and other local regulatory processes, on residential PV prices. We find that variations among and improvements in local regulatory processes can meaningfully affect residential PV prices. Specifically, variations in local permitting procedures are found to drive differences in average residential PV prices of approximately \$0.18/W across all jurisdictions in our Vote Solar sample, and \$0.14 when focusing on the inner 90 percent of jurisdiction scores. For a typical residential PV installation, this equates to a \$700 (2.2%) difference in system costs between jurisdictions with scores in the middle 90 percent of the range (i.e., 5th percentile to 95th percentile). When considering variations not only in permitting practices, but also in other local regulatory procedures, price differences are found to grow to as much as \$0.64-0.93/W between the most-onerous and most-favorable jurisdictions in our RSC sample; this range drops to \$0.50-0.73/W when focusing on the inner 90 percent of jurisdiction scores. For a typical residential PV installation, this corresponds to a price impact of at least \$2500 (8%) between jurisdictions with scores in the middle 90 percent of the range (i.e., 5th percentile to 95th percentile), demonstrating the magnitude of cost reduction that might be possible from streamlining regulatory regimes.

As with Dong and Wiser (2013), these *cross-jurisdiction* results add to the previous literature that has sought to quantify the *national average* impacts of permitting and local procedures on

[15] Moulton (1990) showed that standard errors can be underestimated when variables are measured at different levels. In the present work, the dependent variable, price per watt, is measured at the system level, while the independent variable of primary interest (RSC or VS scores) is measured at the jurisdiction level.

PV prices. In particular, the present results show that estimates of national average impacts can mask the substantial variation of impacts among jurisdictions, and therefore also hide the potential for PV price reductions through streamlining the local procedures in those jurisdictions in which current practices are most onerous.

These results also suggest that the Vote Solar and Rooftop Solar Challenge scores do measure real variations in permitting and other local regulatory processes. First, the Vote Solar and RSC scores are found to have statistically significant impacts on PV prices. Second, the overall size of the effects is broadly consistent with what one might expect, based in part on previous literature. Third, as anticipated, the results show that RSC scores appear to drive larger overall price variations than the Vote Solar scores. Presumably, this is in part because the RSC scores embed not only variations in local permitting requirements, but also variations in interconnection procedures, planning and zoning, financing options, and net metering rules; Vote Solar scores, on the other hand, narrowly focus on local permitting procedures.

Especially given the much-higher PV prices seen in the United States relative to other major solar markets internationally, additional research is warranted to further explore the impact of local regulatory procedures. First, it would be helpful to expand the frame of the analysis to explore more-broadly the impact of these procedures on the participation of (and competition among) installers in certain jurisdictions (expanding on Tong 2012) as well as on PV demand in those jurisdictions (expanding on Li and Yi 2014, Shrimali and Jenner 2013). Second, though the present analysis has focused on smaller, residential PV installations, it would be helpful to expand this type of work to also understanding price variations among larger, commercial installations. Third, as the DOE's Rooftop Solar Challenge continues, it may be useful to evaluate the impact of that specific program by analyzing PV price trends in participating jurisdictions relative to non-participating jurisdictions. Finally, because permitting and other local regulatory processes drive only a fraction of the heterogeneity in PV prices seen in the United States, further research to understand the full suite of driving influences would be valuable, and is underway by LBNL and its partners – Yale University, University of Wisconsin, and University of Texas at Austin.

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Appendix A. Summary Statistics

Summary Statistics: Vote Solar

	mean	s.d.	min	max	count
system price ($/W)	6.061	1.677	1.507	19.673	49864
Vote Solar score	3.104	2.229	0.000	8.500	49864
system size	5.060	2.135	1.000	10.000	49864
system size squared	30.163	23.764	1.000	100.000	49864
new construction	0.036	0.186	0.000	1.000	49864
BIPV	0.008	0.089	0.000	1.000	49864
thin film	0.004	0.062	0.000	1.000	49864
China	0.270	0.444	0.000	1.000	44295
micro-inverter	0.251	0.434	0.000	1.000	44713
TPO	0.405	0.491	0.000	1.000	49864
education level	0.360	0.177	0.000	0.928	49821
mean house value	462.215	219.946	61.647	1182.356	49635
mean income	94.026	34.643	28.300	394.381	49644
household density	0.098	0.163	0.000	2.837	49819
labor cost index	57.032	14.732	25.140	110.007	49679
installer experience	119.388	192.868	1.000	2142.346	49864
aggregate experience	0.003	0.001	0.000	0.009	49819
installer density	0.152	0.096	0.000	1.479	49822
installer market share	0.086	0.140	0.000	1.000	49469
HHI	0.101	0.114	0.024	1.000	49469
value of solar	6.278	1.609	1.844	14.632	49672
time	11.360	5.625	1.000	20.000	49864

Summary Statistics: Rooftop Solar Challenge

	mean	s.d.	min	max	count
system price ($/W)	6.113	1.725	1.507	19.409	16427
RSC score	679.462	106.504	228.000	914.000	16427
system size	4.887	2.149	1.000	10.000	16427
system size squared	28.497	23.108	1.000	100.000	16427
new construction	0.040	0.195	0.000	1.000	16427
BIPV	0.005	0.071	0.000	1.000	16427
thin film	0.004	0.059	0.000	1.000	16427
China	0.261	0.439	0.000	1.000	14055
micro-inverter	0.257	0.437	0.000	1.000	14179
TPO	0.380	0.485	0.000	1.000	16427
education level	0.386	0.183	0.000	0.913	16407
mean house value	489.143	222.126	100.071	1160.356	16391
mean income	95.326	36.752	29.476	320.744	16399
household density	0.138	0.220	0.001	2.837	16422
labor cost index	57.562	12.300	28.130	102.270	16422
installer experience	163.685	270.184	1.000	2142.346	16427
aggregate experience	0.003	0.001	0.000	0.007	16422
installer density	0.140	0.088	0.000	0.717	16423
installer market share	0.059	0.073	0.000	0.895	16295
HHI	0.071	0.041	0.024	0.943	16295
value of solar	6.254	1.663	3.285	14.141	16419
time	11.482	5.700	1.000	20.000	16427

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