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Solar Bait: How States Attract Solar Investments from Large Corporations

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Past literature in solar adoption has focused primarily on households without significant attention to the potential of commercial properties as sites for solar generation. Herein we examine firms' decisions to install solar panels on their properties using state-level data. We are interested in the effects of state-level characteristics, including policies and regulations, on firm decisions regarding solar investments. We find that state characteristics that influence the return-on-investment from solar installations, most notably solar intensity, are important for commercial adoption decisions. Further results suggest that certain state-level policies, in particular solar carve-outs in renewable portfolio standards, financing programs and tax breaks, can incentivize firms to install solar panels. The strongest result we observe across empirical specifications is that firm installation decisions are correlated with personal electric vehicle ownership rates. This may indicate a 'green' business marketing strategy, whereby firms install solar to improve their social responsibility image.

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Solar bait: How states attract solar investments from large corporations

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Abstract

Past literature in solar adoption has focused primarily on households without significant attention to the potential of commercial properties as sites for solar generation. Herein we examine firms' decisions to install solar panels on their properties using state-level data. We are interested in the effects of state-level characteristics, including policies and regulations, on firm decisions regarding solar investments. We find that state characteristics that influence the return-on-investment from solar installations, most notably solar intensity, are important for commercial adoption decisions. Further results suggest that certain state-level policies, in particular solar carve-outs in renewable portfolio standards, financing programs and tax breaks, can incentivize firms to install solar panels. The strongest result we observe across empirical specifications is that firm installation decisions are correlated with personal electric vehicle ownership rates. This may indicate a 'green' business marketing strategy, whereby firms install solar to improve their social responsibility image.

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1 Introduction

Motivated by environmental quality concerns, energy independence, and employment generation prospects, many states have adopted solar-friendly policies and subsidy programs to increase solar adoption and incentivize companies to add solar photovoltaic (PV) units to their facilities (Shrimali and Jenner, 2013). The stakes in this game of attraction are high, with large economic investments hanging in the balance. Commercial solar installations represent a tangible investment in a state's economy and have the potential to create jobs (Wei et al. 2010).

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Nevertheless, thus far, only a small fraction of the total solar potential of corporate properties has been realized. Even Walmart, an avid corporate solar adopter, generates solar power at only 7% of its facilities. High initial cost has generally been argued to be the primary barrier for adoption (Shrimeli and Jenner, 2013).

The Solar Energy Industries Association (SEIA) “Solar Means Business” Reports compile data on solar generation installations for major commercial solar adopters. These are private companies that invest in solar generation capacity in the U.S. The SEIA data account for nearly 1,000 MW of solar capacity installed by private companies through 2015. The data cover an estimated 16% of non-residential and non-utility scale solar installations (SEIA, 2016).⁴ Assuming no sample-selection bias, this figure suggests that the total amount installed by commercial entities through 2015 is approximately 6,250 MW, or enough to power the equivalent of 1 million homes⁵ per year. The SEIA finds that major corporations installed more solar capacity in 2016 than they did in 2015, and that 2013 was the year in which the most commercial solar was installed so far. The report suggests that the reduction in commercial solar installations from 2013 levels is due to “difficulties in obtaining financing for smaller commercial entities and state level policy instability” (SEIA, 2016). Commercial solar installations are concentrated on the East and West Coasts, near population centers, and are placed on all types of corporate buildings, from retail to manufacturing centers. Figure 1 provides an overview of aggregate solar installation capacities through 2015 on commercial properties across the United States. The figure indicates that the amount of solar capacity installed varies across states, both in terms of total installed capacity and population weighted capacity, which suggests that state-level factors are important in determining where companies

⁴ These data are either provided to SEIA by corporations and solar installation companies, or are also collected from public data such as press releases and state regulatory bodies. This dataset is comprised largely of major retailers and contains some of the larger commercial solar installations. Thus, these data likely overstate the average commercial solar system size.

⁵ Based on the SEIA conversion of 1,100 MW per 193,000 homes (SEIA, 2016).

install solar. For instance, West Virginia and Pennsylvania have similar insolation rates. Yet, the SEIA data show zero solar installations on commercial properties in West Virginia, but 25 Pennsylvania installations totaling 15,964 kW. The variability of PV installed capacity on commercial properties across US begs the question: why do firms choose to install solar in some states and not others?

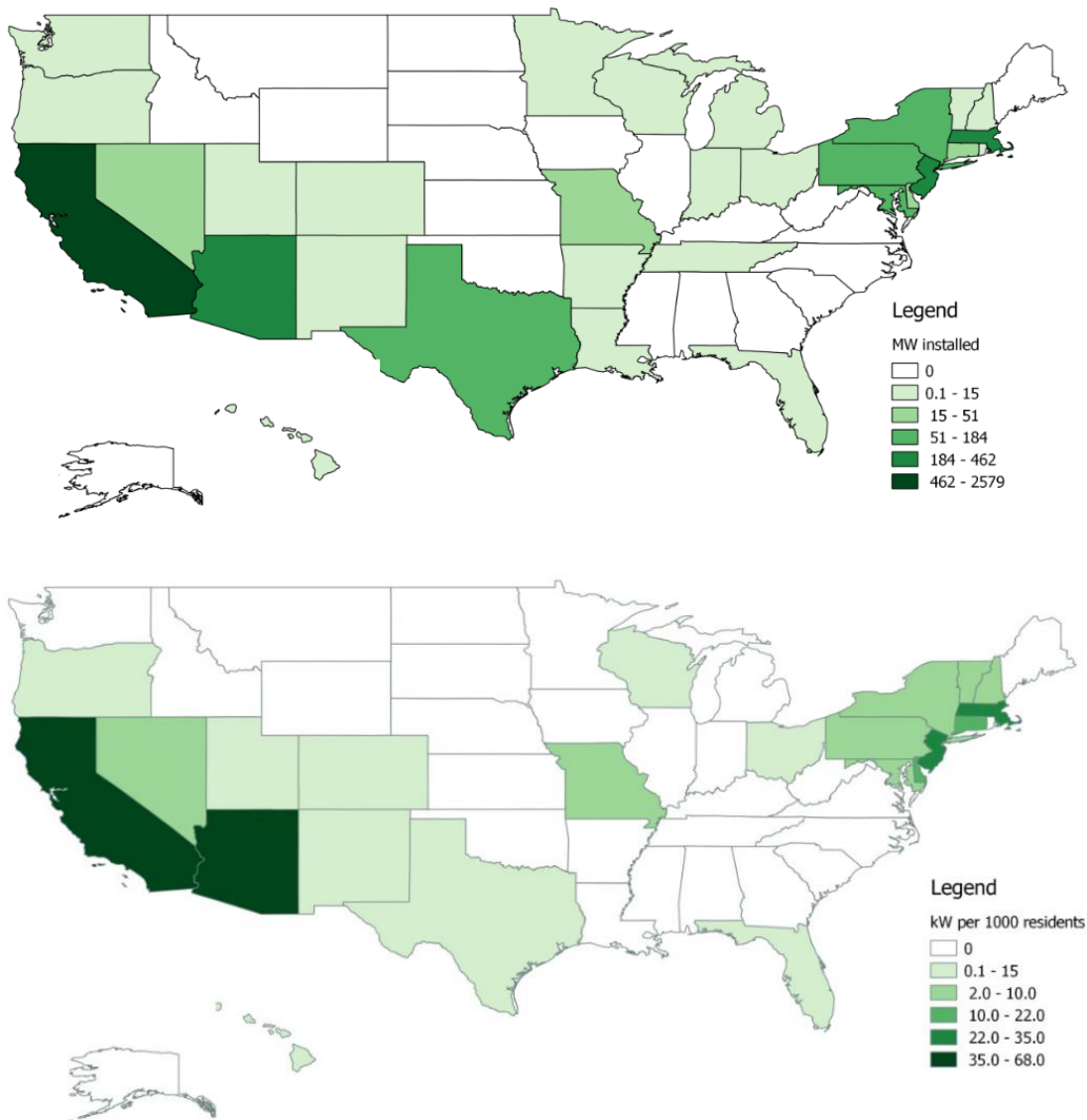


Figure 1: Commercial solar capacity installed 2002-2015, total and per capita (SEIA, 2016)

The objective of this paper is to shed light on this question through exploratory empirical analyses. Specifically, we are interested in state-level environments that may

encourage companies to install solar PV units on their properties. We use the SEIA dataset to examine the PV installation decisions of firms that have revealed a propensity to invest in solar energy generation on their facilities. All firms in our dataset have invested in at least one solar generation facility in at least one state. Therefore, the scope of the analysis in this study is limited to the firms who have shown interest in solar power and have revealed their willingness to invest in solar PV on the properties. We construct and estimate various statistical models that relate the decision to install solar across states and years to state-level characteristics and state policy variables.

Prior studies have examined the effects of various policies, incentive programs, and other factors on residential (Crago and Chernyakovskiy, 2016; Matisoff and Johnson, 2017) and cumulative (Sarzynski et al. 2012) adoption of solar technology in energy generation. However, the literature on installation of solar on commercial properties is sparse relative to the literature on residential adoption. The commercial solar energy adoption can be viewed in terms of two non-exclusive purposes. One is to install solar panels on commercial properties for the sake of direct financial benefits of installation in the form of energy cost savings and subsidies. The other purpose may be to install solar PV systems as part of public relations strategy aimed at enhancing firm's social responsibility image.

From the former camp, Bazen and Brown (2009) analyze the feasibility of installing solar panels on poultry farms in Tennessee. They compare the costs of an installation to the benefits of reduced power expenditure and any financial incentive programs that are in place. They find that in 2009 the net present value of investing in solar generation was negative, however if the price of solar fell by around 10%, then investing in solar became a financially feasible proposition. Current PV installation prices are nearly 50% lower⁶ than the 2009 prices that Bazen et al. (2009) used in their analysis, suggesting that the net present value of installing

⁶ Based on price data from the SEIA (2016).

solar on Tennessee poultry farms would now be positive at the 2009 price of electricity. Borchers et al. (2014) is the only work to explicitly consider the effects of state-level policies on the adoption of non-residential solar. The authors model the decision of farms to adopt renewable energy generation, either solar or wind, as a function of state-level variables including incentive policies, and farm characteristics. They find that the impact of state-level policies on the farm's adoption decision is limited, although net-metering and interconnection policies do have a small positive effect on the probability that a farm invests in renewable energy generation. A case-study from NREL (National Renewable Energy Laboratory) compares the solar financing decisions of two major commercial solar installers, IKEA and Staples (Feldman and Margolis, 2014). The report shows that depending on a firm's cash flow outlook and internal discount rates their preference in regard to owning their solar installation or using its power via a power purchase agreement (PPA) will vary. The report suggests that the existence of state policies that allow for PPAs might be an important factor affecting solar uptake rates. Beckman and Xiarchos (2013) draw attention to the importance of understanding the decision of the scale of adopted solar generation, as well as the decision to adopt versus not adopt. The authors investigate why some California farmers adopt larger solar arrays than others. They find that larger farms, in terms of total value of production and acreage, tend to install larger solar arrays. The prevailing price of electricity is not found to influence the scale of solar capacity installed. In contrast, the decision to adopt versus not adopt is affected by electricity price, internet connection on the farm, and environmental practices.

From the latter camp come studies of corporate renewable energy and energy saving initiatives in terms of corporate public relations strategies and brand marketing. Menon and Menon (1997) discusses how environmental initiatives can be melded with a profit-motivated business plan to create "enviropreneurial" strategies. These strategies can increase profits by marketing to environmentally conscious individuals, who continue to make up an increasing

share of the marketplace, while improving environmental outcomes. This is an example of profit-motivated social responsibility. In its purer form, corporate social responsibility is motivated by a desire to maintain good relations with the public and avoid legal issues, or by environmentalism intrinsic to the firm. Trendafilova et al. (2013) showed how these concerns have been translated into environmental action in the case of professional sports corporations. Perhaps the most notable example of this is the Philadelphia Eagles' stadium, which generates enough energy from a combination of solar panels and wind turbines to offset its annual energy consumption (Trendafilova et al. 2013). Hori et al. (2014) showed how community concerns and social norms have been translated into corporate energy savings initiatives in Asian developing nations. Thus, there is some evidence that profit-motivated social responsibility may encourage firms to invest in solar generation to appeal to an environmentally conscientious segment of their customer base.

This paper adds to this literature by being the first to model aggregate commercial solar adoption at the state-level, and the first to explicitly investigate the multi-state firm's decision of *where* to invest in solar technology, given that the firm is interested in making such an investment. A multi-state firm has the option of placing solar PV units in any state in which they operate. Our analysis empirically examines factors that influence the decision to choose one state over another. In particular, we are interested in the role of state policies and programs in comparison to state characteristics, such as population, insolation, and environmental attitudes of the citizenry.

The results of this analysis suggest that multi-state firms consider a variety of factors in their decisions to add solar panels to their properties in different states. Both types of factors discussed in the previous literature, financial incentives and public perception, are found to affect the choice of where to install. Some of these financial factors are within the control of the state, such as their choice to enact the solar policies described in the next section, while

other important factors are characteristics inherent to the state, such as insolation. Hence, states can attract more commercial solar investment with solar-friendly policies, but their expectations of policy efficacy should be tempered if inherent factors make the application of solar less desirable in their state. We find evidence that public perception/green marketing factors may play a role, whereby states with more 'environmentally-oriented' citizens, as measured by ownership of electric vehicles per capita, have a greater chance to have companies installing solar.

This study represents a first exploratory look into the complex problem of a firm's decision to adopt solar. The results are subject to reasonable caveats. Most notably, the sample of firms present in the SEIA sample data may exhibit self-selection bias, as these firms chose to publicly announce or otherwise report their solar adoption efforts. This data limitation is not surprising in the early stages of solar industry growth, and has appeared in prior literature. For example, Crago and Chernyakovskiy's (2016) study of residential solar adoption uses similar data. Another sample selection problem in our dataset is that we only focus on firms that have decided to install solar power in at least one state. In this respect, our results are to be interpreted within the context of installation decisions of those firms that have revealed interest in solar power. In other words, while the data shed light on why firms that have decided to install solar panels do so in some states rather than others, the data are of limited use for understanding why firms install or do not install solar panels in general.

2 State incentive programs

In addition to, and in accordance with, federal policies and programs, such as the clean power plan and PV production and investment tax credits, states have initiated various policies and programs to encourage renewable energy generation in general and solar energy generation in particular. The extent of implementation of such policies varies across states. Table 1 provides distribution of state level policies across states in 2015. In this study, we include these

state-level policies and programs as explanatory variables to examine firms' solar PV installation decisions.

Renewable portfolio standards (RPS) are one of the most prominent policies implemented by states, and have received the most attention in academic literature (e.g., Wisner et al. 2011; Yin and Powers 2010; Bhattacharya et al. 2017; Bowen and Lacombe, 2017). The specifics of RPS can differ across states in terms of the timing and the required proportion of electricity to be generated from renewable sources. State RPS programs can also be accompanied with “solar carve-out” specifications requiring certain proportions of electricity to be generated using solar energy specifically (Gaul and Carley, 2012; Sarzynski et al. 2012). RPS policies often lead to the creation of Renewable Energy Credits (Yin and Powers, 2010) and Solar Renewable Energy Credits (SREC) (Burns and Kang, 2012), whereby an entity can sell a certificate they obtain by producing electricity from renewable and solar energy sources respectively. The credits can be applied towards mandated RPS requirements by utility companies. Net metering is another policy enabling owners of distributed solar energy generating units to offset the costs of electricity consumed from the grid (Eid et al. 2014, Sarzynski et al. 2012). The specifics of net metering regulations can also differ across states.

States have also implemented various additional financial incentive policies to encourage solar energy generation. Feed-in-tariffs guarantee minimum compensation for each kWh produced using solar technology (Mabee et al. 2012). Tax incentives include: property tax incentives, which offer tax credits or exemptions for properties with installed solar technology; sales tax incentives, which reduce sales taxes associated with purchase and/or maintenance of solar technology; and tax credits and exemptions specifically for reducing corporate tax liability on state taxes (Sarzynski et al. 2012). Rebates are payments to entities that purchase solar technologies, while grants provide financial assistance for eligible purchasers of solar technologies.

States also set up rules and regulations intended to support solar energy adoption including: access rights, which protect the right to purchase, maintain and operate a solar generation facility (Caffrey, 2010), interconnection standards, which establish guidelines for integration of solar generation into the electricity grid (Krasko and Doris, 2013; Shrimali and Jenner, 2013), and Power Purchase Agreements (PPAs), which enable third party financing of in-state solar projects such that electricity generation using solar PV systems is not subject to regulation as a utility.

State	Net Meter	RPS	SREC	Feed in Tariff	Tax breaks	PACE or loan financing	Grant or rebate	Solar access	Interconnection standards	Power purchase agreement
Alabama	-	-	-	X	-	-	-	-	X	-
Alaska	X	-	-	-	-	X	X	-	X	-
Arizona	X	X	-	-	X	-	-	-	-	X
Arkansas	X	-	-	-	X	X	-	-	X	-
California	-	X	-	X	X	-	-	X	X	X
Colorado	X	X	-	-	X	X	X	-	X	X
Connecticut	-	X	X	-	X	X	-	-	X	X
D.C.	X	X	X	X	X	X	X	-	X	X
Delaware	X	X	X	X	-	-	X	X	X	X
Florida	X	-	-	-	X	-	X	-	X	-
Georgia	X	-	-	-	-	-	X	X	X	X
Hawaii	X	X	-	X	X	X	-	-	X	X
Idaho	-	-	-	-	X	-	X	-	-	-
Illinois	X	X	X	X	-	X	X	X	X	-
Indiana	X	X	-	X	X	-	-	X	X	-
Iowa	-	X	-	-	X	-	-	-	X	X
Kansas	X	X	-	-	X	-	-	-	X	-
Kentucky	X	-	-	-	X	-	X	X	X	-
Louisiana	X	-	-	-	X	X	-	-	X	-
Maine	-	X	-	-	-	X	-	X	X	-
Maryland	-	X	X	X	X	-	X	X	X	X
Massachusetts	X	X	X	X	X	X	X	-	X	-
Michigan	-	X	-	-	-	X	-	-	X	X
Minnesota	-	-	-	X	-	X	X	X	-	-
Mississippi	-	-	-	-	-	-	-	-	-	-
Missouri	X	X	-	-	X	X	X	X	X	-
Montana	-	X	-	-	X	X	-	-	-	-
N. Carolina	X	X	-	-	X	X	X	-	X	-
N. Dakota	-	X	-	-	X	-	-	X	-	-
Nebraska	X	-	-	-	X	-	-	-	X	-
Nevada	-	-	-	X	X	X	-	-	-	X
New Hampshire	-	X	-	-	X	X	X	-	-	X
New Jersey	-	-	X	X	X	X	X	X	-	X
New Mexico	X	X	-	-	X	X	X	-	X	X
New York	X	X	-	-	X	X	X	-	-	-
Ohio	X	X	X	X	X	X	X	-	X	X
Oklahoma	X	X	-	-	X	-	-	-	-	-
Oregon	-	X	-	-	X	-	X	-	-	X
Pennsylvania	X	X	X	X	-	-	-	-	X	X
Rhode Island	X	X	-	-	X	X	X	-	X	X
S. Carolina	X	X	-	-	X	X	X	-	X	-
S. Dakota	-	X	-	-	X	-	-	-	X	-
Tennessee	-	-	-	X	X	X	-	-	-	-
Texas	-	-	-	-	X	-	-	-	-	X
Utah	X	X	-	-	X	X	-	-	X	X
Vermont	-	X	-	X	X	X	X	-	-	-
Virginia	X	X	-	-	X	X	-	X	X	X
Washington	-	X	-	X	X	-	-	-	X	-
West Virginia	X	X	-	-	-	-	-	X	X	-
Wisconsin	-	X	-	-	X	-	-	-	X	-
Wyoming	X	-	-	-	-	-	X	-	X	-

Table 1: State-level solar policies in 2015 from DSIRE database

3 Data

Data on commercial solar installations come from the SEIA and include information on solar installations by major companies from 2002-2015. These data cover an estimated 16% of the total non-residential and non-utility scale solar installations in the U.S. (SEIA, 2016). After dropping incomplete observations, we are left with a dataset of 1,727 specific solar installations from 117 companies, which we dub the “full SEIA data.” We summarize these data with the total commercial solar capacity installed (kW), and the number of commercial solar installations in each state/year by the 117 firms in Figure 2 for the sample period 2002-2015. Commercial solar capacity and installations have a strong upward trend over time, likely due to improved PV technology, declining costs and favorable federal policies.

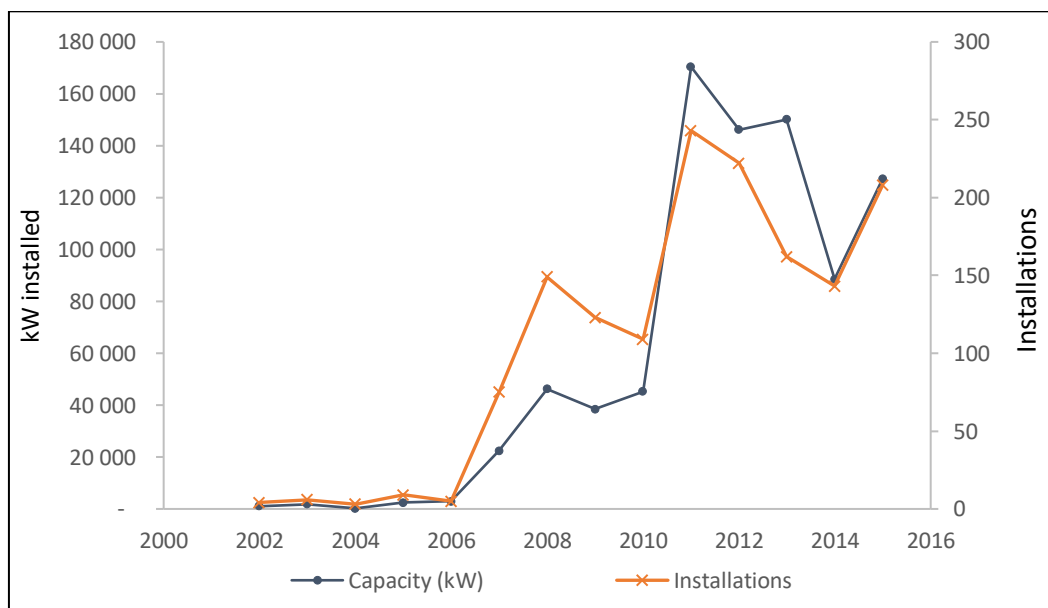


Figure 2: Commercial solar capacity installed and number of installs by year from full SEIA data

Our data on the state-level incentive and regulatory programs in each state come from the DSIRE database (Prasad and Munch, 2012; Shrimalli and Kneifel, 2011; Crago and Chernyakhovskiy, 2017; Li and Yi, 2014). This database is funded by US Department of Energy and maintained by North Carolina State University (NCSU, 2017). From this database, we extract indicator variables, which take the value of 1 if a given incentive/regulation was

present in a state in each year. Specifics of many of the policies and rules can, and do, differ across states (Burns and Kang, 2012; Byrne et al. 2007). For example, RPS targets and timing differ across states. We standardize the policy variables across states by only focusing on whether a form of a given policy or program is present in a given state-year or not. A similar approach was used in the related literature (Crago and Chernyakhovskiy, 2017; Li and Yi, 2014; Sarzynski et al., 2012). To account for the effect of policy stability and the effect of potential policy lags, where a change in policy would begin to have an effect sometime after the change in policy, we create and test variables that sum the number of years a policy has been in place in each state. The policy variables are summarized and described in Table 2, with the indicator variables being named after the policy they represent. Corresponding cumulative variables have a “sum” added to the name of the indicator variable. For example, Arizona’s net metering policy began in 2009, so the variable *net metering* takes a value of 1 in Arizona in years 2009-2015. The corresponding cumulative variable *net metering sum* takes a value of 1 in 2009, a value of 2 in 2010, 3 in 2011, etc. Inclusion of both *net metering* and *net metering sum* in our regression models allows us to ascertain the effect of a net metering policy, in general, and the additional effect of having a net metering policy in place for an extra year.⁷

To augment the policy information taken from DSIRE we also obtain other state level characteristics that may influence the level of commercial solar installation in each state. We generate *electricity sales* using data in each state/year from the U.S. Energy Information Administration (EIA) “sales to ultimate consumers,” “total electricity industry” dataset. This variable controls for the effect of total electricity consumption as well as population, which can reasonably be expected to be correlated with electricity consumption. Larger electricity markets may imply more ‘space’ for new solar generation capacity. We also include per capita

⁷ The DSIRE database also contains some information on the level of incentive policies, for instance, how much is paid-out for state rebate programs. However, these data are not given for every incentive program, and are recorded in varied units, which makes it difficult to include them in our statistical models.

coal mining (*coal per capita*) in each state/year. This variable was generated using EIA’s “Aggregate coal mine production for all coal types” dataset, scaled by the U.S. Census annual population estimates for each state. The coal mining variable is expected to be correlated with general attitudes toward renewables, as it is plausible that states that rely on coal based revenues may be less sympathetic to solar energy. We control for state sales average tax rates (*sales tax*) as this could be a policy tool for states to influence solar and energy markets. Higher sales tax rates could increase the cost of installing solar panels and could also increase end-user electricity rates via taxes on electricity sales, making the expected effect of sales tax on commercial solar adoption unclear. *Electricity price* is obtained from the EIA “Average price, total electricity industry” dataset, and is averaged across all sectors. Generally, higher electricity price can be expected to have a positive effect on solar installation as this would increase the savings on forgone electricity purchases.

Variable	Description	Mean	Std. Dev.	Min	Max
<i>GDP per capita</i>	Gross domestic product per capita (1000's of 2009 USD)	48.66	18.21	29.06	170.69
<i>electricity sales</i>	electricity sales to customers in TWh	71.96	67.99	5.35	392.34
<i>sales tax</i>	average sales tax in percent	4.95	1.9	0	8.25
<i>electricity price</i>	average electricity price (cents/kwh)	9.39	3.65	4.26	34.04
<i>insolation</i>	average annual solar insolation (kWh/m ² /day)	4.62	1.04	2.47	7.65
<i>insolation sd</i>	std. dev. of average annual solar insolation	0.98	0.49	0.4	2.22
<i>deregulated</i>	=1 if the state has a deregulated electricity market	0.33	0.47	0	1
<i>coal per capita</i>	aggregate coal mine production per capita (short tons)	19.65	105.83	0	856.42
<i>PEVs per capita</i>	personal electric vehicles per 1000 inhabitants in 2015	0.77	0.81	0.09	4.68
<i>net metering</i>	presence of net metering per state/year, 1=yes	0.42	0.49	0	1
<i>RPS</i>	presence of renewable portfolio standard per state/year, 1=yes	0.51	0.5	0	1
<i>SREC</i>	presence of SREC per state/year, 1=yes	0.11	0.31	0	1
<i>feed-in-tariff</i>	presence of feed-in-tariff per state/year, 1=yes	0.2	0.4	0	1
<i>tax breaks</i>	corporate, sales, or property tax breaks for solar purchasers	0.65	0.48	0	1
<i>financing</i>	PACE or loan financing program availability per state/year, 1=yes	0.35	0.48	0	1
<i>rebates</i>	grant or rebate program availability per state/year, 1=yes	0.34	0.48	0	1
<i>access</i>	solar access policy presence per state/year, 1=yes	0.22	0.42	0	1
<i>interconnection</i>	presence of interconnection standard per state/year, 1=yes	0.51	0.5	0	1
<i>PPA</i>	presence of PPAs per state/year, 1=yes	0.17	0.38	0	1
<i>capacity</i>	total commercial solar capacity installed per state/year (kW)	1181.14	6010.32	0	80597
<i>installations</i>	total number of commercial solar PV installations per state/year	2.05	8.93	0	112

Table 2: Variable descriptions and summary statistics

Following Crago et al. (2017) we use prevalence of personal electric vehicles (*PEVs per capita*) across states in 2015 as a proxy for the environmentalist sentiment.⁸ We also account for the average annual solar intensity in each state (*insolation*) based on NREL “Concentrating Solar Power” database for the year 2012. We account for month-to-month variation of solar intensity in each state using standard deviation of insolation (*insolation sd*). These variables do not vary within each state over the sample period. The explanatory variables used in the statistical model are summarized and described in Table 2.

Combining the data listed above we generate panel datasets in various forms. The specific form and included observations in each dataset depend on the specific research question being addressed. These research questions and the corresponding analyses are presented next.

4 Empirical Methods

The goal of this study is to investigate the reasons why some states have more investment in commercial solar PV projects than others. We proceed with a two pronged approach to analyze solar energy installations by large firms. First we examine total state level installed capacity and the number of solar installation projects. Next we examine the firm level decisions of where and when to invest in solar energy generation across states. In all models, we account for state policies using indicator variables that take the value of 1 if a given incentive or regulation is present in a state in each year. We also test variables that capture the number of years that a policy or regulation has been in place in each state. This second group of variables allows for temporal dynamics in the effect of policies on solar adoption. The longer a policy is in place, the more confident the investors may be in the state’s supporting environment with respect to investments in solar energy. It could also be possible that the

⁸ Data from the energy.gov fact #936 dataset <https://energy.gov/eere/vehicles/fact-936-august-1-2016-california-had-highest-concentration-plug-vehicles-relative>

existence and the benefits of particular policies may take time to be recognized by decision makers potentially interested in solar PV installations. Conversely, the effectiveness of policies that create price supports for solar investment, such as RPS with solar carve-outs and the subsequent SREC markets, might fade as SREC prices are shown generally to decrease and exhibit volatility over time (Lee et al. 2017). All models contain year fixed effects to account for the trend of increasing solar capacity installed over the sample period, which is likely driven by changes in federal policy and the falling price of solar technology.

4.1 State level analysis of commercial solar investment

Our first objective is to investigate the factors that determine the overall state level commercial solar investment in our sample of large firms. This sheds light on why some states have more solar installed than others. The goal is to identify and compare the effects of state-level characteristics and policies on solar PV installations by commercial entities. The SEIA data are summed over firms in each state and year to generate state level annual *capacity* and *installations*, which contain total capacity (kW) and the number of commercial solar installations by state and year, respectively. Summary statistics for these dependent variables are provided in Table 2.

We use a two-part model (TPM) to examine state level commercial solar capacity installed (Belotti et al., 2015) because we have a high proportion of observations where the dependent variable, *capacity*, is equal to zero. We specify our TPM with the first stage as a logit model that predicts the probability of an observation being greater than zero given a set of explanatory variables (x), and the second stage as an OLS regression that predicts the level of the outcome (y), kW of commercial solar installed, given that the outcome is greater than zero. The intuition for this specification is that the distributions reflecting decisions to invest

in PV or not, and the decisions about how much to install could be determined by different data generating processes. The overall expectation of our outcome is given as follows.

$$E(y|x) = \Pr(y > 0|x) \cdot E(y|y > 0, x)$$

Next, we model the number of commercial *installations* in each state and year as a function of state-level variables. As this dependent variable contains only integers restricted to the non-negative domain, it is preferable to use count data analysis techniques (Cameron and Trivedi, 1998). Because the dependent variable contains a large number of zero values we consider zero-inflated Poisson (ZIP) models to account for the large number of zero observations. We test for the necessity of ZIP models over standard Poisson models using the Vuong test, and find that ZIP models are preferred (Vuong, 1989). These models are also estimated using year fixed effects specifications.

Additionally, there is some concern with overdispersion of the dependent variable *installations*, as the standard deviation is over four times greater than the mean. In a Poisson distribution the standard deviation and mean are assumed to be equal, which is only partially corrected by the ZIP. To investigate this issue we also test zero-inflated negative binomial (ZINB) models of the *installations* variable, with results shown in Table 7 in the Appendix. Two considerations lead us to present ZIP model results in the main text. The first is that the maximum likelihood estimator of the ZINB does not converge when the policy ‘sum’ variables are added to the regression. Secondly, predicted values of *installations* from ZINB appear to be inferior to those from ZIP, with exaggerated mean and standard deviation, and broader support than the true values, as shown in Table 8 in the Appendix. For the purpose of inference the ZIP and ZINB models give similar results.

4.2 Firm level analysis of the probability to invest in solar PV panels

Our next objective is to examine the determinants of where and when a company planning a solar investment chooses to invest in a solar facility. This research question and approach is distinct from that commonly applied to solar adoption literature both at the commercial level (e.g. Borchers et al. 2014; Beckman and Xiarchos, 2013) and at the residential level (e.g. Krasko and Doris, 2013; Crago and Chernyakhovskiy, 2017), which ask *why* certain agents adopt solar and others do not. Instead, we investigate the choice of *where* and *when* do adopters invest in PV systems.

We define our dependent variable, *invest*, to be 1 if a specific company invested in solar in a given state/year, and 0 otherwise. With this dependent variable, we model the probability that a firm chooses to invest in solar in a specific state and year. This analysis assumes that the multistate firm that plans to make a solar investment has different potential locations where this investment can be made. The firm then chooses the location and timing of the solar investment. We hypothesize that state characteristics, such as solar-related policies and energy market factors, play a role in firms choosing where to install.

Two subsamples are used in this analysis. The first estimation sample is a balanced panel where each company has observations for each state and year in the sample period (2002-2015), giving 714 observations per company and a total observation count of 22,848. In this sample we know whether a company installed solar in a given state and year. However, although we have limited the analysis to large companies, we cannot assert with certainty whether each zero represents the decision not to install or it represents absence of the company from a given state during a given year. To further address this challenge, we define a second “trimmed” estimation sample, which only contains observations where we can be reasonably sure that a specific company is present in each state. Specifically, in the trimmed sample we keep all annual observations for a given state and company combination if the company installed any solar in that state throughout the sample period, or if we can verify that the

company operates in that state via publicly available information⁹. Thus, assuming a company that was present in a state at one time from 2002-2015 was present in that state throughout the sample, we can interpret the results in terms of the decision of a company to install or not install solar in each state and year. The trimmed estimation sample results in an unbalanced panel with 6,020 state- company- year observations and consists of 32 large companies that have installed at least five PV systems in different states¹⁰. The purpose of limiting companies included in the data is to mitigate some of the complications that can arise from the regional concentration of firms, and to increase the variation in our dependent variable, which allows us to identify the parameters of the model, by excluding relatively minor and regionally concentrated firms¹¹.

Since our dependent variable, *invest*, is binary we can employ the probit model, whereby the explanatory variables are related to the probability of a company installing a PV system in each state and year. We include fixed effects terms at the company level, as well as year fixed effects, to control for the differences across years and companies, such as size, wealth level and affinity for solar investment. Thus, the probability that a given company invests in a specific state/year is a function of the characteristics of that state in each year, as defined by our explanatory variables shown in Table 2, and a company-specific intercept.

5 Results

⁹ From firm websites and internet searches.

¹⁰ We do not list the companies in this sample due to privacy concerns, but they are all large corporations who operate in multiple states.

¹¹ Inclusion of regional or local companies can introduce a bias into the firm level model of the decision to invest in solar because observations with no solar installations can be due to absence of the company from a given state rather than due to the decision not to invest in solar PV units. For this reason, we narrow our firm level analysis to the sample of large firms. Still, in the estimation sample just 1.56% (357 of 22,848) of the observations take a value of one for the dependent variable. Nevertheless, many of our parameter estimates exhibit statistical significance, suggesting that the low level of variation in the dependent variable is not a major cause for concern.

Table 3 provides the results from state level analysis using the two-part estimation approach and ZIP models, both with year fixed effects. The results are provided in terms of marginal effects, which relate the change in $E(y/x)$ in response to a change in the explanatory variable. Thus, the marginal effect estimates for the TPM and ZIP are a combination of the estimates from the first and second stages of the two-part model. The results from the TPM models of *capacity* indicate that the states with greater numbers of personal electric vehicles and states with longer history of PACE and/or other subsidized financing programs and tax breaks supporting commercial PV projects have a greater capacity of solar energy installed by companies. Policies and regulations, like RPS, net metering, etc., do not seem to affect the capacity of solar energy installed by companies on their properties. Generally, the results from the TPM specification provide a limited number of significant independent variables and have low model fit relative to the ZIP specifications as shown by the 2nd stage adj. R-squared and AIC statistics. This could be due to a high level of idiosyncrasy in the dependent variable *capacity*. Table 2 shows that the *capacity* dependent variable exhibits high levels of dispersion. Thus, we generally prefer the findings from the count data and binary dependent variable models discussed below.

For the count data analysis with dependent variable *installations*, presented in Table 3, we reject the null hypothesis of no zero inflation with a z-statistic of 4.5 and a p-value of 0.001 based on the Young (1989) test. Thus, the ZIP model is preferred over a Poisson. The specifications with *installations* as the dependent variable identify noticeably more statistically significant determinants of solar energy adoption by commercial entities, than do the TPMs. This may suggest that state-level policies and characteristics have a stronger effect on the firm's decision to install vs. not install or how many solar units to install in each state, than on the decision of how much solar capacity to install. Beckman and Xiarchos (2013) found a similar

result in their study of California farms and note the systematic differences between the decision to install solar, and the decision of how much capacity to install.

The results in Table 3 are presented in terms of marginal effects, which relate the expected increase in the annual number of commercial solar installations in a state, in response to changes in the respective explanatory variables. The policies of solar renewable energy credits, subsidized financing programs, and tax incentives are shown to be positively correlated with the number of commercial solar installation projects within the state. State characteristics like insolation, ownership of electric vehicles, and electricity sales are also positively correlated with the number of commercial solar energy projects.

Variable	dep. var. is <i>installations</i>				dep. var. is <i>capacity</i>			
	Marg. Eff.	Std. Err.	Marg. Eff.	Std. Err.	Marg. Eff.	Std. Err.	Marg. Eff.	Std. Err.
<i>GDP per capita</i>	0.041	(0.0542)	0.052	(0.0339)	-0.461	(39.94)	13.37	(30.22)
<i>electricity sales</i>	0.013**	(0.00589)	0.014**	(0.00547)	-2.063	(3.888)	-1.910	(4.340)
<i>sales tax</i>	-0.009	(0.190)	-0.110	(0.278)	336.2***	(110.4)	297.5*	(157.1)
<i>electricity price</i>	0.0871	(0.0954)	0.123	(0.0889)	-157.0*	(90.99)	-102.7	(88.64)
<i>insolation</i>	0.884**	(0.433)	1.391*	(0.802)	276.6	(313.8)	665.7	(548.6)
<i>insolation sd</i>	1.216	(0.930)	1.683*	(0.864)	-1172.8	(942.2)	-642.7	(731.7)
<i>deregulated</i>	-0.434	(1.034)	0.176	(1.785)	591.3	(1012.9)	769.5	(1480.8)
<i>coal per capita</i>	-0.0536	(0.114)	-0.153	(0.1000)	11.96	(35.90)	-24.91	(46.73)
<i>PEVs per capita</i>	1.315***	(0.470)	1.003	(0.680)	1838.6***	(595.9)	1515.6***	(504.6)
<i>net metering</i>	0.505	(0.650)	0.933	(1.081)	-318.7	(512.9)	-1144.0	(1338.1)
<i>RPS</i>	-0.191	(0.672)	-1.348	(1.146)	-48.35	(639.8)	-140.8	(640.0)
<i>SREC</i>	5.612***	(1.430)	3.556*	(1.862)	747.8	(701.2)	-937.2	(933.0)
<i>feed-in-tariff</i>	-0.600	(0.806)	0.455	(1.547)	867.0	(551.6)	649.4	(626.4)
<i>tax breaks</i>	1.803**	(0.768)	1.394	(1.092)	585.1	(589.8)	-153.4	(512.3)
<i>financing</i>	1.312*	(0.750)	0.386	(0.853)	769.8**	(355.4)	-270.3	(620.6)
<i>rebates</i>	0.191	(0.945)	-0.460	(1.075)	533.6	(464.2)	831.1	(732.2)
<i>access</i>	0.306	(0.613)	-0.106	(2.178)	-434.0	(689.0)	-1277.0	(1474.9)
<i>interconnection</i>	-1.805**	(0.737)	-0.881	(1.657)	-1938.0***	(532.5)	-1222.0	(1240.1)
<i>PPA</i>	0.269	(0.800)	0.322	(1.399)	-791.5	(942.4)	-1372.7	(1388.1)
<i>net metering sum</i>			-0.014	(0.146)			112.2	(140.7)
<i>RPS sum</i>			0.092	(0.145)			-27.55	(64.16)
<i>SREC sum</i>			0.439	(0.665)			168.1	(184.1)
<i>feed-in-tariff sum</i>			-0.214	(0.288)			119.4	(136.1)
<i>tax breaks sum</i>			0.186**	(0.0941)			127.4*	(65.00)
<i>financing sum</i>			0.248**	(0.0992)			192.5**	(90.21)
<i>rebates sum</i>			0.094	(0.136)			8.442	(91.69)
<i>access sum</i>			0.107	(0.247)			114.4	(125.2)
<i>interconnection sum</i>			0.053	(0.169)			26.74	(122.1)
<i>PPA sum</i>			0.054	(0.442)			-35.43	(146.2)
N		714		714		714		714
1st stage pseudo R-sq						0.46		0.49
2nd stage Adj. R-sq		0.57		0.58		0.28		0.30
Akaike IC		1688		1615		3795		3783

Table 3. Zero-inflated Poisson and two part model results, respectively, for annual state level solar capacity installed (kW) and number of installation projects (* p<0.1, ** p<0.05, *** p<0.01; all models contain year fixed effects)

Table 4 presents the marginal effects estimates from probit models with the binary dependent variable indicating whether a specific company installed PV panels in each state and year. The marginal effects relate the change in the probability that a company will install solar in a state and year in response to a change in the respective explanatory variable. The model is estimated using two different subsamples. Using the “full sample” of 22,848 observations, marginal effects can be interpreted in terms of the effect on the probability that a company is present in the state *and* chooses to invest in solar in the state. The intermingled nature of this interpretation does not allow for strong statements regarding the quantitative results pertaining

to the propensity to invest in solar without implied assumptions about presence. The estimation using the “trimmed” sample addresses this issue by limiting the analysis only to the state-company combinations where we can be reasonably sure that the company is present in the given state.¹² It is reassuring that generally the results from the full sample and from the trimmed sample are consistent, though with larger magnitudes of marginal effects for the trimmed sample estimation. Using both samples, we observe the signs and significance of the marginal effect estimates to be consistent with prior expectations. GDP per capita has a negative effect, possibly as a reflection of higher wages and costs of installation. Electricity price has a positive effect, which suggests that the economic benefits from installing solar panels in terms of savings from the electricity bills matter. Insolation, deregulated electricity markets, number of personal electric vehicles, and net metering also have positive effects on the probability that a company installs PV panels in a given state. The existence of SREC markets, financing programs, and tax breaks also increase the probability that a company installs solar in a state. The efficacy of these programs in drawing commercial solar investment are shown to improve as they remain in place over time, likely reflecting the positive effects of policy stability over time.

¹² It is important to recognize that while this approach tries to address the problem of zeros due to absence of some of the companies from some of the states, the approach is not a perfect solution. Some of the zeros in this estimation may be still due to lack of available facilities in a given state rather than lack of willingness to invest in solar panels. For example, if a company has only 2 facilities in a state and installed solar PV in both of those facilities in some year(s), then zeros observed in other years are not due to lack of willingness to invest in solar. Nevertheless, given lack of available data on the number of facilities per state over time for each company, this approach represents the best feasible alternative for the company level analyses.

Variable	Trimmed Sample				Full sample of 32 large firms			
	Marg. Eff.	Std. Err.	Marg. Eff.	Std. Err.	Marg. Eff.	Std. Err.	Marg. Eff.	Std. Err.
<i>GDP per capita</i> (10^{-3})	-0.626*	(0.328)	-0.398	(0.327)	-0.269**	(0.111)	-0.187	(0.115)
<i>electricity sales</i> (10^{-3})	0.045	(0.045)	0.058	(0.055)	0.008	(0.023)	0.0170	(0.0233)
<i>sales tax</i>	0.003	(0.002)	0.003	(0.003)	0.002**	(0.001)	0.001	(0.001)
<i>electricity price</i>	0.002	(0.001)	0.003**	(0.001)	0.0005	(0.0004)	0.0008**	(0.0004)
<i>insolation</i>	0.016**	(0.007)	0.018**	(0.007)	0.006**	(0.002)	0.006***	(0.002)
<i>insolation sd</i>	-0.013	(0.013)	0.002	(0.012)	-0.003	(0.005)	0.002	(0.005)
<i>deregulated</i>	0.044**	(0.019)	0.044**	(0.021)	0.021***	(0.007)	0.019***	(0.007)
<i>coal per capita</i> (10^{-3})	-0.681	(0.667)	-1.06	(0.823)	-0.072	(0.177)	-0.262	(0.264)
<i>PEVs per capita</i>	0.031***	(0.008)	0.026***	(0.008)	0.014***	(0.003)	0.011***	(0.003)
<i>net metering</i>	0.015	(0.012)	0.025	(0.018)	0.007*	(0.004)	0.011**	(0.006)
<i>RPS</i>	-0.009	(0.009)	-0.017	(0.019)	-0.006*	(0.003)	-0.001	(0.007)
<i>SREC</i>	0.040***	(0.010)	0.010	(0.022)	0.021***	(0.004)	0.007	(0.008)
<i>feed-in-tariff</i>	-0.015	(0.009)	0.024*	(0.014)	-0.008**	(0.003)	0.003	(0.004)
<i>tax breaks</i>	0.003	(0.012)	-0.013	(0.013)	0.006	(0.004)	-0.001	(0.005)
<i>financing</i>	0.027***	(0.010)	0.015	(0.012)	0.009**	(0.004)	0.005	(0.004)
<i>rebates</i>	0.009	(0.0128)	0.006	(0.016)	0.004	(0.004)	0.002	(0.005)
<i>access</i>	-0.0003	(0.008)	-0.007	(0.016)	0.004	(0.003)	0.001	(0.005)
<i>interconnection</i>	-0.027**	(0.013)	-0.025	(0.019)	-0.013***	(0.004)	-0.011*	(0.006)
<i>PPA</i>	-0.007	(0.016)	-0.019	(0.0212)	-0.001	(0.004)	-0.007	(0.006)
<i>net metering sum</i>			-0.001	(0.00215)			-0.0004	(0.001)
<i>RPS sum</i>			-0.0003	(0.00180)			0.0001	(0.001)
<i>SREC sum</i>			0.006	(0.00461)			0.003**	(0.001)
<i>feed-in-tariff sum</i>			-0.007**	(0.00356)			-0.002**	(0.001)
<i>tax breaks sum</i>			0.004***	(0.00132)			0.001**	(0.001)
<i>financing sum</i>			0.002	(0.00175)			0.001*	(0.001)
<i>rebates sum</i> (10^{-3})			-0.052	(2.21)			0.111	(0.716)
<i>access sum</i>			0.002	(0.002)			0.0006	(0.001)
<i>interconnection sum</i>			0.003	(0.002)			0.0006	(0.001)
<i>PPA sum</i>			0.002	(0.005)			0.001	(0.001)
N		6,020		6,020		22,848		22,848
Pseudo R-sq		0.32		0.33		0.36		0.36

Table 4. Probit results for company level analysis of solar PV installation decisions: dependent variable is invest which is 1 if the company installed solar in a given state and year and 0 otherwise (* p<0.1, ** p<0.05, *** p<0.01; all models contain company and year fixed effects; (10^{-3}) denotes the estimates were scaled up to erase leading zeros

5.1 Robustness Checks

To examine the robustness of the results in Tables 3 and 4, we also examine corresponding linear functional specifications that include state specific fixed effects and examine possible endogeneity of electric vehicle ownership. State specific fixed effects were excluded from the models in Tables 3 and 4 because a) some of the variables of interest, solar insolation and electric vehicle ownership, don't vary over time within states, and b) model convergence could not be attained due to low temporal variability in many of the remaining regressors. Tables 5 and 6, in the Appendix, provide results from linear models that include

state and year fixed effects along with the regressors that vary over time within states. The results in Table 5 appear to be inferior to the results in Table 3, as there are very few estimates that are statistically significant, as is expected with low intrastate temporal variability. The only variable with a consistent sign throughout Table 5 is sales tax, which shows a positive relationship with commercial solar adoption. Although state fixed effects provide additional controls for omitted variable bias in these models, the disadvantage of linear models is their treatment of zero and non-zero observations, which can lead to biased estimates due to misspecification.

Table 6 shows the results from linear probability models with year, firm and state fixed effects and the binary dependent variable indicating whether a specific company installed solar PV panels in each state and year. These results are generally consistent with those shown from the probit specification in Table 4, though some differences are noted. Importantly, as the linear probability model contains state fixed effects, the results are driven by intra-state variation in explanatory variables over time, leading to a different interpretation than the results in Table 4. Specifically, as states see increases in sales tax rates, the size of their electricity market, and electricity price the probability of a corporate solar installation increases; results that were not as robust in the probit specifications. The model concurs with the probit specification in that SRECs, tax breaks, subsidized financing and net metering laws are positively associated with corporate solar adoption. We also note that in both models, probit (Table 4) and linear (Table 6), of the firm-level data the marginal effects from the trimmed sample of observations are systematically larger than the marginal effects from the full sample. This suggests the possibility of attenuation bias, whereby the effect of explanatory variables is diluted when the full sample is used and the ‘unknown firm location’ problem enters the data as random noise. This possibility further motivates the use of the trimmed sample.

There is some concern that electric vehicle ownership could be endogenously determined with solar investment, as some state level policies may incentivize both types of ‘green’ purchases. To address this issue, we rely on an instrumental variable (IV) technique, instrumenting electric vehicle ownership with average automobile gas prices in each state in 2015¹³. We use two stage least squares models for number and capacity of installations at the state level, and for probability of installation at company-state level. We complete Wu-Hausman tests of exogeneity for personal electric vehicle ownership in the state level models of number and capacity of installations. The tests cannot reject the null that electric car ownership is exogenous to the dependent variables with p-values of 0.95 and 0.45, respectively, suggesting that endogeneity is not a concern. With the IV-probit models we calculate Wald tests for exogeneity, which again show that personal electric car ownership is likely exogenous, failing to reject the null of exogeneity with a p-value of 0.33 for the trimmed sample and 0.22 for the full sample of firms. Thus, we interpret our results with respect to the personal electric car ownership as robust to endogeneity concerns.

6 Discussion and Conclusions

Previous research has shown that a variety of factors may influence solar adoption, though most of this research focuses on household adoption decisions, as discussed in the introduction. Herein, we complete the first national analysis of commercial solar adoption as a function of state-level policies. We interpret results with care, keeping in mind that commercial entities’ decisions to invest in solar may be very different than household investment decisions, and subject to the caveats in Section 6.1.

Similar to Crago and Chernyakhovskiy (2017), we observe that across various specifications and samples insolation has a positive effect on solar PV panel installation. We

¹³ Average gas prices in each state are available from the U.S. EIA as the “MGACD” time series. Adjusted R-squared statistics of the first-stage regressions are around 0.64, suggesting this instrument for *PEVs* has reasonable explanatory power.

also observe that electricity price has a positive effect on a firm's decision to install a solar PV system in a particular state. These results are expected as firms install solar panels in locations where the most solar energy can be generated, and the most savings can be realized from avoided electricity expenditures.

The effectiveness of policies in terms of attracting solar energy installation varies. We find that RPS do not have a significant effect on solar energy installation by companies. This result differs from Menz and Vachon (2006), who find a significant effect of RPS on renewable energy generation including wind, from Shrimali and Kniefel (2011), who find positive effect of RPS on solar energy generation, and from Li and Yi (2014), who find that RPS have a significant positive effect on solar PV installation in cities. This might be due to systematic differences between the adoption decisions of large commercial businesses and those of other market actors. Our results are consistent with the argument that RPS have the largest effects on low cost renewable generators such as wind rather than distributed solar generation (Matisoff and Johnson 2017). However, the addition of a solar carve-out and SREC market to RPS has a positive effect on the annual number of commercial solar installations and on the probability that a firm will invest in a PV system in a state. This result is consistent with the findings of Sarzynski et al. (2012) and Shrimali and Jenner (2013) in terms of the importance of cash incentives for adoption of solar PV panels. Furthermore, our results show that SREC markets may have stronger positive effects on solar installations the longer they remain in place, perhaps due to market stability and greater trust from firms that they will be able to sell SRECs over the lifetime of their solar installations. Subsidized financing programs and tax incentives are shown to have a positive effect on solar installation in states with these programs.

With respect to market regulations related to solar installations, we find some evidence that net metering policies increase the probability a company will install within a state. However, these results are not as strong as one might expect, and appear to contradict those

found by Krasko and Doris (2013). One explanation for our result may be that incentives of commercial entities adopting solar generation may differ from incentives of non-commercial adopters, such as residential units and utilities. Residential solar energy adopters mostly sell energy back to the grid during the day when domestic consumption of electricity is low and generation is high. In contrast, commercial adopters tend to use electricity during the day. As a result, relatively smaller amounts of electricity may be sent back to the grid making net metering less significant for the companies' decision to install solar. We also find that deregulation of the electricity market has a positive effect on the decision to install solar in a state. Although power purchase agreements (PPAs) are not found to be statistically significant in this analysis, third party ownership under deregulated electricity generation system may be the explanation for the observed positive correlation between deregulation and solar energy choices of firms. Deregulation in most cases enables third party ownership, which may facilitate solar panel installation (Overholm, 2015; Drury 2012). We find no evidence that higher sales tax rates deter commercial solar investment, and even find some indication that these quantities are positively correlated. Possible explanations for this are that large firms are not paying standard state sales tax on solar units, either through out-of-state purchase orders or official tax incentives as captured in our *tax breaks* variable. Furthermore, higher sales tax implies higher expenditures for electricity purchased from conventional utilities when firms pay taxes on electricity purchases. In this respect, higher sales tax may encourage firms to install solar. The other solar market regulations tested, interconnection standards and solar access rights, are not shown to have a positive effect on commercial solar adoption.

Overall, we find evidence that companies are motivated by financial incentives in their decisions to install solar generation units. Expected return-on-investment from a solar array is an important consideration for a firm when choosing where to install solar. However, grant and rebate programs appear to have limited effects on corporate solar installations, similar to the

findings of Li and Yi (2014). In contrast, SREC programs, subsidized financing, tax incentives, insolation levels, and electricity price are shown to have positive effects on commercial solar adoption and are factors that will influence the bottom-line of a solar investment's cash flow. The strongest of these factors is SREC markets, which are estimated to increase the number of commercial installations by 4-6 per year. States with SREC markets also have an estimated 3.9%¹⁴ higher probability of being chosen as the solar installation site among firms with competing sites across states. Comparatively, a one unit increase in average insolation (kWh/m²/day) leads to about one more commercial installation annually, and a ~1.5% increase in choosing one state over another. As an example, Arizona, a 'sunny' state, has an insolation of 7.6 on average, and New Hampshire has an insolation of 3.7. This difference in insolation results in an estimated four more commercial installations per year and a 6% higher probability of a firm choosing Arizona as an installation site over New Hampshire. This natural difference in insolation between these states is on par with the entire effect of an SREC program being implemented, illustrating the fact that while state solar policies matter, natural characteristics of the state and its electricity market are of equal, if not greater, importance.

The results across all specifications suggest that the per capita number of personal electric vehicles in a state is positively correlated with the probability that firms install solar energy generation units in their facilities within the state. One possible explanation may be that electric vehicle ownership and solar PV installation by companies may be supported by common renewable energy oriented policies or state characteristics. However, our instrumental variables approach finds no evidence of endogeneity for electric vehicle ownership in our analysis. The other possibility is that electric vehicle ownership may reflect environmental attitudes of state populations. This interpretation suggests that firms may be interested in public perception of renewables in the locations where they invest in solar. Installation of solar energy

¹⁴ Figure comes from the trimmed sample probit model in Table 4.

generation units can be part of the firms' corporate social responsibility campaigns targeting an environmentally conscientious customer base. The robustness of this variable's statistical significance across different specifications suggests that environmental/green marketing oriented motives may be a significant factor in firms' decisions to install solar energy systems on their properties.

6.1 Caveats

This study uses a sample of multi-state companies that have adopted solar in at least a few states. One can generalize the results to the companies that are not included in our sample by making the reasonable assumption that the decision-making process as to where to generate solar power is similar across multi-state companies. Some firms may not yet have considered investing in solar, or may have decided against it in the near-term and are thus not in our sample dataset. However, if and when these firms decide to invest in solar they will face a similar decision problem as to *where* to put their solar capacity. Similar to the firms included in our sample, multistate firms interested in solar panels in the future will need to evaluate opportunities across different states with different policies and characteristics. Thus, subject to the caveats associated with this assumption, the results in this study may be relevant to a larger subset of firms than those that appear in our sample.

The results in this analysis are an exploratory first look at the firm-level solar investment decision across U.S. states, and should be interpreted with care considering the limitations inherent in the nature of the data. Only 16% of non-residential and non-utility scale PV installations are included in these data. It is unclear whether this sample can be considered to be representative of all commercial PV installation as the data consist largely of voluntary submissions by companies. Further, our sample includes most of the largest commercial solar adopters, so the extrapolation of the results to smaller commercial entities should be performed with caution. In particular, many of our sample firms are commercial retailers, and many have

chosen to self-report their solar installations to the SEIA. Thus, our sample may lead to overestimates of the importance of green marketing factors in commercial solar adoption decisions; smaller, non-commercial retailers may consider solar adoption more purely on the basis of return-on-investment.

To address some of the sample selection problems we include only the most active 32 largest installers within our data when we analyze the company's decision to invest in a specific state and year. The results from the ensuing probit models are thus only applicable to larger multi-state companies. However, the structure of the data implies that some of the observations might correspond to company-state-year combinations in which the company might not be present in a given state and year. This limitation is somewhat overcome by limiting the sample to the 32 largest installers, as very large companies are likely to be present in most state and year combinations. We then analyze the data of only those company-state-year combinations where we can be reasonably sure that the company is present in each state and year.

Bibliography

- Bazen, E. F. and M. A. Brown (2009). Feasibility of solar technology (photovoltaic) adoption: A case study on Tennessee's poultry industry. *Renewable Energy* 34(3), 748 – 754
- Beckman, J. and I. Xiarchos (2013). Why are Californian farmers adopting more (and larger) renewable energy operations? *Renewable Energy* 55, 322 – 330
- Belotti, F., P. Deb, W. Manning and E.C. Norton (2015) Two-part models, *The Stata Journal*, 15(1):3-20
- Bhattacharya, S., K. Giannakas, and K. Schoengold (2017) Market and welfare effects of renewable portfolio standards in United States electricity market, *Energy Economics*, 64:384-401
- Borchers, A. M., I. Xiarchos, and J. Beckman (2014). Determinants of wind and solar energy system adoption by U.S. farms: A multilevel modeling approach. *Energy Policy* 69, 106 – 115
- Bowen E. and D. J. Lacombe (2017) Spatial dependence in state renewable policy: Effects of Renewable Portfolio Standards on renewable generation within NERC regions, *Energy Journal*, 38(3):117-193
- Burns, J. E. and J. Kung (2012) Comparative economic analysis of supporting policies for residential solar PV in the United States: Solar Renewable Energy credit (SREC) potential, *Energy Policy*, 44:217-225
- Byrne J., K. Hughes, W. Rickerson, L. Kurdgelashvili (2007) American policy conflict in the greenhouse Divergent trends in federal, regional, state, and local green energy and climate change policy, *Energy Policy*, 35(9): 4555-4573
- Caffrey, C. (2010) The House of the Rising Sun: Homeowners' Associations, Restrictive Covenants, Solar Panels, and the Contract Clause, *Natural Resources Journal*, 50(3):721-759
- Cameron C. A. and P. K. Trivedi (1998) *Regression Analysis of Count Data*. Cambridge: Cambridge University Press, 1998
- Crago, C. L. and I. Chernyakhovskiy (2017). Are policy incentives for solar power effective? evidence from residential installations in the northeast. *Journal of Environmental Economics and Management* 81, 132 – 151
- Drury, E., M. Miller, C.M. Macal, D.J.Graziano, D. Heimiller, J. Ozik, and T.D. Perry IV (2012) The transformation of southern California's residential photovoltaics market through third-party ownership, *Energy Policy*, 42:681-690
- Eid, C., J. R. Guillen, P. F. Marin, and R. Hakvoort (2014) The economic effect of electricity net-metering with solar PV: Consequences for network cost recovery, cross subsidies and policy objectives, *Energy Policy*, 75:244-254
- Feldman, D. and R. Margolis (2014). To own or lease solar: Understanding commercial retailers' decisions to use alternative financing models. Technical Report NREL/TP-6A20-63216, NREL

- Hori, S., M. Shinozaki, D. Nogata, and T. Fujita (2014). The role of CSR in promoting companies energy-saving actions in two Asian cities. *Energy Policy* 69, 116 – 121
- Krasko, V. A. and E Doris (2013) State distributed PV policies: can low cost (to government) policies have a market impact? *Energy Policy* 59:172-181
- Kwan, C. L. (2012) Influence of location environmental, social, economic and political variables on spatial distribution of residential solar PV arrays across the United States, *Energy Policy*, 47:332-344
- Lee, M., T. Hong, H. Yoo, C. Koo, J. Kim, K. Jeong, J. Jeong, and C. Ji (2017) Establishment of a base price for the Solar Renewable Energy Credit (SREC) from the perspective of residents and state governments in the United States, *Renewable and Sustainable Energy Reviews*, 75:1066-1080
- Li, H. and H. Yi (2014) Multilevel governance and deployment of solar PV panels in the US cities, *Energy Policy*, 69:19-27
- Mabee, W. E., J. Mannion, and T. Carpenter (2012) Comparing the feed-in-tariff incentives for renewable electricity in Ontario and Germany, *Energy Policy*, 40:480-489
- Menon, A. and A. Menon (1997). Enviropreneurial marketing strategy: The emergence of corporate environmentalism as market strategy. *Journal of Marketing* 61(1), 51–67.
- Matisoff, D. C. and E. P. Johnson (2017) The comparative effectiveness of residential solar incentives, *Energy Policy*, 108:44-54
- Menz, F. C. and S. Vachon (2006) the effectiveness of different policy regime for promoting wind power: Experiences from the states, *Energy Policy*, 34:1786-1796
- North Carolina State University (NCSU) (2017). Database of state incentives for renewables & efficiency. <http://www.dsireusa.org/>
- Overholm H. (2015) Spreading the rooftop revolution: What policies enable solar-as-a-service? *Energy Policy*, 84:69-69
- Prasad, M. and S. Munch (2012) State-level renewable electricity policies and reductions in carbon emissions, *Energy Policy*, 45:237-242
- Sarzynski, A., J. Larrieu, and G. Shrimali (2012) The impact of state financial incentives on market deployment of solar technology, *Energy Policy*, 46:550-557
- SEIA (2016). Solar means business. Technical report, Solar Energy Industries Association.
- Shrimali, G. and S. Jenner (2013) The impact of state policy on deployment and cost of solar photovoltaic technology in the U.S.: A sector-specific empirical analysis, *Renewable Energy*, 60:679-690
- Trendafilova, S., K. Babiak, and K. Heinze (2013). Corporate social responsibility and environmental sustainability: Why professional sport is greening the playing field. *Sport Management Review* 16(3), 298 – 313
- Vuong, Quang H. (1989). Likelihood Ratio Tests for Model Selection and non-nested Hypotheses. *Econometrica*. 57 (2): 307–333.
- Wei, M., S. Patadia, and D. M. Kemman (2010) Putting renewables and energy efficiency to work: How many jobs can the clean energy industry generate in the US? *Energy Policy*, 38(2):919-931

Wiser, R., G. Barbose, and E. Holt (2011) Supporting solar power in renewables portfolio standards: Experience from the United States, *Energy Policy*, 39(7):3894-3905

Yin, H., Powers, N. (2010). Do state renewable portfolio standards promote in-state renewable generation? *Energy Policy*, 38:1140–1149

Appendix of Tables

Variable	dep. var. is <i>installations</i>				dep. var. is <i>capacity</i>			
	Marg. Eff.	Std. Err.	Marg. Eff.	Std. Err.	Marg. Eff.	Std. Err.	Marg. Eff.	Std. Err.
<i>GDP per capita</i>	0.030	(0.130)	-0.057	(0.124)	-131.3	(99.97)	-199.4*	(107.3)
<i>electricity sales</i>	0.174	(0.169)	0.225	(0.178)	49.75	(60.26)	98.64	(68.90)
<i>sales tax</i>	3.680**	(1.606)	3.029**	(1.266)	2903*	(1468.6)	2374*	(1329.0)
<i>electricity price deregulated</i>	0.174	(0.290)	0.242	(0.326)	15.93	(120.9)	163.4	(178.3)
<i>coal per capita</i>	-7.125	(5.682)	-6.917	(4.741)	-5762	(4189.6)	-4096*	(2137.7)
<i>net metering</i>	0.017	(0.014)	-0.006	(0.014)	29.4*	(15.86)	10.11	(12.27)
<i>net metering</i>	1.034	(1.212)	1.839	(1.217)	273.5	(753.9)	770.2	(1116.4)
<i>RPS</i>	-1.337	(1.083)	-1.632	(1.240)	-858.2	(918.3)	-712.0	(653.5)
<i>SREC</i>	-0.038	(4.459)	-0.971	(3.721)	-651.7	(2245.5)	-1774.3	(1955.8)
<i>feed-in-tariff</i>	4.245	(4.068)	3.745	(3.129)	2124.6	(2147.9)	686.8	(1583.6)
<i>tax breaks</i>	-2.435	(2.184)	-2.328	(2.315)	-2272.6	(1486.2)	-2252.4	(1512.2)
<i>financing</i>	-1.441	(1.392)	-2.320	(1.545)	-1430.4	(942.8)	-2007.6*	(1004.6)
<i>rebates</i>	1.170	(2.100)	1.128	(2.449)	431.1	(885.2)	201.7	(914.3)
<i>access</i>	4.215	(5.616)	3.406	(4.744)	3253.6	(4168.9)	1714.5	(2032.6)
<i>interconnection</i>	-0.679	(1.161)	-0.782	(1.001)	-937.9	(780.4)	-366.9	(1313.2)
<i>PPA</i>	3.226	(2.626)	1.178	(3.213)	606.1	(1547.2)	-1137.9	(1907.9)
<i>net metering sum</i>			-0.102	(0.175)			121.7	(209.2)
<i>RPS sum</i>			0.162	(0.264)			-77.68	(186.1)
<i>SREC sum</i>			0.293	(0.428)			327.8	(452.8)
<i>feed-in-tariff sum</i>			0.125	(0.308)			438.9**	(207.9)
<i>tax breaks sum</i>			0.368	(0.273)			360.2	(236.0)
<i>financing sum</i>			0.409*	(0.216)			377.7**	(150.9)
<i>rebates sum</i>			-0.113	(0.288)			13.01	(200.1)
<i>access sum</i>			0.531	(0.366)			433.4**	(214.5)
<i>interconnection sum</i>			-0.074	(0.178)			-379.3*	(189.3)
<i>PPA sum</i>			0.438	(0.417)			318.3	(276.9)
N		714		714		714		714
adj. R-sq		0.47		0.48		0.34		0.39

Table 5. OLS results for annual number of solar installations and capacity installed per state (* p<0.1, ** p<0.05, *** p<0.01; all models contain state and year fixed effects)

Variable	Trimmed Sample				Full sample of 32 large firms			
	Marg. Eff.	Std. Err.	Marg. Eff.	Std. Err.	Marg. Eff.	Std. Err.	Marg. Eff.	Std. Err.
<i>GDP per capita</i> (10^{-3})	-0.830	(2.27)	-2.07	(2.28)	-0.098	(0.720)	-0.734	(0.768)
<i>electricity sales</i> (10^{-3})	2.008***	(0.738)	3.035***	(0.892)	0.595*	(0.340)	0.985**	(0.462)
<i>sales tax</i>	0.046***	(0.012)	0.033***	(0.011)	0.022**	(0.009)	0.017**	(0.007)
<i>electricity price</i>	0.009**	(0.004)	0.008**	(0.004)	0.002	(0.002)	0.003*	(0.002)
<i>deregulated</i>	-0.094**	(0.042)	-0.087**	(0.039)	-0.044	(0.034)	-0.034*	(0.022)
<i>coal per capita</i> (10^{-3})	0.728**	(0.293)	0.348	(0.224)	0.191*	(0.098)	0.073	(0.077)
<i>net metering</i>	0.035	(0.025)	0.039**	(0.019)	0.011	(0.009)	0.015**	(0.007)
<i>RPS</i>	-0.012	(0.012)	-0.018	(0.014)	-0.008	(0.006)	-0.008	(0.005)
<i>SREC</i>	0.039	(0.029)	-0.018	(0.033)	0.017	(0.015)	-0.008	(0.015)
<i>feed-in-tariff</i>	0.021	(0.030)	0.050	(0.031)	0.008	(0.013)	0.014	(0.012)
<i>tax breaks</i>	-0.046*	(0.026)	-0.046*	(0.025)	-0.015	(0.010)	-0.015	(0.010)
<i>financing</i>	0.004	(0.018)	-0.011	(0.017)	-0.001	(0.007)	-0.004	(0.007)
<i>rebates</i>	-0.002	(0.022)	0.00003	(0.023)	0.00004	(0.008)	-0.002	(0.009)
<i>access</i>	0.031	(0.038)	0.004	(0.026)	0.024	(0.033)	0.015	(0.020)
<i>interconnection</i>	-0.030	(0.021)	-0.024	(0.019)	-0.010	(0.007)	-0.008	(0.006)
<i>PPA</i>	0.026	(0.034)	-0.012	(0.053)	0.013	(0.012)	-0.001	(0.018)
<i>net metering sum</i>			0.0015	(0.004)			-0.001	(0.001)
<i>RPS sum</i>			0.003	(0.003)			-0.0002	(0.001)
<i>SREC sum</i>			0.013*	(0.007)			0.007**	(0.003)
<i>feed-in-tariff sum</i>			-0.006	(0.006)			-0.001	(0.002)
<i>tax breaks sum</i>			0.009***	(0.003)			0.004**	(0.002)
<i>financing sum</i>			0.008**	(0.004)			0.002*	(0.001)
<i>rebates sum</i> (10^{-3})			-2.07	(3.93)			-0.162	(1.36)
<i>access sum</i>			0.005**	(0.002)			0.003**	(0.001)
<i>interconnection sum</i>			-0.0001	(0.004)			-0.001	(0.001)
<i>PPA sum</i>			0.007	(0.007)			0.003	(0.002)
N		6020		6020		22848		22848
adj. R-sq		0.150		0.156		0.100		0.105

Table 6. OLS results for company level analysis of solar PV installation decisions: dependent variable is *invest* which is 1 if the company installed solar in a given state and year and 0 otherwise (* p<0.1, ** p<0.05, *** p<0.01; all models contain company, year and state fixed effects); (10^{-3}) denotes the estimates were scaled up to erase leading zeros

dep. var. is <i>installations</i>		
Variable	Marg. Eff.	Std. Err.
<i>GDP per capita</i>	0.135**	(0.064)
<i>electricity sales</i>	0.009**	(0.005)
<i>sales tax</i>	0.300	(0.205)
<i>electricity price</i>	-0.133	(0.129)
<i>insolation</i>	0.714*	(0.430)
<i>insolation sd</i>	0.235	(1.144)
<i>deregulated</i>	-0.805	(1.312)
<i>coal per capita</i>	-0.182*	(0.094)
<i>PEVs per capita</i>	2.162**	(0.893)
<i>net metering</i>	-0.025	(0.671)
<i>RPS</i>	0.045	(0.735)
<i>SREC</i>	5.105***	(1.340)
<i>feed-in-tariff</i>	0.328	(0.825)
<i>tax breaks</i>	1.406*	(0.738)
<i>financing</i>	1.878**	(0.763)
<i>rebates</i>	0.133	(0.668)
<i>access</i>	-1.123	(0.941)
<i>interconnection</i>	-2.583**	(1.043)
<i>PPA</i>	1.225	(0.827)
N		714
AIC		1245

Table 7. Zero-inflated negative binomial model for number of annual commercial solar installation projects in a state (* p<0.1, ** p<0.05, *** p<0.01; all models contain year fixed effects)

	N	Mean	Std. Dev.	Min.	Max.
true values	714	2.05	8.93	0	112
ZIP predicted	714	2.07	7.39	0	87.64
ZINB predicted	714	2.47	11.47	0	169.67

Table 8. Sample statistics of *installations* dependent variable and predicted values from zero-inflated Poisson and zero-inflated negative binomial models