THE IMPACT OF CITY-LEVEL PERMITTING PROCESSES ON RESIDENTIAL PV INSTALLATION PRICES AND DEVELOPMENT TIMES

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ABSTRACT

This study evaluates the effect of city-level permitting processes on the installed price and development time of residential photovoltaic (PV) systems. Using a unique dataset from the U.S. DOE's Rooftop Solar Challenge Program, which includes city-level permitting process "scores," econometric methods are employed to quantify the effects of city-level permitting processes across 44 California cities in 2011. Results suggest that: (1) the most favourable (i.e., highest scoring) permitting practices can reduce average residential PV prices by \$0.27–\$0.41/W compared with the most taxing (i.e., lowest scoring) permitting practices, depending on the regression model used; (2) the most streamlined permitting practices may shorten development times by around 24 days, though this empirical model is less robust. These findings illustrate the potential price and development-time benefits of streamlining local permitting procedures for PV systems.

1. INTRODUCTION

The installed price of photovoltaic (PV) systems has declined dramatically, driven primarily by the reduction in the price of PV modules (Barbose et al., 2012; Bazilian et al., 2013). In part 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.

This study builds on the available literature by focusing squarely on understanding one component of non-hardware PV costs: the effect of city-level permitting processes in the U.S. on the installed price of residential PV systems and on the time required to develop and install those systems. Local, city-level permitting processes are one core driver of business process costs, and potentially add considerable expense and development-time to PV installations. A typical PV permitting process in the United States involves many local government departmental reviews, such as building, electrical, mechanical, plumbing, fire, structural, and zoning reviews, as well as a permitting fee. In addition, site inspection and final approvals are required for permitting and interconnection.

The diversity of PV permitting documentation requirements, application procedures, inspection processes, and fees used by local jurisdictions complicates the business of PV installers that seek to market systems in multiple jurisdictions. 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, and that average permitting process times are almost eight weeks in duration (Tong, 2012); earlier, Sunrun (2011) reported PV installation delays that averaged three-and-a-half weeks as a result of permitting procedures.

Several approaches have been used to estimate 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 California cities (Mills et. al, 2009; Mills and Newick, 2011). Building on that, Vote Solar created a Solar Permit Map, with additional city-level permitting data contributed by users (Vote Solar, 2013). In a National Renewable Energy Laboratory survey of U.S. PV installers, residential PV permitting, inspection, and interconnection (PII) labor costs averaged \$0.13/W;

[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 U.S. in 2010. With current PV module prices well below what was observed in 2010, non-hardware costs now constitute more than 60% of typical installation prices in the United States.

an assumed average permitting fee added $0.09/W (Ardani 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).[2] Earlier, Sunrun (2011) estimated that local permitting and inspection could cost $0.5/W in total for a typical residential installation in the U.S., 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 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).

Responding to the above challenges, many efforts are underway in the U.S. to streamline and bring down the cost of local permitting processes, including DOE's Rooftop Solar Challenge Program, SolarTech's Solar3.0, the Solar America Board for Codes and Standards (Brooks, 2012), and Clean Power Finance's National Solar Permitting Database. States such as California, and the organizations such as the Interstate Renewable Energy Council (IREC), have also initiated efforts to expedite permitting and field inspections (OPR, 2012; IREC, 2010). 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 for PV installations.

This study builds on the previous work by examining a unique set of detailed permitting data from the U.S. DOE's Rooftop Solar Challenge Program, which includes city-level permitting process "scores." It addresses two specific research questions. First, how does the permitting process at the city level affect residential PV installation prices? Second, how does the permitting process determine the time needed to develop a residential PV system? 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. This research complements the bottom-up approaches used in previous studies by 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.

2. DATA

Comprehensive and comparable data on the residential PV permitting and inspection process in a multitude of jurisdictions are scarce, and previous work has focused primarily on compiling information on local permitting practices and fees, and on assessing the average labor costs associated with PII. 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.[3] Through this program, DOE surveyed more than 290 participating jurisdictions nationwide in 2011 and allocated quantitative permitting scores based on a detailed questionnaire and a weighting methodology. The questionnaire contained 21 questions related to seven categories of the city permitting process, including application, information access, process time, fees, model process, inspection, and communication with the utility.

Our final dataset contains residential permitting scores for 44 cities in California, ranging from 71 to 223. 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 Bay Area. These cities represent approximately 27% of California's total population.

2.2 PV Prices, Development Times and Other Data

California Solar Initiative (CSI) information 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 (# days), the latter of which approximates the length of time the customer/installer spent completing development tasks for a system.

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

[2] Langen (2010), meanwhile, estimated PII costs of $0.8/W for the U.S. and $0.4/W for Germany.

[3] We investigated other possible PV permitting data sources, including 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."

(2012). In addition, we use average 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 the relationship between permitting process scores and PV installation prices or development times.

2.3 Summary Statistics

The final dataset used for the analysis includes 3,277 residential PV systems installed in 2011 in the 44 California cities for which we have residential permitting process scores from the U.S. DOE (these PV systems represent 16% of 2011 systems reported in the CSI database). Only systems smaller than 10 kW are included.

We excluded from our analysis—where possible—*appraised-value* third-party-owned (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 an average estimated "value" of a collection of PV systems. Barbose et al. (2012) provide more information on why it is important to exclude certain TPO systems from PV price analyses.

The variable names, definitions, and descriptive statistics used in the regression analysis are summarized in Table 1. Most of these are self-explanatory. 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. The residential permitting scores are downscaled 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 and the variable itself.

We calculate three additional variables using the raw data. The variable *Month_perstart* denotes a continuous month number representing when the customer/installer initiated system development, intending to capture observed lower system pricing over time. The variable *Installationdensity* represents the total number of residential PV systems installed per unit of city area from 2007 to 2011, which may capture potential local learning effects. 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, in order to capture the potential congestion effect during the incentive application and permitting process.

3. REGRESSION MODELS AND FACTOR ANALYSIS

The regression analyses presented in the next section include various combinations of the dependent and independent variables discussed previously, in an attempt to minimize omitted variable bias while also only including variables for which clear hypotheses could be formed. Possible additional variables were considered (such as age groups and races) as were variable combinations. We chose the final variables and regressions based on hypotheses for variable impacts, statistical significance, and model parsimony.

We estimate two core sets of regressions: one for PV installation prices, and one for development times. 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 error. The key regressor is the residential permitting score. About half of the control variables vary with systems (X) including system sizes, utility area dummies, and system development starting time; the other half of the control variables (Z) only vary with cities, such as city 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, similar to the way the permitting scores were assigned.

The key hypothesis is straightforward: after controlling for all other variables, more favourable 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—such as economies of scale, technology advancement over time, and local learning—are discussed in the results below.

TABLE 1: VARIABLE DEFINITIONS AND SUMMARY STATISTICS FOR FULL SAMPLE OF 3,277 PV 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)	6.62	1.46	2.37	13.84	nominal $ / W
develop_time	Approximate number of days the customer/installer spent completing development tasks for a system (from incentive application to installation), logarithm form	4.57	0.78	0	6.45	log(days)
res_permitting	Permitting score for residential sector	1.52	0.35	0.71	2.23	# / 100
csize	System size centered	0.00	2.11	-3.48	5.37	kW
csize2	Square term of system size centered	4.46	5.44	0.00	28.87	kW^2
PG&E	Indicator for systems located in the Pacific Gas and Electric (PG&E) service area	0.66	0.48	0	1	0 or 1
CCSE	Indicator for systems located in the California Center for Sustainable Energy (CCSE, San Diego) area	0.20	0.40	0	1	0 or 1
SCE	Indicator for systems located in the Southern California Edison (SCE) area	0.14	0.35	0	1	0 or 1
month_perstart	Continuous month number when the customer/installer initiated development tasks for a particular system (i.e., applied for CSI incentives)	26.24	5.24	7	36	integer value
electrician	Average electrician wage for each city	54.66	2.70	50.52	60.25	nominal $ / 1,000
medHHincome	Median household income for each city	61.0	12.8	26.7	120.3	nominal $ / 1,000
medHHvalue	Median household value for each city	48.36	17.27	16.14	98.55	nominal $ / 10^4
popdensity	Population density for each city	5.90	4.34	1.38	16.84	# / $Mile^2$ / 100
roomnumber	Median number of rooms per household for each city	4.98	0.56	3.4	6.6	decimal value
installationdensity	Total number of residential PV systems installed per city per unit of area from 2007 to 2011	0.22	0.35	0.00	1.91	# / $Mile^2$ / 100
weekcount	Number of PV systems entering the development pipeline in a week from 2007 to 2011 for each utility (i.e., applied for CSI incentives)	4.09	4.21	0.1	27.8	integer value / 10
college	% of population in city that has any college education (but has not earned a bachelor's degree)	29.84	6.16	12.6	39.6	%
bachelor	% of population in city that has earned a bachelors degree	34.27	13.39	1.3	68.9	%

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, electrician wage, population density and median number of rooms—overlap, at least to some degree, and all may relate to the cost of living in a city. We use principle component analysis (PCA) to extract this common factor out of these relevant individual variables, which contains 73.9% of the variance within these variables.

3. RESULTS

This section presents estimates for the price regressions first and then for the development time regressions.

3.1. Price Regressions

Table 2 presents results from the price-based analysis under five different regression models. Table 1, earlier, shows the definitions of the independent variables used in these models. 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 of 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.

Based on the results for the two system size terms, PV systems exhibit strong economies of scale and diminishing returns of scale; both of which are significant at the 99% confidence level. The interpretation of the coefficients must consider both terms (*csize* and *csize2*). Taking model P5 as an example, a 1-kW increase in system size from the mean value decreases the installed 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 installed price by about \$0.42/W, making the price reduction due to the second kW increase only \$0.14/W.

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. 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) would lower the average installation price by around \$0.20/W. This effect is statistically significant at the 95% confidence level or more.

As for other control variables, 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 coefficients of *month_perstart* indicate that system-level installation prices have been declining over time.

"Cost of living," captured by either the common factor or the separate variables, has a significantly positive impact on installation prices, which is consistent with the expectation that cities with a high cost of living generally would have high installation prices. Taking model P3 as an example, after controlling for other variables, higher "cost of living" cities are found to have average installation prices that are about \$0.40/W higher than other cities. 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: further exploration of learning effects is warranted. On the other hand, the city-level education variables are generally negative, with the variable *bachelor* exhibiting a stronger price-decreasing effect than the variable *college*.

Based on the regression results above, we can predict installed prices for each system. We can then average the predictions from the system level to the city level. We use

TABLE 2: REGRESSION OUTPUTS OF INSTALLATION PRICE

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

*R*obust standard errors in parenthesis; $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

models P2–P5 to display the marginal effects of permitting across model sensitivities. Fig. 1 does this by calculating predicted installed prices using the coefficients of permitting scores from models P2–P5, while using mean values for all other model variables. The city with the lowest permitting score is depicted on the left side of the chart as the baseline, 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.

In Fig. 1, 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.

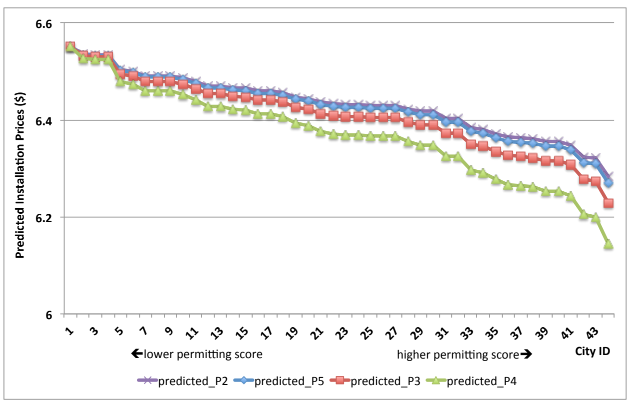

Fig. 1: Predicted prices using permitting scores, all else being equal.

Across these four models, permitting processes are found to cause differences in average PV installed prices among cities of up to \$0.27–\$0.41/W, depending on the model chosen.[4] It is not clear which of the four models better captures the real effect size. Regardless, across all models, this represents 4%–6% 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 can occur at a local level.

[4] The core analysis presented in this paper excluded appraised-value TPO systems from the data-set, but included other TPO systems. We also ran similar models with all TPO systems excluded from the data-set, and in that instance found larger price differences among cities of up to \$0.43–\$0.77/W.

3.2. Development Time Regressions

Table 3 presents the results of the development-time analysis. Model specifications for development times are slightly different than those for installation prices. First, only the level term of system size is used. Second, we remove the *month_perstart* variable since we need not control for the same time-influenced price-reduction effect as in the price regression. Third, we add one control variable—*weekcount*—to account for the possibility that more systems in the incentive application and permitting queue could slow down the whole process.

As before, Model T1 is a reference. Focusing on models T2-T5, the centered size (*csize*) variable has a positive sign, suggesting that larger PV systems require slightly more development time, but the coefficient is not statistically significant at the 90% level.

The permitting score coefficients in models T2–T5 are all negative and statistically 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 the effects of the individual "cost of living" variables on development time could push the results in opposite directions (e.g., *medHHincome* and *popdensity* in TABLE 3), 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 could, all else being equal, speed development times by roughly 10%.

The average 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.

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. The negative coefficient of *MedHHincome* suggests 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 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 due to education levels or installation density.

Overall, while models T2-T5 find that challenging permitting practices lead to lengthier PV development times, 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, some of the control variables are found to have effects that are less intuitively persuasive than in the price regressions. Third, while the overall explanatory power of both the price and development-time regressions is relative low (see the R^2), this is especially true in the case of development time.

We predict development times in a similar way as installed prices, earlier. Fig. 2 highlights the marginal contributions from the permitting process. 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. The marginal effects of the permitting process in models T4 and T5 are very close to each other (Fig. 2), 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.

4. CONCLUSIONS

In conclusion, city-level permitting processes – as one core driver 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 favourable permitting processes reduce average residential PV system prices by \$0.27–\$0.41/W (4-6% relative to median pricing) and shorten development times by around 24 days (25% compared to median development time) compared with those cities with the most taxing 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 *across city* results are consistent with the literature and add to previous attempts to quantify the

TABLE 3: REGRESSION OUTPUTS OF DEVELOPMENT TIME

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

*R*obust standard errors in parenthesis; *p < 0.10, **p < 0.05, ***p < 0.01.

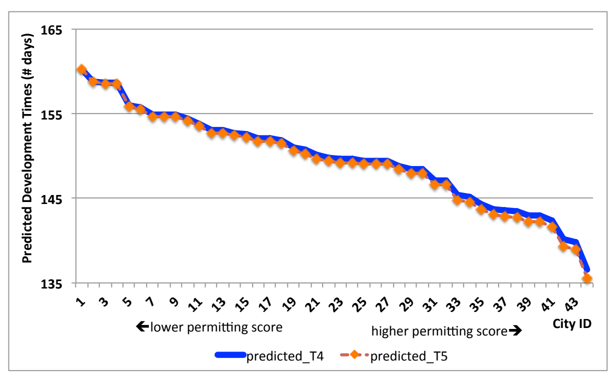

Fig. 2: Predicted development time using permitting scores, all else being equal.

national or regional average impact of permitting on installed costs and development times (e.g., Sunrun, 2011; Ardani et al., 2012; Tong, 2012). In particular, they demonstrate that national or regional average impacts can mask the more-substantial impacts that occur at a local level within 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. All else being equal, streamlining the permitting process is found to potentially reduce the price of a 4-kW residential PV system by $1,000 or more, on average, and cut development time by about a month.

Future work might extend the geographic reach of the present study to additional cities both within and outside of California. Because the development-time results presented in this study are relatively weaker than those for installed prices, further effort to improve the robustness of those results is warranted. Moving beyond installed prices and development time, it may also be useful to assess the impact of permitting on the amount of PV installed at the city level and/or PV installer interest in those cities.

5. REFERENCES

(1) Ardani, K.; Barbose, G.; Margolis, R.; Wiser, R.; Feldman, D.; Ong, S. 2012. *Benchmarking Non-Hardware Balance of System (Soft) Costs for U.S. Photovoltaic Systems Using a Data-Driven Analysis from PV Installer Survey Results*. Golden, CO: National Renewable Energy Laboratory. Berkeley, CA: Lawrence Berkeley National Laboratory

(2) Barbose, G.; Darghouth, N.; Wiser, R. 2012. *Tracking the Sun V: The Installed Price of Photovoltaics in the United States from 1998-2011*. Berkeley, CA: Lawrence Berkeley National Laboratory

(3) Bazilian, M.; Onyeji, I.; Liebreich, M.; MacGill, I.; Chase, J.; Shah, J.; Gielen, D.; Arent, D.; Landfear, D.; Zhengrong, S. 2013. "Re-considering the economics of photovoltaic power." *Renewable Energy* 53 (0): 329–338

(4) Brooks, B. 2012. *Expedited Permit Process for PV Systems: A Standardized Process for the Review of Small-Scale PV Systems*. Solar America Board for Codes and Standards

(5) Goodrich, A.; James, T.; Woodhouse, M. (2012). *Residential, Commercial, and Utility-Scale Photovoltaic (PV) System Prices in the United States: Current Drivers and Cost-Reduction Opportunities.* NREL/TP-6A20-53347. Golden, CO: National Renewable Energy Lab

(6) Interstate Renewable Energy Council (IREC). 2010. *Field Inspection Guidelines for PV Systems*. Prepared by Brooks Engineering

(7) Langen, C. 2010. *Complexity Cost and Economies of Scale: Why Residential Customers in Germany Pay 25% Less for a PV System than US Customers*. SolarPower International, Sovello AG

(8) Mills, C.; Newick, K.; Stewart, J.; Compeán T. W. 2009. *Solar Electric Permit Fees in Southern California: A Comparative Report.* San Francisco, CA: Sierra Club

(9) Mills, C.; Newick, K. 2011. *Solar Electric Permit Fees in Northern California: A Comparative Study*. San Francisco, CA: Sierra Club

(10) Office of Planning and Research (OPR). 2012. *California Solar Permitting Guidebook*. Sacramento, CA: Governor's Office of Planning and Research

(11) Seel, J.; Barbose, G.; Wiser, R. 2013. *Why Are Residential PV Prices in Germany So Much Lower Than in the United States? A Scoping Analysis*. Berkeley, CA: Lawrence Berkeley National Laboratory

(12) Stanfield, S.; Schroeder, E.; Culley, T. 2012. *Sharing Success: Emerging Approaches to Efficient Rooftop Solar Permitting*. Interstate Renewable Energy Council

(13) Sunrun. 2011. *The Impact of Local Permitting on the Cost of Solar Power*. San Francisco, CA: Sunrun

(14) Tong, J. 2012. *Nationwide Analysis of Solar Permitting and the Implications for Soft Costs.* Clean Power Finance, Inc

(15) U.S. Census Bureau. 2012. *The American FactFinder*. Available at http://factfinder2.census.gov/faces/nav/jsf/pages/index.xhtml. Accessed June 10, 2012

(16) Vote Solar. 2013. *Project Permit Interactive Permitting Map*. Available at http://votesolar.org/solar-map/. Accessed February 5, 2013