Supplement to "Hurdles and Steps: Estimating Demand for Solar Photovoltaics"

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Online Appendix

A Consumer Expectations, Dynamics, and Subsidies

While several prominent recent papers on solar PV adoption have used reduced form approaches, rather than dynamic discrete choice models (see, e.g., Rogers and Sexton 2014; Hughes and Podolefsky 2015), many economists may instinctively consider the purchase of a solar PV system as a "buy-or-wait" decision that is best modeled with a dynamic discrete choice model. For example, consumers may recognize that subsidies are about to change in the near future and time their purchase to ensure the higher subsidy. Indeed, in California, Rogers and Sexton (2014) finds intriguing evidence of such dynamics in consumer behavior, with a considerable "bunching" of adoptions just before a step decline in the subsidy. Papers such as Hendel and Nevo (2006) point out that static demand elasticities are over-estimated in the context of temporary sales or price reductions that lead to large increases in the quantity sold due to consumer recognition of the temporary nature of the price increases. Burr (2014) and Bollinger and Gillingham (2016) implement structural dynamic discrete choice models of solar PV demand to attempt to model such features of consumer decision making in California.

However, it is quite likely that the California setting may not transfer to many other settings around the country and around the world. In California the subsidies were phased out in a way that depended on the total amount of installed PV capacity, which allows consumers and firms to reasonably anticipate the timing of subsidy declines. Moreover, the subsidy changes were large and firms occasionally advertised using the upcoming subsidy change as the key message. Such features do not exist in Connecticut (or most other states).

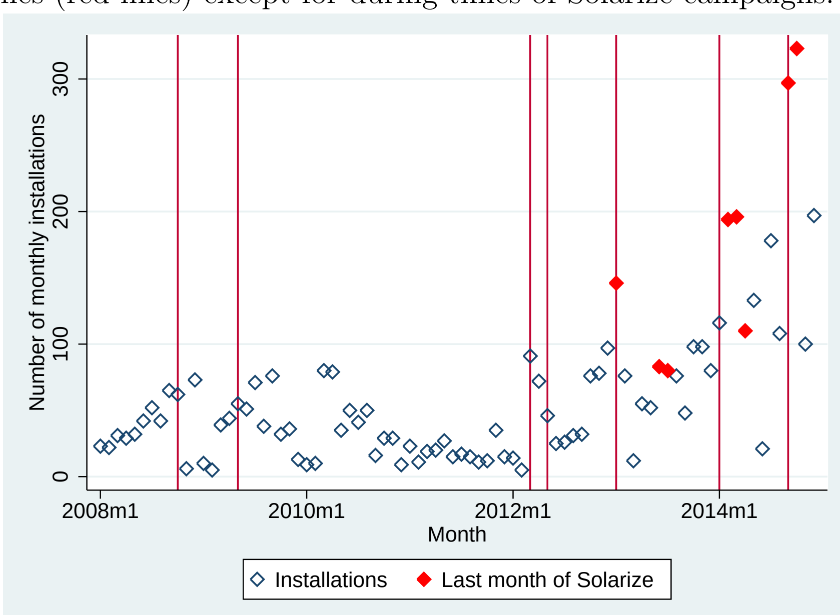
The changes in rebates in Connecticut were abrupt and not easily forecastable. In some cases, they changed with votes in the state legislature. In others, they changed due to the budget for that set of incentives running out. These end dates are very plausibly random. Equally importantly, unlike in California, consumers and firms could not precisely time purchases, since consumers and firms had little information about when the change would occur. In Connecticut, there was no messaging or advertising about future subsidy declines. The only case where timing of any sort occurred is when CGB explicitly timed two rounds of Solarize programs to end just before a change in the incentive (others ended at a different time).

This appendix provides two types of evidence supporting the contention that dynamics are a dominant force in this context. First, we show that there is no obvious bunching in the Connecticut data that would come about due to consumers treating the solar PV adoption decision as an optimal stopping problem. Second, we provide evidence from a survey of consumers that highlights the key factors in the solar adoption decision process and suggests that expectations of future changes in subsidies–or other dynamic factors–are not likely to be key influences in the decision process for most solar PV adopters in Connecticut.

A.1 No obvious bunching in Connecticut

Figure A1 shows the number of installations per month (the most disaggregated our data permits with any accuracy). The red lines in the figure indicate the dates of changes in incentives. After early 2012, the figure shows several months of very large numbers of installations, which correspond to months at the end of Solarize programs. Sometimes they correspond to steps that decline, but more often they do not, with months of high sales before, during, and after changes in steps. In general, there is no clear pattern of bunching before changes in incentives in Connecticut. The high levels of installations in the Solarize months are due to the Solarize programs, rather than the changing incentives (there is no uptick in non-Solarize municipalities). These high levels of installations during those months underscore the value of performing our analysis both with and without the Solarize programs included.

Figure A1: The number of installations over time does not show bunching at the steps of incentive declines (red lines) except for during times of Solarize campaigns.



Examining the data in this way is useful for it demonstrates that there is no obvious bunching or "harvesting" effect (Rogers and Sexton 2014) in our data, which could confound identification of the demand elasticity. Furthermore, by aggregating our data to the yearly level, as we do for our estimation, we can be even more confident that harvesting is not an identification concern in our setting.

A.2 Consumer expectations

Our evidence of a lack of bunching indicates that consumers in Connecticut are not obviously making decisions considering the expectations of future subsidy declines. We can also examine survey evidence to better understand how consumers are making decisions.

We use survey data that was conducted in Connecticut just shortly after each of the first three Solarize rounds. The surveys were conducted online in March 2013, September 2013, and June 2014 using the Qualtrics survey tool. Respondents were contacted via e-mail. The e-mail addresses were obtained from the Solarize campaigns. The response rate for those who had solar or signed a contract to install was approximately 40 percent. The response rate for those who expressed interest, but did not adopt, was approximately 17 percent. We received 1,392 full responses, 36 percent of whom either had installed or had signed a contract to install solar PV.

The responses provided deep insight into how consumers make decisions about solar PV. A few survey questions are most relevant for the question at hand here: do consumers in Connecticut appear to time their decision to adopt? While this evidence is certainly only suggestive, the short answer is no, it appears that timing is not a dominant factor in the decision process.

Our first evidence of this is in an open-ended qualitative question at the end of the survey where respondents were asked to provide any further thoughts about solar PV. Typical responses from those who did not install a panel are “My house faces in wrong direction and my age (79) would not see return on investment” or “Had my home evaluated - roof wasn’t large enough, so the only other option was a large array structure in my backyard” or “I just can’t justify cutting beautiful, old trees down to become more environmentally friendly” or “took too long to get back investment in solar.” Typical responses from those who did install are “LOVE IT!” or “Great program! Keep up with incentives so that more people can access solar power” or “Communication by the town is critical in getting the word out about the Solarize program.” Notably, not a single response mentions anything about timing the installation in any way (e.g., before incentives dropped). Some responses mentioned that they are interested but the numbers do not work out for solar to be financially attractive on their home right now and that they would consider solar PV in the future if the cost comes down. But this is very different than households anticipating the expiration of subsidies and timing their installations. If such timing was a critical factor in this market, it stands to reason that at least one consumer would have mentioned this in their comments.

Further evidence is from a question that asks consumers who did not install to rate the importance of different factors in their decision not to install. Respondents could rate each of the factors on a scale from "not at all important" to "extremely important." The two factors that rose to the top: whether their home is suitable for solar and the current cost of solar. 46 percent of the respondents indicated that whether their home is suitable for solar was extremely important for their choice not to install solar PV. 41 percent of the respondents indicated that the current cost of solar is extremely important for their choice not to install solar. In contrast, only 23 percent of the respondents indicated that future costs of solar were extremely important. 100 percent of those who indicated that future costs of solar PV were extremely important also indicated that the current costs of solar were extremely important in their decision. This evidence suggests that at most only a relatively small group of potential consumers did not install due to expectations of lower future prices, and that these consumers also simply saw current prices as a dominant factor.

While this survey evidence is by no means definitive, when considered along with the evidence of a lack of bunching just before subsidy declines and the fact that there was no easy way for consumers to know that the subsidies were about decline, it builds a reasonable case that our estimated static demand elasticities are not substantially biased from neglecting dynamics. To be clear, we cannot rule out that the consumers in our setting are forward-looking, we just have not found evidence consistent with forward-looking behavior in our explorations of the data. If there was very substantial forward-looking behavior, we would expect the true elasticity to be closer to zero than our elasticity.

References

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Hughes JE, Podolefsky M. 2015. Getting green with solar subsidies: Evidence from the California Solar Initiative. *Journal of the Association of Environmental and Resource Economists* **2**: 235–275.

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B Monte Carlo Simulations

In what follows, we describe three different data generation processes used in our Monte Carlo simulations. In particular, we generate panel data from a random Poisson model, a hurdle model with individual fixed effects and an endogenous regressor, and a Poisson model with individual fixed effects and an endogenous regressor.

B.1 Random Poisson Model

We use the following model in this set of Monte Carlo simulations:

$$y_{it} \sim Po(\lambda_{it}), \tag{B.1}$$

$$\lambda_{it} = \exp(\alpha_{it} + \delta x_{it}), \tag{B.2}$$

$$x_{it} = 2 + u_{it}, \tag{B.3}$$

$$\alpha_{it} = -5 + e_{it}, \tag{B.4}$$

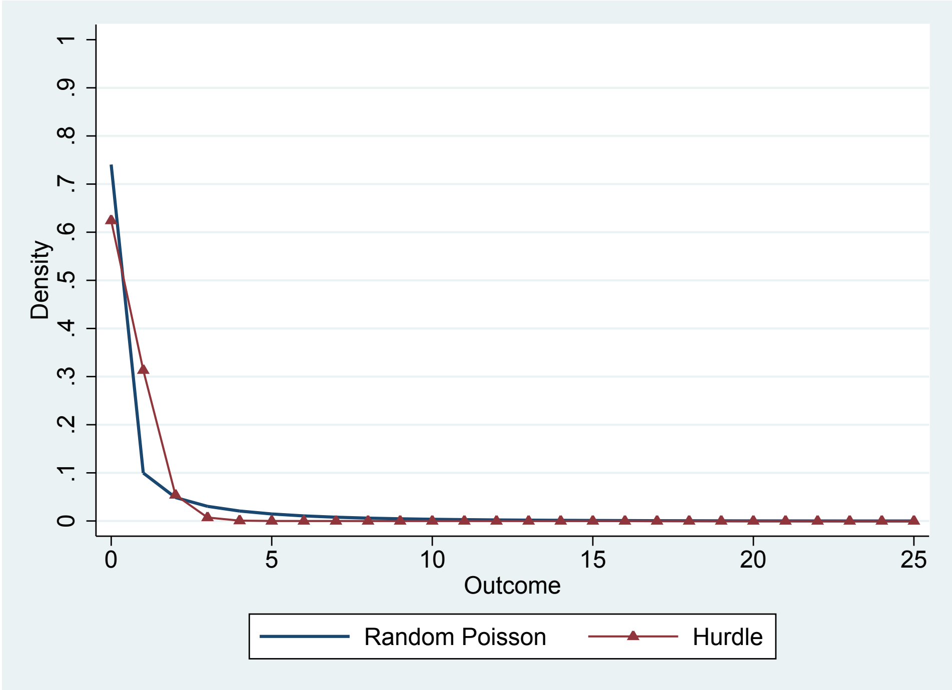
$$u_{it} \perp\!\!\!\perp e_{it},\ u_{it} \sim Unif(0,2),\ e_{it} \sim Unif(0,10), \tag{B.5}$$

where $i = 1, ..., N$, and $t = 1, ..., T$. In other words, the Poisson parameter λ_{it} is affected by an individual- and time-specific shock α_{it} which is unobserved, but also uncorrelated with the observed regressor x_{it}.

To generate data, we first draw u_{it} and e_{it} from the distributions shown in (B.5). We then construct the variables α_{it} and x_{it} as shown in (B.4) and (B.3), respectively. Next, we calculate λ_{it} using the formula in (B.2). Finally, we draw y_{it} from the Poisson distribution shown in (B.1). We set the parameter values as δ = -1, N = 5000, and T = 4, and replicate the estimation 5,000 times, each time re-drawing different u_{it} and e_{it}.

Such data generation process can give rise to a distribution of the outcome count variable y with most of its mass centered around zero and variance vastly exceeding the sample mean. Figure B1 displays the distribution of the data from one of the random draws. The thick line traces the true distribution of the outcome variable under the random Poisson data generation process. Note that more than 70 percent of the outcomes are zeros. Furthermore, the sample mean for the data is 0.86 and the variance 4.85, indicating overdispersion relative to the standard Poisson model. Hence, in general, a random Poisson model can yield a distribution similar to the data in our analysis. Figure B1 also shows how a hurdle model distribution would fit through the generated data. Aside from a slightly lower mass at low counts, the hurdle model comes quite close to the actual distribution. We found this trend to hold under a number of different parameter values.

Figure B1: Data distribution under a random Poisson specification



In each replication of the above data generation process, we estimate the logit and truncated Poisson components of a hurdle model with a single exogenous regressor x_{it}. Using the estimated coefficient on the regressor and the formulas in Section 5.4, we then derive the implied elasticity from each component of the model, as well as the combined hurdle model elasticity. As shown in Table B1, the average elasticity estimate from the 5,000 replications is very close to the true value (also averaged over 5,000 replications) of -3. The bias is less than 0.6 percent, which lends support to the use of a Poisson hurdle model even in instances where the true model is a random Poisson.

Table B1: Random Poisson Simulation Results

Specification	Elasticity		
	True Value	Implied Estimated	Implied Bias
Logit	n/a	-1.1727	n/a
Truncated Poisson	n/a	-1.8091	n/a
Poisson hurdle	-3	-2.9818	0.0182

B.2 Hurdle Model with Fixed Effects and Endogeneity

We use the following model:

$$\iota_{it} = \begin{cases} 1 & \text{if } l_{it} > \kappa_{it}, \\ 0 & \text{if } l_{it} \leq \kappa_{it}, \end{cases} \tag{B.6}$$

$$l_{it} = \frac{\exp(\alpha_i + \delta_1 w_{it} + u_{it})}{1 + \exp(\alpha_i + \delta_1 w_{it} + u_{it})}, \tag{B.7}$$

$$\kappa_{it} \sim Unif[0, 1], \tag{B.8}$$

$$y_{it} = 0, \text{ if } \iota_{it} = 0, \tag{B.9}$$

$$y_{it} \sim trPo(\lambda_{it}), \text{ if } \iota_{it} = 1, \tag{B.10}$$

$$\lambda_{it} = \exp(\beta_i + \delta_2 w_{it} + v_{it}), \tag{B.11}$$

$$w_{it} = \tau_1 \alpha_i + \tau_2 \beta_i + \pi z_{it} + \rho_1 u_{it} + \rho_2 v_{it} + e_{it}, \tag{B.12}$$

$$u_{it} \perp\!\!\!\perp v_{it}, \ (u_{it}, v_{it}, e_{it}) \perp\!\!\!\perp z_{it},$$

$$u_{it} \sim N(0, \sigma_u), \ v_{it} \sim N(0, \sigma_v), \ e_{it} \sim N(0, \sigma_e), \tag{B.13}$$

where $i = 1, ..., N$, and $t = 1, ..., T$. Note that w_{it} is correlated both with the error terms u_{it} and v_{it}, as well as with the individual-specific parameters α_i and β_i, with the magnitude of correlation determined by parameters ρ_k and τ_k, $k \in \{1, 2\}$, respectively. The variable z_{it} is exogenous to the model and is used to instrument for w_{it}. The parameter π measures the strength of this instrument.

The data generation process is as follows. First, we draw each α_i and β_i from a uniform distribution with support $[0, 1]$. Next, we generate a random variable $z_{it} \sim Unif[0, 5]$. After drawing the random error terms u_{it}, v_{it}, and e_{it} from the distributions shown in (B.13), we plug them into (B.12), (B.11), and (B.7) to obtain w_{it}, λ_{it}, and l_{it}, respectively. Finally, we proceed to generate the outcome variable in each of the two stages of the hurdle model. We draw κ_{it} from the distribution shown in (B.8) and then follow the decision rule in (B.6) to generate ι_{it}. We set y_{it} to equal zero for all observations where $\iota_{it} = 0$, as indicated in (B.9). Then, if $\iota_{it} = 1$, y_{it} is drawn from the truncated Poisson distribution in (B.10). To obtain the truncated Poisson draws, we follow Cameron and Trivedi (2013) by drawing from a Poisson distribution with parameter λ_{it} and then replacing each zero draw with another draw from the same distribution until all draws are positive.

The parameters to be chosen are δ_1, δ_2, τ_1, τ_2, π, ρ_1, ρ_2, σ_u, σ_v, σ_e, N, and T. We set $\delta_1 = \delta_2 =$ -0.1, $\tau_1 = \tau_2 = 0.2$, $\pi = 0.8$, $\rho_1 = \rho_2 = 0.5$, $\sigma_u = \sigma_v = \sigma_e = 0.5$, $N = 5000$, and $T = 4$. We replicate the estimation 5,000 times, each time re-drawing different u_{it}, v_{it}, and e_{it}.

B.3 Poisson Model with Fixed Effects and Endogeneity

This Monte Carlo simulation shows that even if the true data generating process was simply Poisson (with endogeneity), our hurdle model performs well in recovering the true values. We use the following model:

$$y_{it} \sim Po(\lambda_{it}), \tag{B.14}$$

$$\lambda_{it} = \exp(\alpha_i + \delta w_{it} + u_{it}), \tag{B.15}$$

$$w_{it} = \tau\alpha_i + \pi z_{it} + \rho u_{it} + v_{it}, \tag{B.16}$$

$$u_{it} \perp\!\!\!\perp v_{it},\ (u_{it}, v_{it}) \perp\!\!\!\perp z_{it},$$

$$u_{it} \sim N(0, \sigma_u),\ v_{it} \sim N(0, \sigma_v), \tag{B.17}$$

where $i = 1, ..., N$, and $t = 1, ..., T$. Note that w_{it} is correlated with the error term u_{it} and with the individual-specific parameter α_i, with the magnitude of correlation determined by parameters ρ and τ, respectively. The variable z_{it} is exogenous to the model and is used to instrument for w_{it}. The parameter π measures the strength of this instrument.

The data generation process is as follows. First, we draw each α_i from a uniform distribution with support $[-1, 1]$. Next, we generate a random variable $z_{it} \sim Unif[0, 5]$. After drawing u_{it} and v_{it} from the distributions shown in (B.17), we plug them into (B.16) and (B.15) to obtain w_{it} and λ_{it}, respectively. Finally, we draw y_{it} from the Poisson distribution shown in (B.14). The parameters to be chosen are δ, τ, π, ρ, σ_u, σ_v, N, and T. We set δ = -0.5, $\tau = 0.2$, $\pi = 0.8$, $\rho = 0.5$, $\sigma_u = \sigma_v = 0.5$, $N = 5000$, and $T = 4$. We replicate the estimation 5,000 times, each time re-drawing different u_{it} and v_{it}.

In each replication, we estimate a fixed effects logit CF and a fixed effects truncated Poisson GMM model with the data, using z_{it} as an instrument for the endogenous variable w_{it}. We then calculate the corresponding elasticity values in each of the two components of the hurdle model and add them up to obtain the total elasticity implied by the model. The true elasticity from the Poisson model, averaged over 5,000 replications, is approximately -1. As shown in Table B2, the average elasticity estimate from the hurdle model lies very close to the true value, with bias of less than 0.7 percent.

Table B2: FE Poisson with Endogeneity Simulation Results

Specification	Elasticity		
	True Value	Implied	
		Estimated	Bias
Logit CF	n/a	-0.7776	n/a
Tr. Poisson GMM	n/a	-0.2293	n/a
Poisson hurdle	-1.0001	-1.0069	-0.0068

C First-stage Instrumental Variable Results

To demonstrate the strength of our instruments, Table C1 shows the results of a first-stage regression of the post-incentive PV system price per W on all instruments for both the full and truncated sample. The coefficients on incentives are highly statistically significant. A joint F-test of statistical significance of the excluded instruments provides a test statistic of 43.06 in the full sample and 117.52 in the truncated sample.

Table C1: First-stage Instrumental Variable Regression Results

Variable	Full Sample	Truncated Sample
Incentive level	-0.453***	-0.574***
	(0.0515)	(0.038)
Wage rates	0.00036**	0.00008
	(0.00017)	(0.00045)
Solarize	-0.134	-0.27***
	(0.0838)	(0.0805)
Pop. density	7×10^{-6}	0.00016
	(3×10^{-5})	(0.00014)
Income	-0.0007	-0.00179
	(0.001)	(0.00136)
Age	-0.00217	-0.00666
	(0.00331)	(0.00427)
% (some) college	-0.00049	0.00198
	(0.00193)	(0.00385)
% grad/professional	-0.00043	0.00541
	(0.00309)	(0.00448)
% Republican	0.0154	0.0159
	(0.0285)	(0.0271)
% Democrat	-0.00886	-0.00158
	(0.0214)	(0.0219)
BG FE	yes	yes
Year Dummies	yes	yes
F-statistic	43.06	117.52
Observations	10,738	3,238

Notes: Dependent variable is post-incentive PV system price per W. Unit of observation is block group-year. Specification is a linear least squares regression. BG FE refers to block group fixed effects. Standard errors clustered on town in parentheses. $p < 0.1$ (*), $p < 0.05$ (**), $p < 0.01$ (***).

D Non-instrumented Regression Output

Table D1: Non-instrumented Regression Results

Variable	Linear	Poisson	Hurdle	
			Logit	Truncated Poisson
	OLS[i]	MLE[ii]	CMLE[ii]	CMLE[i]
	(1)	(2)	(3)	(4)
Price	0.119***	0.223***	0.572***	-0.123**
	(0.0162)	(0.0497)	(0.0787)	(0.0574)
Solarize	0.953***	0.962***	0.948***	0.897***
	(0.24	(0.15)	(0.2)	(0.161)
Pop. density	-0.00001	-0.00019**	-0.00021**	0.00024
	(0.00001)	(0.00008)	(0.00009)	(0.00042)
Income	0.00101	0.00084	-0.00055	0.00273
	(0.000738)	(0.00139)	(0.00142)	(0.00269)
Age	-0.0026	-0.0099**	-0.0084	-0.00926
	(0.0025)	(0.0045)	(0.0052)	(0.0119)
% (some) college	0.00077	0.00193	0.0045	0.00348
	(0.00129)	(0.00299)	(0.00365)	(0.00626)
% grad/prof degree	0.00108	-0.0002	0.00582	-0.00743
	(0.00153)	(0.00405)	(0.00483)	(0.00791)
% Republican	0.0542**	0.0545	-0.0005	0.159***
	(0.0239)	(0.0397)	(0.0443)	(0.0592)
% Democrat	0.0263**	0.0433*	0.0107	0.109***
	(0.0125)	(0.0222)	(0.0252)	(0.0377)
BG FE	yes	yes	yes	yes
Year Dummies	yes	yes	yes	yes
Instruments	no	no	no	no
Price elasticity[iii]	0.935***	0.84	1.504***	-0.052**
	(0.128)	(0.186)	(0.207)	(0.024)
Observations	10,738	10,738	10,738	2,636

Notes: Dependent variable is number of residential PV installations. Unit of observation is block group-year. BG FE refers to block group fixed effects. $p < 0.1$ (*), $p < 0.05$ (**), $p < 0.01$ (***).

[i] Clustered standard errors at the town level in parentheses.

[ii] Block bootstrapped standard errors (100 replications), clustered at the town level, in parentheses.

[iii] Standard errors of price elasticity coefficients obtained by the delta method.

E Including Third-party-owned Systems

Table E1: Regression Results with Purchased and Third-party-owned Systems

Variable	Linear	Poisson	Hurdle	
			Logit	Truncated Poisson
	2SLS[i]	CF[ii]	CF[ii]	GMM[i]
	(1)	(2)	(3)	(4)
Price	0.037	-0.0503	-0.00323	-0.156
	(0.0429)	(0.104)	(0.109)	(0.133)
Solarize	1.294***	0.724***	0.678***	0.794***
	(0.333)	(0.111)	(0.2)	(0.119)
TPO	-0.335***	-0.210**	0.155	-0.429***
	(0.107)	(0.0912)	(0.102)	(0.126)
Pop. density	3.7×10^{-5}***	-9.9×10^{-5}*	-0.00015	0.00079**
	(8.8×10^{-6})	(0.00006)	(0.00009)	(0.00038)
Income	0.00259***	0.00049	-0.0016	0.00313
	(0.000827)	(0.00124)	(0.00154)	(0.00252)
Age	0.00035	-0.0101**	-0.0119**	-0.00149
	(0.00244)	(0.00412)	(0.00553)	(0.0097)
% (some) college	0.00067	0.00057	0.00283	0.00173
	(0.00133)	(0.00293)	(0.00441)	(0.00503)
% grad/prof degree	-0.00169	-0.00803**	0.00321	-0.0201***
	(0.00173)	(0.0032)	(0.00498)	(0.0073)
% Republican	0.0942***	0.0417	0.0203	0.0806*
	(0.0363)	(0.0364)	(0.0418)	(0.0484)
% Democrat	0.0341*	0.0307	0.00735	0.0694**
	(0.0197)	(0.023)	(0.0284)	(0.0313)
BG FE	yes	yes	yes	yes
Year Dummies	yes	yes	yes	yes
Instruments	yes	yes	yes	yes
Price elasticity[iii]	0.204	-0.194	-0.008	-0.097
	(0.2364)	(0.4025)	(0.2787)	(0.083)
Observations	13,510	13,510	13,510	4,513

Notes: Dependent variable is number of residential PV installations. Unit of observation is block group-year. TPO measures the fraction of new installations that are third-party-owned. The number of observations increases from our primary results because TPO systems are included. All other variables are the same as in Table 6. $p < 0.1$ (*), $p < 0.05$ (**), $p < 0.01$ (***).

[i] Clustered standard errors at the town level in parentheses.

[ii] Block bootstrapped standard errors (100 replications), clustered at the town level, in parentheses.

[iii] Standard errors of price elasticity coefficients obtained by the delta method.

F Inputs for the Policy Simulations

Table F1 lists the values of the main parameters and variables used in our policy simulations in Section 7. As an estimate of system costs in 2015, we assume that the trend of declining module and inverter costs continues. In order to derive the predicted change in pre-incentive average system costs (i.e., the sum of installer reported module, inverter, labor, and permitting costs) during 2015, we extrapolate the trend from 2008 to 2014. More specifically, we calculate the year-to-year percentage change in the average pre-incentive cost per W (calculated as the ratio of the average cost to the average system size) over this time period and fit a simple exponential curve through these percentage changes. We then take the extrapolated 2015 value as our forecasted cost per W in 2015. This value is shown in the top row of Table F1.

The average 2014 values of all installation-related variables are obtained directly from our core dataset. In addition, the average EPBB/HOPBI rate is derived using the mean system capacity value in 2014 at Step 4 and Step 5 incentive levels and taking the average of the two resultant rates. Lastly, our data contains information on the structure of municipal solar PV system permit fees. While some CT towns charge a flat fee per installation, in most towns the fee depends on the capacity of the installation. In those towns, we use our system size data for each installation in 2014 to obtain the fee for that installation. We average across all installations to derive an average town fee per installation and then average across all towns. After dividing the resultant number by average system capacity, we obtain the average town fee per W, reported in the last row of Table F1.

Table F1: Input Values for Policy Simulations

Parameter/Variable	Value
Change in average system cost from Jan 1, 2015 to Dec 31, 2015 (%)	-5.30
Number of block groups	1534
Average number of installations per block group in 2014	1.287
Average system capacity (kW) in 2014	7.819
Average system price ($/W) in 2014	2.946
Average rebate rate ($/W) in 2014	0.935
Average town permit fee ($/W) in 2014	0.0518