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The Impact of City-level Permitting Processes on Residential Photovoltaic Installation Prices and Development Times:

An Empirical Analysis of Solar Systems in California Cities

Ryan Wiser and Changgui Dong

Environmental Energy Technologies Division

April 2013

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Prepared for the
Office of Energy Efficiency and Renewable Energy
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Abstract

Business process or “soft” costs account for well over 50% of the installed price of residential photovoltaic (PV) systems in the United States, so understanding these costs is crucial for identifying PV cost-reduction opportunities. Among these costs are those imposed by city-level permitting processes, which may add both expense and time to the PV development process. Building on previous research, this study evaluates the effect of city-level permitting processes on the installed price of residential PV systems and on the time required to develop and install those systems. The study uses a unique dataset from the U.S. Department of Energy’s Rooftop Solar Challenge Program, which includes city-level permitting process “scores,” plus data from the California Solar Initiative and the U.S. Census. Econometric methods are used to quantify the price and development-time effects of city-level permitting processes on more than 3,000 PV installations across 44 California cities in 2011. Results indicate that city-level permitting processes have a substantial and statistically significant effect on average installation prices and project development times. The results suggest that cities with the most favorable (i.e., highest-scoring) permitting practices can reduce average residential PV prices by \$0.27–\$0.77/W (4%–12% of median PV prices in California) compared with cities with the most onerous (i.e., lowest-scoring) permitting practices, depending on the regression model used. Though the empirical models for development times are less robust, results suggest that the most streamlined permitting practices may shorten development times by around 24 days on average (25% of the median development time). These findings illustrate the potential price and development-time benefits of streamlining local permitting procedures for PV systems.

Key Words: photovoltaic; permitting process; installation prices; development times

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1. Introduction

The cost of photovoltaic (PV) systems has declined dramatically (Barbose et al., 2012), opening new and growing markets for solar energy (Bazilian et al., 2013). Recent literature has sought to understand these cost trends (Wiser et al., 2007; Branker et al., 2011; Peters et al., 2011; Hernandez-Moro and Martinez-Duart, 2013) and the variation in costs caused by altered assumptions and market contexts (Zweibel, 2010; Darling et al., 2011; Reichelstein and Yorston, 2013; Seel et al., 2013). Additionally, a substantial literature on learning and experience has been applied to solar energy (e.g., Schaeffer et al., 2004; Soderholm and Sundqvist, 2007; Neij, 2008; van Benthem et al., 2008; Kahouli-Brahmi, 2009; Nemet, 2009; Junginger et al., 2010; Green, 2011). Despite this body of work, further research is required to better understand the geographic scope of learning (Shum and Watanabe, 2008; Martinsen, 2011), to isolate learning-induced cost reductions from the variety of other factors that impact cost trends (e.g., Nemet, 2006; Mukora et al., 2009; Yu et al., 2011), and to explore learning and cost-reduction possibilities for non-hardware balance-of-system costs (Schaeffer et al., 2004; Hoff et al., 2010).

This study builds on this literature by focusing squarely on understanding one component of non-hardware PV costs: the effect of U.S. city-level permitting processes on the installed price of residential PV systems and on the time required to develop and install those systems. Recent declines in PV system prices have been driven primarily by declining PV module prices (Barbose et al., 2012; Bazilian et al., 2013). As a result, non-hardware business process (or "soft") costs currently account for well over 50% of the installed price of residential PV systems in the United States, [1] and understanding these costs is crucial for identifying further PV cost-reduction opportunities. City-level permitting processes are one core element of these business process costs, and they potentially add both considerable costs[2] and development time to PV installations. The U.S. Department of Energy (DOE)

[1] Ardani, et al. (2012) and Goodrich, et al. (2012) report non-hardware costs at roughly 50% of the total price of a typical residential PV system in the United States in 2010. With current PV module prices well below what was observed in 2010, non-hardware costs now constitute more than 60% of a typical installation price in the United States. Even as early as 1978, there was recognition that non-hardware costs were important, with NASA estimating very substantial balance-of-system costs (Rosenblum, 1978).
[2] Note that these costs could include both direct costs, in the form of administrative labor and fees imposed on PV installers, as well as indirect costs, in the form of economic rents that accrue to installers as a result of barriers to entry into local markets created by onerous permitting processes.

identified permitting procedures as a barrier to widespread PV deployment and launched the SunShot Rooftop Solar Challenge Program[3] to address this barrier.

A typical PV permitting process in the United States may involve many local government departmental reviews—such as building, electrical, mechanical, plumbing, fire, structural, zoning, and aesthetic reviews—as well as a permitting fee. In addition, site inspections and final approvals are required for permitting (by local agencies) and interconnection (by local utilities) purposes. On the one hand, these permitting processes could add long-term value to the PV industry by protecting consumers, promoting public safety, and rewarding the most diligent installers. However, the quantity and diversity of PV permitting documentation requirements, application procedures, inspection processes, and fees used by local jurisdictions complicates the business of PV installers: there are more than 18,000 local jurisdictions in the United States, each with unique and sometimes time-consuming and costly permitting requirements. Clean Power Finance surveyed 273 installers across 12 states and found that more than one third of installers avoid jurisdictions with particularly challenging permitting processes (Tong, 2012). In sum, though permitting procedures do serve important public purposes, onerous procedures may impose unnecessary direct costs (administrative labor and permitting fees) and time on the PV development process and may also raise PV prices by creating entry barriers and thereby restraining competition among PV installers.

Many efforts are underway in the United States to streamline and bring down the cost of local permitting processes. DOE's Rooftop Solar Challenge is engaging diverse teams of local and state governments along with utilities, installers, non-governmental organizations, and others to make solar energy more accessible and affordable, including by working to reduce administrative barriers to residential and small commercial PV installations. SolarTech, a non-profit industry consortium, developed Solar3.0—A National Platform for Process Innovation to Deliver PV "to increase the competitiveness of solar PV by reducing non-hardware balance-of-system costs by 50% in identified U.S. solar communities by 2014."[4] SolarFreedomNow, a grassroots initiative, advocates a single national policy to cut paperwork and red tape.[5] The DOE-funded Solar America Board for

[3] For program information see http://www.eere.energy.gov/solarchallenge/.
[4] For information see http://solar30.org/.
[5] For information see http://solarfreedomnow.org/.

Codes and Standards (Solar ABCs) has developed an expedited permit process for PV systems (Brooks, 2012). Also funded by DOE, Clean Power Finance created a National Solar Permitting Database, an online tool that compiles solar permitting requirements from around the nation.[6] In addition, states, such as California and organizations such as the Interstate Renewable Energy Council (IREC) have initiated efforts to expedite permitting and field inspections (OPR, 2012; IREC, 2010). California, Colorado, and a limited number of other states have created caps on the permit fees that can be automatically charged for PV installations, while Vermont uses a streamlined state-wide registration process for PV and eliminates local permitting requirements. Stanfield et al. (2012) describe the diversity of approaches that can and have been used to streamline and lower the cost of local permitting requirements.

Several approaches have been used to compile and analyze the cost impacts of local permitting processes for PV installations. The Sierra Club's California Solar Permit Fee Campaign collected data to compare permit fees and time requirements across northern and southern California cities (Mills et. al, 2009; Mills and Newick, 2011). Building on the Sierra Club effort, Vote Solar created a Solar Permit Map, with additional city-level permitting data contributed by users (Vote Solar, 2013).[7] A National Renewable Energy Laboratory survey of U.S. PV installers reported that residential PV permitting, inspection, and interconnection (PII) labor costs averaged $0.13/W; with an assumed average permitting fee of $0.09/W, total PII costs averaged $0.22/W (Ardani et al., 2012). This compares with a median total installed price of $6.10/W for PV systems less than 10 kW in size and installed in 2011 (Barbose et al., 2012). Lawrence Berkeley National Laboratory (LBNL) showed that PII costs in Germany averaged only about $0.03/W, almost $0.20/W lower than U.S. costs, owing to Germany's uniform and simplified regulatory structure (Seel et al., 2013; see also the PVGrid project[8]).[9] Earlier, Sunrun (2011) estimated that local permitting and inspection could cost $0.50/W in total for a typical residential installation in the United States, or $0.28/W if excluding the impact of permitting on sales and marketing costs as well as variations in building requirements. Only considering the labor

[6] For information see http://www.solarpermit.org/.
[7] For information see http://votesolar.org/solar-map/.
[8] For information see http://www.pvgrid.eu/.
[9] Langen (2010), meanwhile, estimated PII costs of $0.8/W for the United States and $0.4/W for Germany.

costs of permitting (and excluding the permit fee), Clean Power Finance's recent survey of PV installers yields an average estimate of roughly $0.11/W (Tong, 2012). As for impacts on development times, Clean Power Finance estimates that the average permitting process requires 8 weeks (Tong, 2012). Earlier, Sunrun (2011) reported that PV installation delays as a result of permitting procedures averaged 3.5 weeks.

This study addresses two specific research questions. First, how does the permitting process at the city level affect residential PV installation prices, considering not only the permitting fee but also any labor or entry costs borne by PV installers? Second, how does the permitting process determine the time needed to develop a residential PV system? These questions are important because both cost and time requirements are crucial to the market viability of residential PV systems.

To address these questions, this research examines a unique set of detailed permitting data from DOE's Rooftop Solar Challenge Program, which includes city-level permitting process "scores," plus data from the California Solar Initiative (CSI) and the U.S. Census. Econometric methods are used to quantify the price and development-time effects of city-level permitting processes on more than 3,000 PV installations across 44 California cities in 2011. The econometric methods used in this study complement the bottom-up approaches used in previous studies by empirically evaluating the importance of permitting on residential PV installation prices and development times across many cities after controlling for other influential factors, while focusing not on average impacts but rather on the range of impacts observed across cities. The results can further inform efforts to streamline residential PV permitting processes.

The next section describes the data sources used for the present study, followed by descriptions of the econometric models for both installation prices and development times. The next two core sections present results from several different model configurations and an interpretation of these results. Finally, conclusions and suggestions for further work are discussed.

2. Data

Comprehensive and comparable data on the residential PV permitting and inspection process in a multitude of jurisdictions have, until recently, been scarce because gathering such data from numerous local permitting authorities and installers requires considerable effort. Translating this information into simple quantitative metrics that are amenable to empirical analysis presents additional challenges. Previous work has focused primarily on compiling information on local permitting practices and fees and assessing the average labor costs associated with PII. These efforts, while valuable, do not enable a detailed econometric investigation of process variability at the city level. Below we discuss the permitting dataset used in the present study as well as the other data used to conduct our empirical analysis.

2.1. Permitting process data

The principal data source for this study is a unique dataset from DOE's Rooftop Solar Challenge Program.[10] Through this program, DOE surveyed more than 290 jurisdictions nationwide in 2011 (those participating in the program[11]) and developed quantitative permitting scores for each jurisdiction, based on a detailed questionnaire and weighting methodology. The questionnaire contained 21 questions related to seven categories of city permitting processes, including application, information access, process time, fees, best-practice processes, inspection, and communication with the utility (see Appendix A for the list of questions; the specific scoring and weighting methodology is not publicly available). The maximum weighted permitting score for residential PV systems is 250, which would represent the most favorable city-level permitting process for residential PV considering the full range of possible issues addressed by the questionnaire.[12]

[10] We investigated other possible PV permitting data sources, including data from Vote Solar, the Sierra Club, and Clean Power Finance. None of these sources enabled the ready creation of a comprehensive, comparable, current, geographically broad, quantitative permitting "score."
[11] Because only the scores of participating jurisdictions are included in our analysis, there is some risk of self-selection bias. Though this concern cannot be completely dismissed, we note that regional teams were selected for participation (not individual cities), ensuring a range of permitting procedures within the selected participants. In fact, the resulting permitting scores span a wide range, demonstrating that within our sample are cities that have both onerous and favorable permitting procedures.
[12] DOE also scored—but we do not include in our analyses—the local interconnection process, interconnection standards, net-metering standards, financing options, and planning and zoning. Similarly,

Our final dataset contains residential permitting scores for 44 cities in California (Figure 1), with scores ranging from 71 to 223 and with a mean of 138. The state's largest cities—including Los Angeles, San Diego, San Jose, and San Francisco—are included in the sample, and the density of cities included is highest in the San Francisco Bay Area. These 44 cities represent approximately 27% of California's total population and around 20% of the state's PV capacity for systems under 10 kW installed in 2011. As described in more detail later, our analysis approach is to assess the relationship between permitting scores in these cities with prices and development times for residential PV systems installed in 2011 in the same cities.

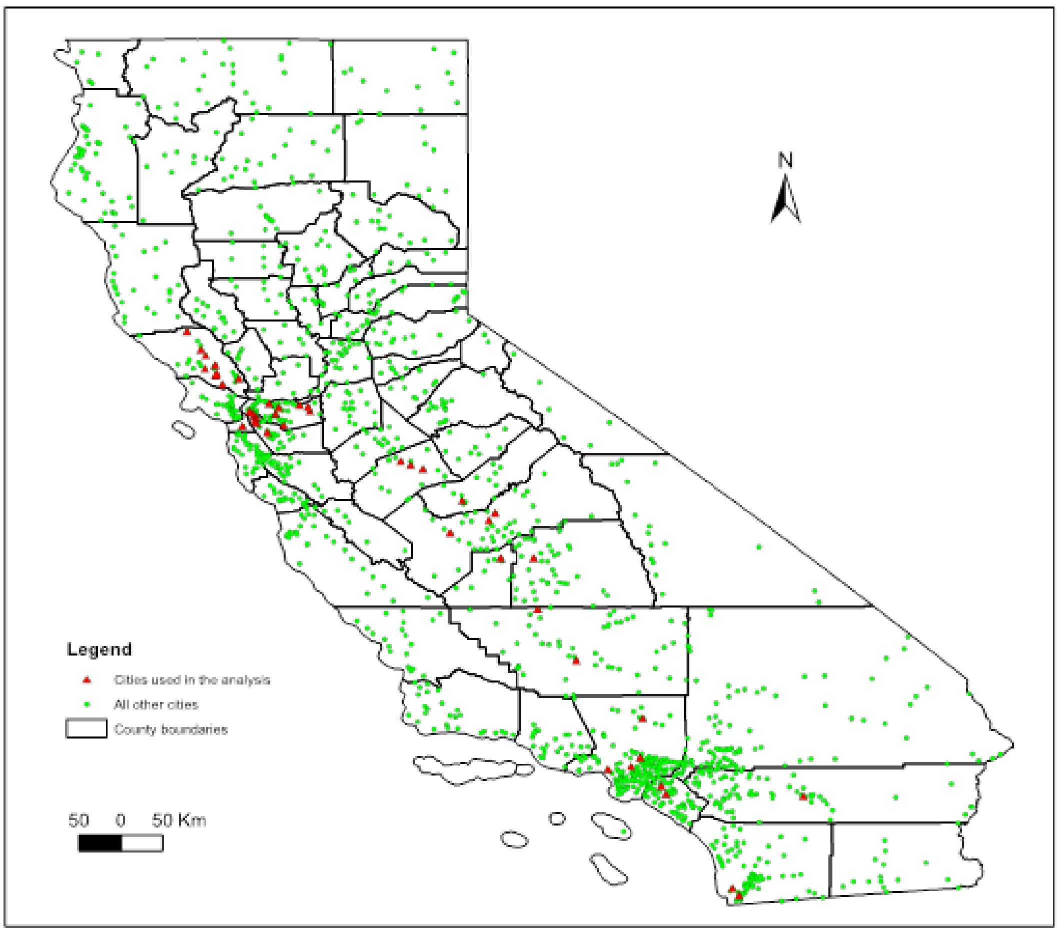

Figure 1. California cities used in the analysis

DOE scored the permitting process for larger commercial PV systems, but those data also are not included in our assessment.

2.2. PV system prices, development times, and other data

California Solar Initiative information collected by LBNL constituted the second key data source. These data cover all California PV systems that received a CSI financial incentive and include pre-incentive system installation price, system size, utility area, city, various dates in the installation process, and whether the system is third-party owned (TPO). We use these data to calculate two dependent variables for each system: pre-incentive installed prices ($/W) and development times. To calculate the development time in total days for any individual system, we use the “reservation request review date” as the start date. This date represents the point in time when an application is received by the CSI program to reserve a future state financial incentive for the PV system and is assumed to correlate with the initiation of the development process, because installers are able to earn the highest-possible incentive level if they reserve early. We then use the “online incentive claim request submitted date” as the end date for the development process, because companies must complete the installation before they claim an incentive payment. The system development time is the difference between these start and end dates. Admittedly, this variable is an imperfect proxy for PV development times, which is one of a number of reasons that we are somewhat less confident in the development-time results presented later in this paper.

Also used in the analysis are city-level variables—such as median household income, median household value, education level, population density, and median number of rooms per household—from the U.S. Census Bureau (2012). In addition, we use average annual electrician wage data from Salary.com, which estimates career-specific wages by city. These independent variables are used to control for confounding factors that could affect PV installation prices and development times. For instance, cities with greater median household income tend to have both higher permitting scores and higher installation prices; failing to control for such a variable could bias the bivariate correlation between permitting score and price.

2.3. Summary statistics

The final dataset used for the analysis includes 3,277 residential PV systems installed in the 44 California cities in 2011 (16% of the under 10 kW, 2011 systems reported in the

CSI database), as this timeframe corresponds to DOE's scoring of the cities' residential permitting processes. Only residential systems smaller than 10 kW are included, as residential systems over 10 kW are considered inapplicable to our analysis (e.g., many are multi-family housing or are otherwise outliers).

We include in our analysis *customer-owned* residential PV systems. However, a growing percentage of California residential PV systems are owned by third parties, with the host customer leasing or purchasing the power from such systems. We excluded from our analysis—where possible—*appraised-value* TPO PV systems, because the prices reported for such systems are not actual transaction prices as paid by a customer for a specific PV system but rather are based on the assessed "value" of a collection of PV systems. The price reported for *non-appraised TPO* systems typically represents the transaction between the installer of the system and the third-party service provider; whether this price is "biased" relative to customer-owned PV systems is unclear, so we run the price-based regression analysis both with these systems included and with these systems excluded.[13] When all TPO systems are excluded (as opposed to only appraised-value TPO systems), the sample size is reduced from 3,277 to 2,450 systems. Barbose et al. (2012) provide more information on price reporting for TPO and customer-owned PV and why it is important to exclude appraised-value TPO systems from analysis of PV prices.

The variable names, definitions, and descriptive statistics used in the regression analysis are summarized in Table 1. System-level installation prices are measured in nominal 2011 U.S. dollars. The mean price of the full sample is about \$6.60/W (compared with \$6.70/W for the California-wide mean residential price for systems installed in 2011 (Barbose et al., 2012)). The development-time variable is converted to logarithmic form to better approximate a normal distribution.[14] The residential permitting scores are divided by 100 to be more compatible with the scale of the dependent variables. We centered the system size variable (*csize*) by subtracting the sample mean from the actual size. This method is used to reduce collinearity when including both the square term of a variable

[13] The development-time analysis presented here excluded appraised-value-based TPO systems but did not exclude non-appraised-value TPO systems, as there was little reason to believe that development-time reporting would be impacted by such systems.

[14] Though not as necessary for the purpose of approximating a normal distribution, we did estimate regressions for the log of installation prices as well; the results (not shown in this paper) were similar to those presented here without the logarithmic conversion.

and the variable itself. After this transformation, the new mean of system size is zero, as shown in the table. Both the level and square terms are included to test for economies of scale and diminishing returns of scale.

We calculate three additional variables using the raw data that have not already been mentioned. The variable *month_perstart* denotes a continuous month number representing when the customer/installer applied for CSI incentives (a proxy for the time at which system pricing was established). This time-trend variable intends to capture observed lower system pricing over time, even within the narrow 1-year installation window that is the focus of the present analysis.[15] The variable *installationdensity* represents the total number of residential PV systems installed per city per unit of city area from 2007 to 2011, which may capture potential local learning effects or other local impacts due to the overall density of recent solar installations. The variable *weekcount* indicates the total number of PV systems entering the CSI incentive program (and therefore development pipeline) every week for each utility service area; a large number of systems entering this pipeline in any given week could cause congestion during the incentive processing, interconnection, or permitting process and therefore impact the development times of PV systems that are in our sample.[16]

[15] We used the variable *month_perstart* as a continuous variable starting from the first month, instead of a series of monthly dummy variables, because: (1) our analysis is focused on cross-sectional variation in the dependent variable rather than time-series analysis, and using monthly dummy variables would reduce degrees of freedom; and (2) the coefficients for this variable, shown later, are relatively stable across models, indicating the sufficiency of this variable in capturing time-series variations in the dependent variable.
[16] This may be especially true right before a drop in CSI incentive levels, as applications stream in to receive the higher incentive level.

Table 1. Variable definitions and summary statistics for full sample of 3,277 systems

Variable Name	Definition	Mean	Std. Dev.	Min	Max	Unit
priceperwatt	System-level total installation price (pre-incentives) per watt (direct current, standard test conditions)	6.620	1.459	2.371	13.841	nominal $ / W
develop_time	Number of days between incentive application submittal and incentive request, logarithm form (proxy for the number of days the customer/installer spent completing development tasks for a system)	4.571	0.797	0[17]	6.454	log(days)
res_permitting	DOE Solar Rooftop Challenge permitting score for residential sector for each city	1.517	0.349	0.71	2.23	integer / 100
csize	System size centered	0	2.112	-3.477	5.373	kW
csize2	Square term of system size centered	4.459	5.442	0	28.865	kW^2
PG&E	Indicator for systems located in the Pacific Gas and Electric (PG&E) service area	0.658	0.475	0	1	0 or 1
CCSE	Indicator for systems located in the California Center for Sustainable Energy (CCSE, San Diego) area	0.204	0.403	0	1	0 or 1
SCE	Indicator for systems located in the Southern California Edison (SCE) area	0.139	0.346	0	1	0 or 1
month_perstart	Continuous month number when the customer/installer applied for CSI incentives (proxy for the month in which system pricing was established, starting with January 2009)	26.237	5.236	7	36	integer
electrician	Average annual electrician wage for each city	54.657	2.702	50.522	60.248	nominal $ / 1,000
medHHincome	Median household income for each city	61.032	12.797	26.731	120.326	nominal $ / 1,000
medHHvalue	Median household value for each city	48.359	17.268	16.140	98.550	nominal $ / 10,000
popdensity	Population density for each city	5.898	4.343	1.380	16.836	persons / $mile^2$ / 100
roomnumber	Median number of rooms per household for each city	4.984	0.556	3.4	6.6	decimal value
installationdensity	Total number of residential PV systems installed per city per unit of area from 2007 to 2011	0.224	0.350	0.002	1.910	systems / $mile^2$ / 100
weekcount	Number of PV systems applying for a CSI incentive within each week for each CSI program administrator	4.091	4.208	0.1	27.8	integer / 10
college	% of population in city that has any college education (but has not earned a bachelor's degree)	29.836	6.159	12.6	39.6	percentage
bachelor	% of population in city that has earned a bachelor's degree or above	34.267	13.385	1.3	68.9	percentage

[17] There are two systems with a calculated development time of 1 day and five systems with less than 7 days; on the other end, there are eight systems with calculated development times of more than 550 days and 26 with more than 500 days. Though these systems might be considered outliers, it is challenging to define strict cut-offs for such outliers. We did experiment with the removal of possible outliers (results not shown in the present paper); these regressions did not change the sign but in some cases did reduce the statistical significance of our development-time results.

3. Regression Models and Factor Analysis

The regression analyses presented in this section include various combinations of the dependent and independent variables discussed previously, in an attempt to reduce the impact of omitted variable bias while also only including variables for which clear hypotheses could be formed. Possible additional variables were considered (such as city-level solar insolation, number of firms and other installer and local competition variables, political affiliation, age groups and races, and seasonality) as were variable combinations.[18] We chose the final variables and regressions based on hypotheses for variable impacts, statistical significance, and model parsimony.

We estimate three core sets of regressions: one for PV installation prices including customer-owned and non-appraised-value TPO systems, one for PV installation prices excluding all TPO systems, and one for development times including customer-owned and non-appraised-value TPO systems. We do not present results for development times with all TPO systems excluded, because there was no obvious reason to believe that development times would be reported differently for non-appraised-value TPO systems than for customer-owned systems.[19]

The general regression model is as follows:

$$Y_{ij} = \beta_0 + \beta_1 * res\_permitting_j + \beta_2 X_{ij} + \beta_3 Z_j + \varepsilon_{ij}$$

where i denotes a solar system, j is a city ID, β represents the typical regression coefficients including the constant term, and ε captures the idiosyncratic errors. The key regressor is the residential permitting score. About half of the control variables vary with systems (X) including system sizes, utility-area dummies,[20] and system development starting time; the other half of the control variables (Z) only vary with cities, such as city-

[18] We specifically investigated the addition of controls for seasonality and installer-specific factors in the model. The inclusion of seasonality did not have any impact on the core results of our analysis, for either installation prices or development times, and these results are therefore not reported here. The inclusion of installer-specific factors in the form of larger-installer (≥ 10 installations in 2011) dummy variables did not meaningfully change our core results for price regressions but did render the coefficients of permitting scores for the development-time regressions insignificant in many cases. That is one reason that we are less confident in the development-time regression results presented in this study.

[19] We did test this assumption by running regressions for development times with all TPO systems excluded; the results of those regressions are similar to those presented here.

[20] Utility-area dummy variables are included to imperfectly control for several possible effects: different CSI incentive steps and PV deployment levels, different interconnection procedures, and different electricity rates and therefore PV investment attractiveness.

level electrician wages, median household incomes, installation density, and education variables. Because different cities have very different numbers of systems in the sample, we weighted each system using the inverse of system counts for its city to ensure every city is considered equally,[21] similar to the way the permitting scores were assigned.

The key hypothesis is straightforward: after controlling for all other variables, more favorable permitting processes for PV systems (i.e., cities with higher permitting scores) will yield reduced installation prices and shortened development times. Thus, we expect β_1 to be negative. Other hypotheses that are unrelated to the core purpose of our work but are instead related to our control variables—such as economies of scale, technology advancement over time, and local learning—are discussed in the results below.

Before presenting the results, one additional control variable, "cost of living," must be explained further. We use this composite variable in a subset of the regressions that follow, because we found that many individual control variables—such as median household income, median household value, and electrician wage—overlap, at least to some degree, and many may relate to the cost of living in a city. We use principle component analysis (PCA) to extract common factors out of these relevant individual variables, and the proportion of variance accounted for by the common factors indicates the goodness of the extraction.

More specifically, our factor analysis is based on five related variables: median household income, median household value, electrician wage, population density, and median number of rooms.[22] These variables possibly capture both demand- and supply-side factors impacting PV adoption and final installation prices. For example, electrician wages might impact the underlying cost of PV installations (supply-side influence), whereas median household income might impact the willingness of homeowners to pay a premium for their PV installations (demand-side influence). Unfortunately, it is not possible to easily separate these demand- and supply-side influences. Figure 2 shows the

[21] We also ran regressions without such weights; however, the results are less useful in that instance because larger cities with a great number of the installed solar systems dominate the regression results, not allowing for clean cross-city comparisons as is the goal of our analysis.

[22] Education was included in the regressions separately, not within the factor analysis. Though education levels might be correlated with "cost of living," education might also impact PV prices through better price negotiation and more price comparison on the part of more-educated customers.

factor analysis results.[23] Only one common factor ("cost of living") is successfully extracted to capture the variation within the five variables, absorbing both demand- and supply-side influences. This common factor uses a standardized index to represent each city with a range from –2 to 2, and it contains 73.9% of the variance within these variables. In Figure 2, the numbers on the arrows are the factor loadings, which indicate how the variables are weighted in relation to the common factor and the correlation between the variables and the factor.[24]

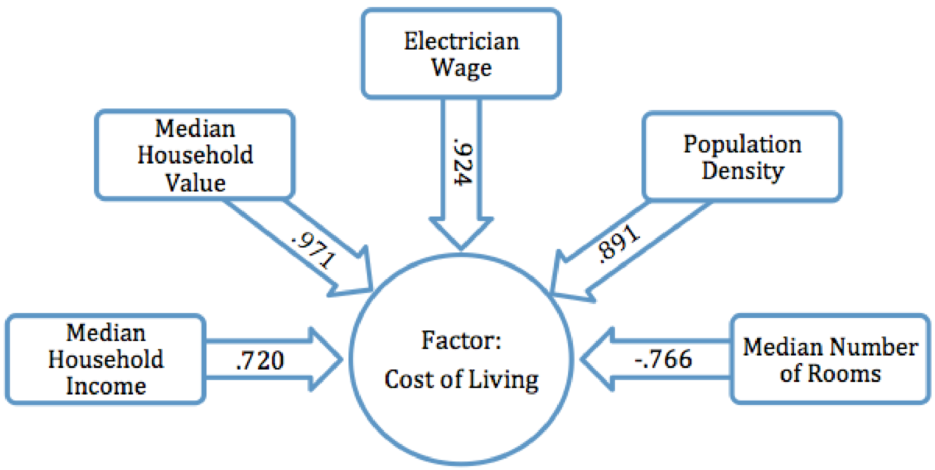

Figure 2. Factor analysis output: cost of living

[23] Different combinations of variables were explored for the factor analysis, and these final five variables were selected to be reasonably comprehensive and representative. Using a subset of variables would produce similar results, since there is only one common factor that is extracted.

[24] The factor loading for *roomnumber* is negative because, all else being equal, areas with a higher cost of living are often more densely populated and host smaller homes.

4. Results

This section presents estimates for the two installed-price regressions (one including both customer-owned systems and non-appraised-value TPO systems and one including only customer-owned systems) and the development-time regression.

4.1. Price regressions: customer-owned and non-appraised-value TPO systems

Table 2 presents results of the analysis on the larger sample that includes both customer-owned PV systems and non-appraised-value TPO systems. Table 1, earlier, shows the definitions of the independent variables used in these models. We ran five configurations of this analysis. Model P1 is the simplest form, including only a basic set of variables and very few controls. P2 adds the "cost of living" factor, and P3 adds the variables installation density and education. P4 and P5 are the same as P2 and P3, respectively, but with three major individual "cost of living" variables included instead of the common factor.

The coefficients for residential permitting scores are negative in most models, except for P1, which did not control for the "cost of living" factor or the corresponding individual variables. Because model P1 lacks critical control variables, it suffers from omitted variable bias and is presented here only as a comparison point. As shown, the impact of excluding these essential control variables is substantial, reversing the sign from negative to positive. For models P2 through P5, the coefficients move around –$0.20/W. This implies that, with all else being equal, improving the permitting process by 100 points (using the DOE scale) appears to lower the average installation price by around $0.20/W. This effect is statistically significant at a 90-99% confidence level, depending on the model.

As for the control variables, consistent with past analysis, PV systems exhibit strong economies of scale and diminishing returns of scale with respect to system size, both of which are significant at the 99% confidence level. The interpretation of the system size coefficients must consider both terms together (*csize* and *csize2*). Taking model P5 as an example, a 1-kW increase in system size from the mean value decreases the installation price by about $0.28/W ($0.349/W minus $0.069/W), all else being equal. However, a 2-kW increase in size decreases the installation price by about $0.42/W, making the price reduction due to the second kW increase only $0.14/W.

Table 2. Regression outputs of installation prices: full sample

Installation Price: $/W	P1	P2	P3	P4	P5
csize	-0.394***	-0.349***	-0.347***	-0.349***	-0.349***
	(0.016)	(0.019)	(0.019)	(0.019)	(0.019)
csize2	0.079***	0.068***	0.068***	0.069***	0.069***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
res_permitting	0.281***	-0.176**	-0.212***	-0.268***	-0.185*
	(0.075)	(0.073)	(0.079)	(0.090)	(0.100)
PG&E	-0.462***	-0.626***	-0.566***	-0.671***	-0.564***
	(0.089)	(0.087)	(0.089)	(0.087)	(0.094)
CCSE	-0.467***	-0.449***	-0.302***	-0.395***	-0.366***
	(0.103)	(0.104)	(0.111)	(0.124)	(0.124)
month_perstart	-0.017***	-0.012**	-0.012**	-0.012**	-0.012**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
factor_costofliving		0.270***	0.383***		
		(0.035)	(0.061)		
electrician				0.071***	0.046*
				(0.022)	(0.024)
medHHincome				0.006*	0.015***
				(0.003)	(0.005)
roomnumber				-0.169**	-0.295**
				(0.085)	(0.127)
installationdensity			-0.036		0.041
			(0.068)		(0.080)
college			0.004		-0.008
			(0.006)		(0.007)
bachelor			-0.009***		-0.010**
			(0.003)		(0.004)
N	3,277	3,277	3,277	3,277	3,277
r2_a	0.328	0.343	0.343	0.342	0.342
df_m	6	7	10	9	12

Note: robust standard errors in parentheses; *p < 0.10, **p < 0.05, ***p < 0.01.
Among the three utility dummy variables, SCE is the baseline and thus is excluded in the regression.
Data for *factor_costofliving* are calculated based on the factor analysis (see Section 3).

After controlling for other factors, PV systems in the sample that are located in the Southern California Edison (SCE) service area show higher installation prices than systems in the Pacific Gas and Electric (PG&E) and California Center for Sustainable Energy (CCSE) areas; the specific reasons for this difference are not explored here but may warrant further study. The coefficients of *month_perstart* indicate that system-level installation prices have been declining over time, consistent with expectations.

"Cost of living," captured by either the common factor or the separate variables, has a significantly positive impact on installation prices. Taking model P3 as an example, after controlling for other variables, higher "cost of living" cities (with the corresponding index increased from 0 to 1) are found to have average installation prices that are about \$0.40/W higher than other cities. Though this result is consistent with the idea that cities with high costs of living generally have high installation prices, it is unclear whether this is dominated by a supply-side effect (e.g., higher underlying costs of installation labor) or a demand-side effect (e.g., wealthier areas being willing to pay more for premium PV systems). Regardless, without controlling for this relationship, the permitting scores inappropriately pick up the "cost of living" effect, as shown in model P1. The individual-variable "cost of living" results are self-explanatory, with higher city-level electrician labor costs and median household incomes yielding higher-priced PV systems, on average. The *roomnumber* variable is negatively correlated with the extracted "cost of living" factor, so the negative coefficients for this variable in models P4 and P5 are expected.

The coefficients of *installationdensity* are not statistically different from zero in models P3 and P5, meaning that local learning experience was not significant or prevalent across these 44 cities in 2011, at least as defined by this single variable. This does not mean that local learning never occurs, however, as this variable is a relatively crude measure for such learning, and further exploration of learning effects is warranted.

Finally, the city-level education variables are generally negative, with the variable *bachelor* exhibiting a stronger price-decreasing effect than the variable *college*. All else being equal, these results suggest that average installation prices could be \$0.30/W lower in a city in which 35% of the population has a bachelor's degree or higher compared with a city in which only 5% of the population has this level of education. The reasons for this relationship are not well known but may reflect better price negotiation and more price comparison on the part of more-educated customers.

4.2. Price regressions: excluding all TPO systems

Table 3 presents results of the installed price regression analyses that exclude all TPO PV systems and therefore consist of only customer-owned systems. The purpose of this analysis is to assess whether inclusion of non-appraised-value TPO systems in the preceding regressions (Section 4.1) affects the results, using the same independent variables and model specification.

As shown in the tabular regression summaries, the effect of the permitting process on installation prices is relatively larger when all TPO systems are excluded from the analysis. Based on models P3_v2 through P5_v2, improving the permitting process by 100 points is found to reduce average installation prices by about $0.30–0.50/W, in some cases up to twice as high as in the analysis that included non-appraised-value TPO systems. Many of the non-appraised-value TPO systems are located in cities with relatively low permitting scores and have relatively low prices; thus, excluding these systems creates a stronger (negative) effect on system prices by assigning more weight to systems with similarly low permitting scores but higher prices.

As for the control variables, comparing the new model P5_v2 with P5, the economies-of-scale effect increases from $0.28/W (P5) to $0.32/W (P5_v2) per 1-kW increase, while the diminishing returns of scale is almost the same for these two versions. The effects of the two utility dummy variables—PG&E and CCSE—are larger in the non-TPO version, indicating a stronger price advantage for these utilities relative to SCE. However, these effects might also have captured the time effect in the variable *month_perstart*, which becomes smaller and statistically insignificant as a result. The coefficients for "cost of living" remain relatively consistent. Among the individual "cost of living" variables, however, only *electrician* is statistically significant in the non-TPO version, with a higher coefficient estimate. *Installationdensity* and *college* are still insignificant, while *bachelor* passes the significance test in one of the two models.

Table 3. Regression outputs of installation prices: non-TPO version

Installation Price: $/W	P1_v2	P2_v2	P3_v2	P4_v2	P5_v2
Csize	-0.438***	-0.389***	-0.389***	-0.389***	-0.389***
	(0.020)	(0.024)	(0.024)	(0.024)	(0.024)
csize2	0.081***	0.069***	0.069***	0.070***	0.070***
	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
res_permitting	0.04	-0.280***	-0.332***	-0.508***	-0.448***
	(0.086)	(0.087)	(0.095)	(0.106)	(0.121)
PG&E	-0.759***	-0.936***	-0.791***	-1.159***	-1.093***
	(0.140)	(0.138)	(0.149)	(0.146)	(0.176)
CCSE	-0.722***	-0.725***	-0.337	-0.558***	-0.536***
	(0.150)	(0.150)	(0.207)	(0.165)	(0.205)
month_perstart	-0.013*	-0.006	-0.006	-0.007	-0.007
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
factor_costofliving		0.265***	0.397***		
		(0.038)	(0.065)		
electrician				0.133***	0.119***
				(0.030)	(0.034)
medHHincome				0.001	0.004
				(0.004)	(0.007)
roomnumber				0.067	0.026
				(0.118)	(0.205)
installationdensity			-0.096		-0.008
			(0.059)		(0.065)
college			-0.0002		-0.006
			(0.007)		(0.008)
bachelor			-0.012***		-0.004
			(0.004)		(0.005)
N	2,450	2,450	2,450	2,450	2,450
r2_a	0.297	0.313	0.313	0.313	0.312
df_m	6	7	10	9	12

Note: robust standard errors in parentheses; *p < 0.10, **p < 0.05, ***p < 0.01.
Among the three utility dummy variables, SCE is the baseline and thus is excluded in the regression.
Data for *factor_costofliving* are calculated based on the factor analysis (see Section 3).

4.3. Development-time regressions

Table 4 presents results of the development-time analysis. The results suggest that better permitting practices would shorten development times significantly, though these results are less robust to alternative model specifications.

Model specifications for development times are slightly different than those for installation prices. First, though PV system size might have a relationship with development times, economies of scale and diminishing returns of scale may not be as applicable as in the price-based regressions; we therefore retain system size but eliminate size-squared in the core regression results.[25] Second, though "cost of living" is included in a subset of the models presented here, it is less intuitively obvious why such a factor would impact development times. As a result, when the factor is excluded in models T4 and T5, we replace it with two individual variables for which an impact on development time seems plausible: median household income and population density. Third, we remove the *month_perstart* variable since we need not control for the same time-influenced price-reduction effect as in the price regression. Finally, we add one control variable—*weekcount*—to account for the possibility that more systems in the incentive application, interconnection, and permitting queue could slow down the whole process. Other than these differences, the overall structures in the price and time regressions are similar.

Model T1 is a reference, to show the results when not controlling for many important factors. Model T2 adds the "cost of living" factor, whereas T4 adds the individual variables *medHHincome* and *popdensity*. Model T3 adds four other variables to those included in T2, and T5 adds these same four other variables to those included in T4. As in the price regressions, because model T1 lacks critical control variables, it suffers from omitted variable bias with results that are opposite of what one might expect for the permitting variable and peculiar for other variables as well.

The permitting score coefficients in models T2–T5 are all negative and significant, which is consistent with expectations. However, the magnitudes of the effect in models T2 and T3 are greater than in the other two models. One possible explanation is that, because

[25] We did conduct regressions with a square term for system sizes, but that coefficient was not found to be statistically significant.

the effects of the individual "cost of living" variables on development times could push the results in opposite directions (e.g., *medHHincome* and *popdensity* in Table 4), combining them (as in models T2 and T3) might not be appropriate. Focusing on models T4 and T5, improving the permitting process by 100 points is found, all else being equal, to speed development by roughly 10%.

Table 4. Regression outputs of development times

Development time: log(days)	T1	T2	T3	T4	T5
csize	-0.034***	0.006	0.007	0.011	0.008
	(0.009)	(0.010)	(0.009)	(0.010)	(0.009)
res_permitting	0.104*	-0.354***	-0.193***	-0.097*	-0.101*
	(0.055)	(0.059)	(0.057)	(0.052)	(0.052)
PG&E	0.210***	0.026	-0.166***	0.117**	-0.173***
	(0.046)	(0.046)	(0.052)	(0.047)	(0.052)
CCSE	-0.214***	-0.185***	-0.103*	0.045	-0.013
	(0.052)	(0.051)	(0.058)	(0.055)	(0.059)
factor_costofliving		0.263***	0.201***		
		(0.020)	(0.035)		
medHHincome				-0.005***	-0.006***
				(0.001)	(0.002)
popdensity				0.066***	0.059***
				(0.004)	(0.006)
weekcount			0.066***		0.065***
			(0.003)		(0.003)
installationdensity			0.074*		-0.008
			(0.041)		(0.043)
college			-0.019***		0.004
			(0.004)		(0.004)
bachelor			-0.009***		0.001
			(0.002)		(0.002)
N	3,277	3,277	3,277	3,277	3,277
r2_a	0.067	0.125	0.212	0.143	0.221
df_m	4	5	9	6	10

Note: robust standard errors in parentheses; *p < 0.10, **p < 0.05, ***p < 0.01.
Among the three utility dummy variables, SCE is the baseline and thus is excluded in the regression.
Data for *factor_costofliving* are calculated based on the factor analysis (see Section 3).

As for the control variables, the centered size (*csize*) variable is positive, suggesting that larger PV systems require slightly more development time (as might be expected), but the coefficient is not statistically significant at the 90% level. The development times for installations in PG&E and CCSE areas depend in part on whether *weekcount* is controlled for. After considering this congestion factor, results seem to suggest that systems in the PG&E area move through the development process more rapidly than in SCE's service territory, while results for CCSE are less clear (understanding the reasons for these apparent differences is a subject for additional analysis).

It is difficult to interpret the implication of using the "cost of living" factor in T2 and T3, but the individual variables included in models T4 and T5 have plausible (if untested) explanations. *MedHHincome* appears to affect development times negatively, suggesting that areas with higher income levels tend to have lower development times. Two possible explanations are that higher-income earners may place higher value in speeding the development process, or they may be willing and able to pay to speed that process. High *popdensity*, on the other hand, is found to slow the development process, possibly because denser neighborhoods might present additional PV-installation challenges in terms of neighbor complaints.

Weekcount seems to have a significantly positive impact on development times, meaning that congestion causes delays in the installation process. As to the last three variables, models T3 and T5 find divergent results. Because T5 has a higher R^2 value and *medHHincome* may have already captured the effect of high education levels, we tend to place more trust in T5, which finds no evidence of effects from education levels or installation density.

Overall, while models T2–T5 find that challenging permitting practices lead to lengthier PV development processes, the statistical robustness of this result is not as persuasive as in the price-based regressions. First, the coefficient for the permitting variable is less stable to the alternative model specifications shown. Second, additional model specifications—not shown here—that include different sets or combinations of control variables and have different treatments for possible outliers lead to unstable coefficient estimates for the residential permitting variable that are sometimes statistically insignificant. Third, some of the control variables are found to have effects that are less intuitively persuasive than in the price regressions. Fourth, while the overall explanatory power of both the price and development-time regressions is relatively low (see the R^2), this is especially true in the case of development times; this is depicted graphically in the next section on model interpretation. Finally, as noted earlier and perhaps related to the concerns noted above, the definition of our development-time variable may be imperfect.

5. Model Interpretations

Based on the regression results, we can predict installed prices and development times for each system. We can then average the predictions from the system level to the city level. To help interpret the regression results presented in the last section, below we show two predictions for installed prices and development times. The first shows the overall predictive performance of the regression models, while the second focuses on the marginal effects of the permitting process only.

5.1. Installation prices

To illustrate the overall goodness-of-fit of the installed-price regressions, we use model P5.[26] We then use models P2–P5 and P2_v2–P5_v2 to display the marginal effects of permitting across model sensitivities.

Figure **3** shows the overall performance of model P5. The observed values are shown as circles. The predicted values are shown as diamonds with 95% confidence intervals (CIs). With few exceptions, the predicted prices are reasonably close to observed prices and within the model's confidence intervals, providing confidence in the model's specification and results. As also shown, San Francisco, Los Angeles, and Long Beach have both relatively high permitting scores and high installation prices. Such counter-intuitive correlations can only be explained after controlling for factors such as "cost of living" and education, as was done in most of the regression models. Otherwise, this scatter plot shows a counter-intuitively positive correlation between permitting scores and PV installation prices, consistent with model P1.

[26] To minimize visual clutter, we do not use all the models to show the quality of the overall prediction.

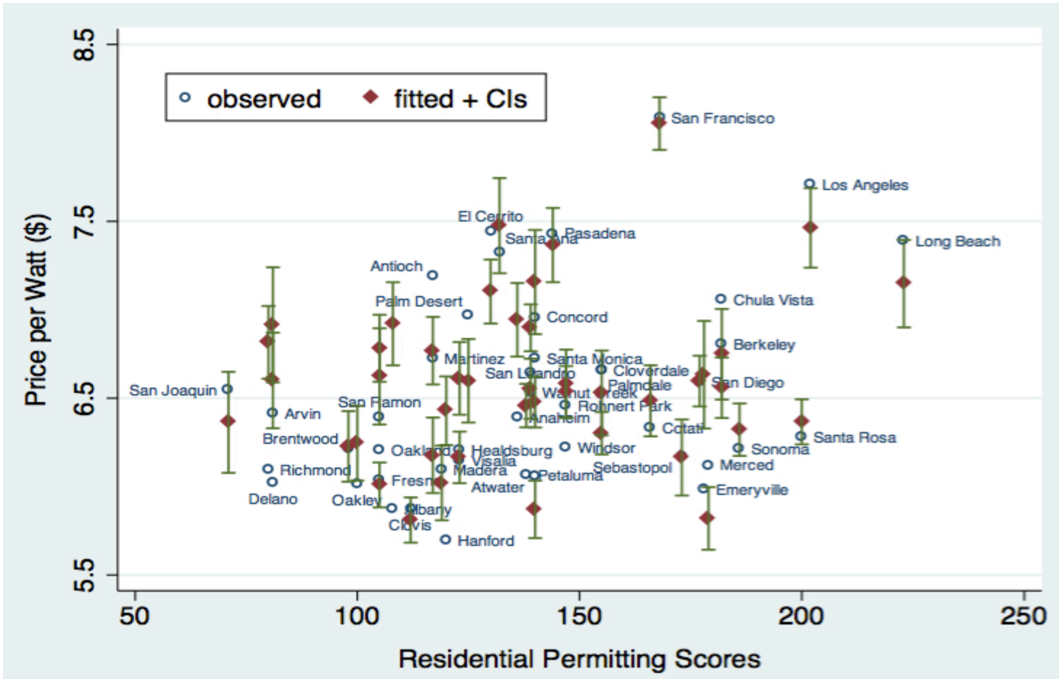

Figure 3. Overall goodness-of-fit of model P5 for installation prices

The above prediction includes all of the information in the regression model and therefore tests the goodness-of-fit of the entire model, but it does not show the relationship between permitting scores and installed prices, i.e., the marginal effects of permitting. Figure 4 does this by calculating predicted installed prices using the coefficients of permitting scores from models P2–P5 and P2_v2–P5_v2, while using average values for all other model variables (because we use average values, not city-specific values, we label cities by ID number, not by name, in this figure). The city with the lowest permitting score is depicted on the left side of the chart as the baseline, with its 2011 mean installation price as the starting point, and every other city has a predicted average installed price determined by how it outperforms the baseline city in terms of permitting score and the coefficient of permitting scores in each model.

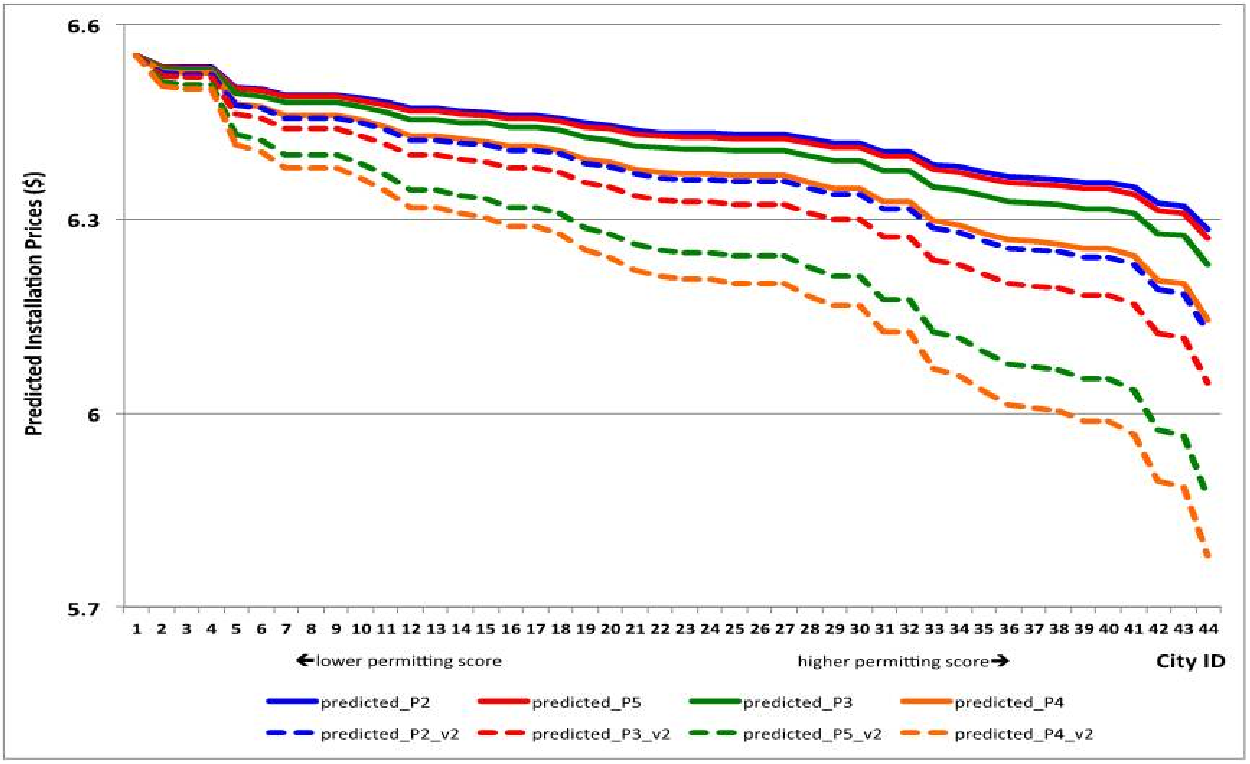

Figure 4. Predicted prices using permitting scores, all else being equal (permitting scores increase from left to right)

In Figure 4, the 44 cities are listed in ascending order in terms of permitting scores. Therefore, the predicted installation prices decrease from left to right. Each curve represents the prediction results using one regression model. The curves are nonlinear because the permitting score steps between two cities are not necessarily equal. As reflected in the regression model results described earlier, the "v_2" models that exclude all TPO systems have larger variations than the equivalent models that include non-appraised-value TPO systems.

Across these eight models, permitting processes are found to cause differences in average PV installed prices among cities of up to \$0.27–\$0.77/W, depending on the model chosen. It is not clear which of the eight models better captures the real effect size. Regardless, across all models, this represents 4%–12% of median PV prices in California and indicates that different permitting procedures can have a meaningful impact on relative PV prices among cities. The magnitude of these price differences *across cities* can be compared with studies that quantify absolute average permitting costs at the *national level* (e.g., Ardani et al., 2012 found a national average price impact of \$0.22/W for PII, as reported earlier), demonstrating that estimated national average impacts mask more-substantial impacts that occur at a local level.

5.2. Development times

We predict development times in a similar way. Figure 5 shows the overall predictive performance of model T5. Figure 6 highlights the marginal contributions from the permitting process (note that a log scale is used in Figure 5, while a linear scale is used in Figure 6). We only use models T4 and T5 to compare the marginal differences. We do not use T2 and T3 because interpretation of the "cost of living" factor is challenging, and we place more trust in alternative model forms. Again, the city on the far left has the lowest permitting score, while the city on the far right has the highest score.

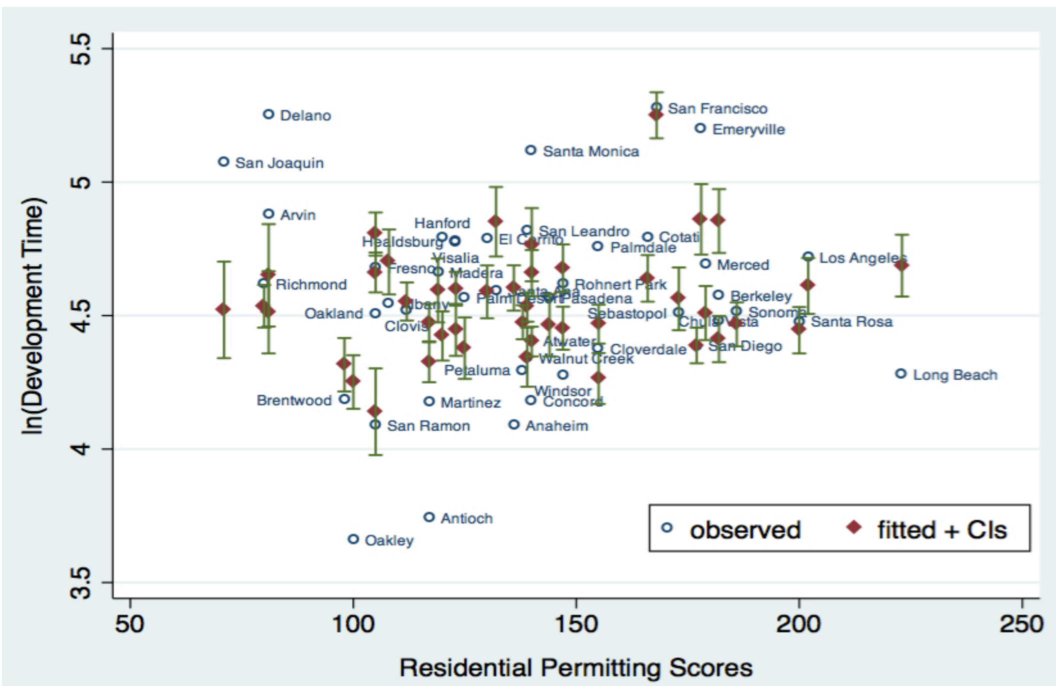

Figure 5. Overall goodness-of-fit of model T5 for development times (logarithm term[27])

The overall predictive performance of the models for development times is not as good as for installed prices, as illustrated by a comparison of Figure 3 and Figure 5. Focusing on Figure 5, it is clear that the ability of model T5 to accurately predict average

[27] Although it is more intuitive to use the absolute value (not logarithm) of development times, computing the standard errors and confidence intervals for the former from the latter is complicated. Thus, we retain the logarithmic term here but convert to the level term in Figure 6.

development times at the city level is limited, especially at the extremes. Consequently, and for the reasons noted in the previous section, the statistical robustness of our results for development times is not as strong or persuasive as in the price-based regressions.

The marginal effects of the permitting process in models T4 and T5 are very close to each other (Figure 6), masking the general instability of the coefficient for the permitting variable to alternative model specifications, as discussed earlier. Regardless, based on these two models alone, different permitting processes (as approximated by permitting scores) are found to cause average development-time differences among cities of up to about 24 days, or 25% of the median development time.

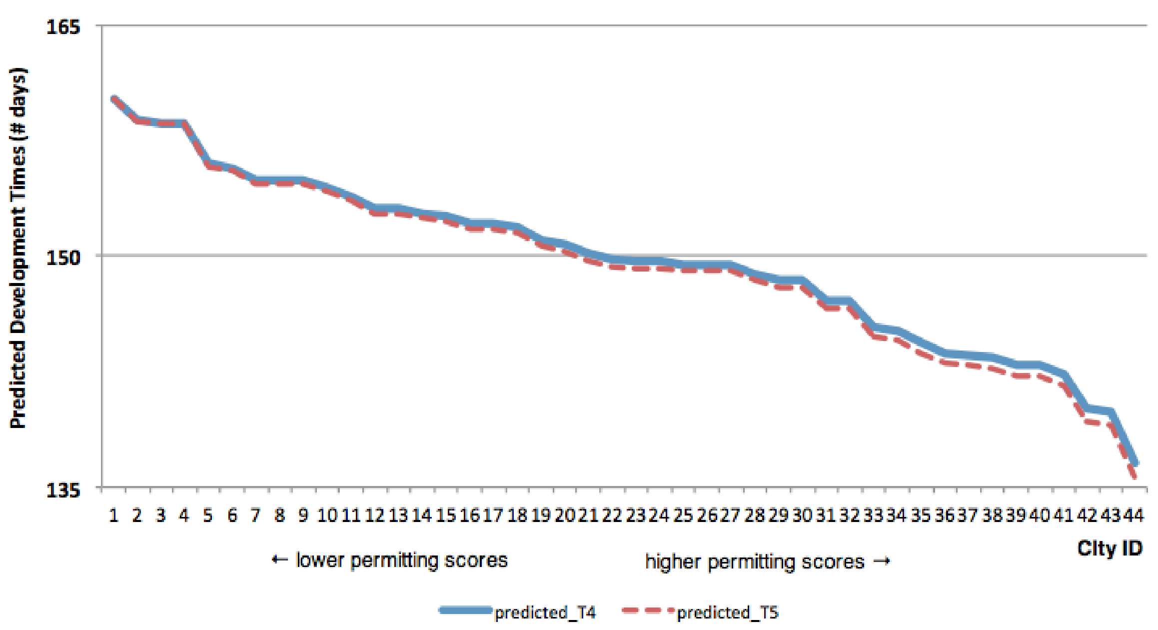

Figure 6. Predicted development times using permitting scores, all else being equal (permitting scores increase from left to right)

6. Conclusions and Further Work

Non-hardware business process (or "soft") costs currently account for well over 50% of the installed price of residential PV systems in the United States, and understanding these costs is crucial for identifying further PV cost-reduction opportunities. City-level permitting processes—as one core element of business process costs—appear to have significant effects on installed PV prices and, though the analytical results are less robust, on project development times. Among the sample of California cities analyzed, those with the most favorable permitting processes are found to reduce average residential PV system prices by \$0.27–\$0.77/W (4%–12% relative to median pricing) and shorten development times by around 24 days (25% compared to the median development time) compared with cities with the most onerous permitting practices. The range of values depends on the regression model used, and results are more stable and persuasive for price impacts than they are for development-time impacts.

Overall, these *cross-city* results are consistent with and add to previous attempts to quantify the *national or regional average* impact of permitting on installed costs and development times (e.g., Sunrun, 2011; Ardani et al., 2012; Clean Power Finance, 2012). In particular, they demonstrate that national or regional average impacts can mask the more-substantial impacts that occur at a local level across individual cities.

These findings provide some confirmation that the scoring mechanism used in the DOE Rooftop Solar Challenge is capturing real effects and, more importantly, illustrate the potential benefits of streamlining city-level permitting procedures for residential PV systems. Specifically, our results suggest that, all else being equal, streamlining the permitting process could potentially reduce the price of a 4-kW residential PV system by \$1,000 or more,[28] on average, and cut development time by about a month.

As indicated earlier, multiple local, regional, state, and national efforts are already underway in the United States to streamline and bring down the cost of local permitting

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[28] As indicated earlier, these price impacts could include both direct costs, in the form of administrative labor and fees imposed on PV installers, as well as indirect costs, in the form of economic rents that accrue to installers as a result of barriers to entry into local markets created by onerous permitting processes. Though our analysis does not have the ability to separate these effects, the average permitting fee as documented by VoteSolar is around \$400, and California law now establishes a ceiling on permitting fees of \$500 for systems up to 15 kW.

procedures. Streamlined procedures must take care to adequately fund local governments for their time while not eviscerating the benefits of permitting for protecting consumers, promoting public safety, and rewarding the most diligent installers. Commonly discussed elements for streamlining are described in detail in other studies (Brooks, 2012; Stanfield et al., 2012; OPR, 2012), including the following: (1) developing regional or state-wide technical and procedural requirements to minimize local variations; (2) creating clear guidelines and checklists on permitting procedures and timelines; (3) using simple, standardized online application forms; (4) minimizing the number of departmental reviews; (5) limiting wait times; and (6) lowering permit fees. It is also increasingly recognized even within the solar community that responsibility for the present permitting challenges must be shared (because the source of delay is often inadequate documentation submissions by installers) and that a streamlined procedure should offer benefits not only to solar installers and their customers, but also to city permitting departments (Stanfield et al., 2012). Though the simplified and streamlined procedures used in Germany (Seel et al., 2013; see also the PVGrid project[29]) may not be wholly transferrable to the United States, reforms can clearly help lower the cost of and speed PV deployment.

As for future research that would extend the analysis presented in this paper, one might expand the geographic reach of the present study to additional cities both within and outside of California. As sample size grows, it may also be appropriate to expand the analysis to include larger, commercial PV installations. Because the development-time results presented in this study are weaker than those for installed prices, further effort to improve the robustness of those results is warranted. Moving beyond installed prices and development times, it may also be useful to assess the impact of permitting on the amount of PV installed at the city level and/or PV installers' interest in those cities. And, once multiple years of data on permitting scores are available, it may be possible to evaluate more directly the impact of the Rooftop Solar Challenge Program on all of these permitting-impact variables. Finally, one might use methods similar to those applied in this study to investigate other PV soft costs beyond permitting.

[29] For information see http://www.pvgrid.eu/.

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Appendix A. DOE Questionnaire—Residential Permitting Questions

Section ---- Application

1. What is the average number of business days between application submission and decision (issuance or denial) regarding permit? (a municipal utility does not count as a city department here)

A. 1 B. 2 C. >3

2. What types of departmental approvals are required for a typical installation? (check all that apply)

A. Building B. Electrical C. Fire D. Mechanical E. Planning
F. Plumbing G. Structural H. Zoning I. Other, specify__________

3. What approvals from Professional Engineers are required as part of the permit package for a typical installation? (Check all that apply)

A. Civil B. Electrical C. Environmental
D. Fire Protection E. Mechanical F. Structural

4. What is the average time required for an installer/customer to complete a permit application for a typical installation?

A. ≤ half day B. 1 - 2 days C. 1 - 2 days

5. What are the options for obtaining an application? (Check all that apply)

A. Online B. Email C. In person D. Mail

6. What are the options for submitting an application? (Check all that apply)

A. Online B. Email C. In person D. Mail

Section ---- Information Access

7. How is information describing the permitting process accessible? (Check all that apply)

A. Online and easily accessible B. Online C. Email D. In person/mail

8. Is there an accessible designated point of contact, with contact information available online, for questions about the PV permitting process?

A. Yes B. No

Section ---- Permitting Process Time

9. Is there a policy to issue/deny PV permits within a specified number of business days from submission of application?

A. Yes, ≤ 3 days B. 4-10 days C. > 10 days

10. Does the jurisdiction track the number of days each permit takes to process?
A. Yes B. No

11. What is the average number of business days between application submission and decision (issuance or denial) regarding permit?
A. ≤ 3 days B. 4-5 days C. 6-10 days D. > 10 days

12. Are there mechanisms in place for accelerating PV permitting processes under certain conditions?
A. Yes, specify__________ B. No

Section ---- Fee
13. How is information on permit fees made available? (Check all that apply)
A. Online B. Email C. In person D. Mail E. Not Available

14. What is the average total for the applicable permit fee(s) for typical installations?
A. ≤$250 B. $251 – 500 C. > $500

15. Is/are the permit fee(s) structured as flat, cost recovery, valuation open ended, or valuation capped?
A. Flat B. Cost Recovery C. Valuation Open Ended D. Valuation Capped
E. Valuation with Exclusions F. Other, specify__________

Section ---- Model Process
16. To what degree do you use the Solar ABCs expedited permitting process template for typical installations?
A. Default template B. Optional template
C. Have reviewed and considered D. Unaware/Reject

Section ---- Inspection
17. What is the average number of business days from inspection request to actual inspection?
A. ≤ 2 days B. 3-5 days C. 6 -10 days D. > 10 days

18. What is the typical window of time given to the installer for final onsite inspection?
A. 2 hrs B. 3-4 hrs C. 5-8 hrs D. > 1 day

19. How is information on inspection requirements made available? (Check all that apply)
A. Online B. Email C. In person D. Mail E. Not Available

20. How many separate inspection trips are required for a typical installation? (Check all that apply)
A. Single Comprehensive Inspection B. Electrical Rough-in C. Electrical Final
D. Roof Penetrations (pre-install) E. Structural / Building Final
F. Other, specify__________

Section ---- Communication Protocol with Utility

21. Do the utility and local jurisdiction coordinate regarding inspection requirements and on-site inspection times for the permit inspection and interconnection inspection?
A. Yes, specify__________ B. No