

# Drivers of growth in commercial-scale solar PV capacity<sup>☆</sup>

Christine L. Crago<sup>a,\*</sup>, Eric Koegler<sup>b</sup>

<sup>a</sup> Department of Resource Economics, University of Massachusetts Amherst, 216 Stockbridge Hall, 80 Campus Center Way, Amherst, MA 01003, USA

<sup>b</sup> ISO New England, USA

## ARTICLE INFO

### Keywords:

Commercial solar PV  
Solar incentives  
Renewable energy policies

## ABSTRACT

This paper examines the impact of policy incentives for solar power on capacity growth of the commercial market segment. We use county level data from 2005 to 2013 for 13 states in the Northeast United States including the District of Columbia. In estimating the relationship between incentives and solar PV capacity, we control for insolation, market factors, and demographic characteristics. We also account for indicators of pro-environmental attitudes and preferences for solar technology. Results indicate that factors affecting financial returns from a solar PV installation like electricity price and insolation are highly significant. Among policy variables, rebates, solar renewable energy credit price, and sales tax waivers are significant, along with years of Renewable Portfolio Standard implementation. Indicators of environmental preferences and familiarity with solar technology are not as important, which is in contrast with findings in the residential solar market. This suggests that commercial installations are driven mostly by its promise of financial returns, and continued growth in this market segment is likely to depend on falling installation costs and availability of incentives.

## 1. Introduction

The solar photovoltaic (PV) market in the United States has grown dramatically over the last decade, with cumulative capacity growing from 218 MW in 2005 to roughly 51,000 MW in 2017 (GTM Research and Solar Energy Industries Association, 2015, 2016, 2017b). Typical justifications for solar installations include concerns about greenhouse gas (GHG) emissions, and the environmental and health impacts of energy use, which has led many states to enact policies in support of solar power (DSIRE, 2015). In addition, technological advances have dramatically decreased the cost of solar PV installations. The cost of commercial solar PV installation decreased 72%, from an average cost of \$5.71 per watt in 2010 to \$1.62 per watt in 2016 (GTM Research and Solar Energy Industries Association, 2017a, 2017b). As solar system costs decline, it becomes more and more feasible to adopt solar power. However, public policy and incentives continue to play a large role in supporting the solar PV market. In 2013 alone, the federal government provided \$5.3 billion in subsidies and support for the solar market (U.S. Energy Information Administration, 2015a). In addition, state governments have spent millions of dollars in solar incentives.

This paper examines the role of state policy incentives in driving the growth of commercial solar PV capacity. Commercial-scale solar PV is one of three market segments comprising the total PV market in the

United States, the other two being residential-scale and utility-scale. The commercial (also referred to as nonresidential) segment initially dominated the PV market with a share of 50% between 2000 and 2010, but over the years has declined in market share, accounting for 22% of the market between 2010 and 2015 (Hart and Birson, 2016).

There are several reasons why it is important to consider the commercial segment separately from the overall PV market. First, even with its low current market share, it is still a key contributor to continued growth in solar PV capacity, especially with projected declines in the residential market segment (GTM Research and Solar Energy Industries Association, 2016). Second, many state and local governments are promoting community solar projects which fall under the commercial market segment (GTM Research and Solar Energy Industries Association, 2016, 2017b). Community solar is attractive because community engagement around solar projects is valuable to many local governments. Furthermore, community solar expands the customer base for solar PV to those households who are renting or whose properties are not ideal for installation of rooftop solar PV (Coughlin et al., 2016). Several states have special incentives that apply specifically to commercial systems. These programs include Property Accessed Clean Energy (PACE) financing and loan programs for multifamily housing units (DSIRE, 2015; PACENation, 2017).

In this paper, we examine factors driving growth in commercial PV

<sup>☆</sup> This project was supported by a seed grant from the UMass Clean Energy. Extension with funds from the Massachusetts Department of Energy Resources Grant/Contract S13250000000017. We are grateful to Bernie Morzuch for his comments on early versions of this manuscript and to Sam Dauphinais for research assistance. All remaining errors are ours.

\* Corresponding author.

E-mail address: [ccrago@umass.edu](mailto:ccrago@umass.edu) (C.L. Crago).

capacity in the Northeastern United States, using county-level panel data from 2005 to 2013. We focus on the impact of policy incentives, while controlling for market factors, demographic characteristics, geographical variables, and environmental and technological preferences affecting adoption of solar PV. Our estimation strategy uses Tobit estimators to account for the high percentage of counties with no PV capacity added for certain years. We also utilize instrumental variables to address possible endogeneity of some policies.

This paper is most closely related to previous studies that examine the different factors affecting growth in the solar PV market. Existing studies examine growth in the overall solar PV market or focus on the residential sector. [Sarzynski et al. \(2012\)](#) evaluate the effects of different types of state-level incentives on grid-tied PV capacity in the United States from 1997 to 2009. They find that cash incentives are effective because they help decrease upfront cost, while tax incentives were not effective.

Other studies focus on the residential sector. Using data from year 2000, [Kwan \(2012\)](#) considers the effect of environmental, political, social, and economic variables on the spatial distribution of residential solar PV in the United States. He finds that solar insolation, electricity prices and financial incentives are key drivers of solar PV adoption. [Hughes and Podolefsky \(2015\)](#) examine the effect of the California Solar Initiative on the number of residential solar installations between 2007 and 2012. They take advantage of the difference in utility providers in adjacent areas to provide exogenous variation in rebate rates, and find that a \$0.1 per watt increase in the rebate increases installations by 7–15% per day. [Crago and Chernyakhovskiy \(2017\)](#) use county-level panel data from 2005 to 2012 to examine the effect of policy incentives for residential solar PV capacity while controlling for demographic and geographic characteristics. They find that rebates had the most impact on capacity growth, with a \$0.1 increase in rebate leading to a 5% increase in new capacity. In addition, they find that pro-environmental preferences were also positively related to solar PV capacity.

Other studies on residential solar PV adoption focus on non-financial factors instead of financial incentives ([Krasko and Doris, 2013](#); [Steward et al., 2014](#)). [Krasko and Doris \(2013\)](#) use cross section data to examine the role of market creation and preparation policies on grid-tied solar PV adoption. Policies in their study include interconnection standards, net metering, and mandates for renewables and solar. A study by [Steward et al. \(2014\)](#) evaluates the effect of market support policies targeted at different states grouped by demographic characteristics and resource availability. Both studies find market support policies to be effective at increasing overall PV capacity in the United States.

This paper is also related to the broader literature examining the relationship between policy incentives and the growth of other renewable energy sources. A closely related study is that of [Hitaj \(2013\)](#), who examines the effect of state and federal incentives on wind power capacity. The study finds that tax and production incentives, along with access to the electricity grid, are key factors affecting the growth of wind power capacity in the United States.

This paper contributes to the literature examining the growth of the solar PV market by identifying factors that are uniquely important to the growth of the commercial solar PV market. To our knowledge this is the first paper that focuses on examining growth in this market segment. We include detailed representation of different policy incentives, which allows us to estimate the individual impacts of these policies. This is in contrast to studies that do not consider policy incentives ([Krasko and Doris, 2013](#); [Steward et al., 2014](#)), group many policies in one variable ([Kwan, 2012](#)), or focus only on a specific policy ([Hughes and Podolefsky, 2015](#)).

Results of our empirical analysis show that rebates, sales tax waivers, solar renewable energy credit (SREC) price, and the number of years a Renewable Portfolio Standard (RPS) has been in place are all significant drivers of solar PV capacity. Factors that affect financial

returns on solar installations such as solar insolation, electricity prices, and time trend (which captures falling installation costs) also have a significant effect on the amount of solar PV capacity installed in a given year. Unlike prior studies focusing on the residential sector, we find that pro-environmental preferences represented by percentage of Democratic party votes are not significant in driving commercial PV growth. This suggests that the decision to install a commercial PV system is primarily driven by financial considerations. Thus, policies that seek to lower costs and improve payback of PV systems are important to continued growth in this market.

The next section provides background on the solar PV market. [Section 3](#) describes our data and data sources. [Section 4](#) discusses our estimation strategy and empirical results. [Section 5](#) concludes.

## 2. Trends and incentives in the solar PV market

There has been rapid growth in the commercial solar market since late the 2000s, which coincides with the introduction of solar incentives. From 2000 to 2010, there was just over 1000 MW of commercial solar installed across the country. Over the next six years, growth averaged 1100 MW per year, reaching a total of 7684 MW by 2016. Improved SREC market conditions in Massachusetts and New Jersey spurred solar adoption in the Northeast ([GTM Research and Solar Energy Industries Association, 2014](#)). Additionally, there were several market expansion tools, such as rebates and loan programs, introduced between 2008 and 2010. In the following years, commercial growth slowed as incentives expired, and in 2014 and 2015, commercial solar growth decreased 6% and 5%, respectively. Incentive scale-backs were cited as one primary reason for the national decline ([GTM Research and Solar Energy Industries Association, 2015](#)). In recent years, installed capacity has once again followed an upward trend. Commercial solar capacity increased 1600 MW, or 49%, from 2014 to 2015. The Solar Energy Industries Association (SEIA) suggests that an increase in community solar projects and impending incentive deadlines may have caused the recent increase in installations ([GTM Research and Solar Energy Industries Association, 2017b](#)).

In order to understand the impact of incentives on solar capacity additions, we describe trends in PV capacity growth, as well as various incentive structures included in our study. [Fig. 1](#) shows the trend in solar PV installations for states included our analysis that have the highest cumulative capacity. In total, 1550 MW of commercial capacity were installed across the Northeast and the District of Columbia between 2005 and 2013. New Jersey and Massachusetts are leaders in installed capacity based on total kilowatts, with nearly 1000 MW and 260 MW, respectively. Other than Pennsylvania with 111 MW installed, all other states had total installed capacity below 100 MW ([National Renewable Energy Laboratory, 2015a](#)).

[Fig. 2](#) shows cumulative PV capacity at the county level as of 2013. Considerable heterogeneity exists in the level of solar PV penetration. Our goal in this paper is to examine the effect of different factors affecting annual increases in solar PV capacity, with an emphasis on the impact of policy incentives. Below, we discuss the different incentives relevant to the commercial solar PV market. We also present other important control variables that are included in our empirical model.

### 2.1. Solar incentives

A wide range of incentives offer varying benefits, which are all meant to increase the amount of solar adoption. For example, rebates and sales tax exemptions decrease the upfront cost of installation, while SRECs provide annual revenue to owners of PV systems. We discuss these incentives and others in turn. Our primary source of information on availability of incentives and details about their implementation is the Database of State Incentives for Renewables and Efficiency ([DSIRE, 2015](#)). DSIRE provides descriptions of different incentives and policies, and usually includes links to state program administration documents.

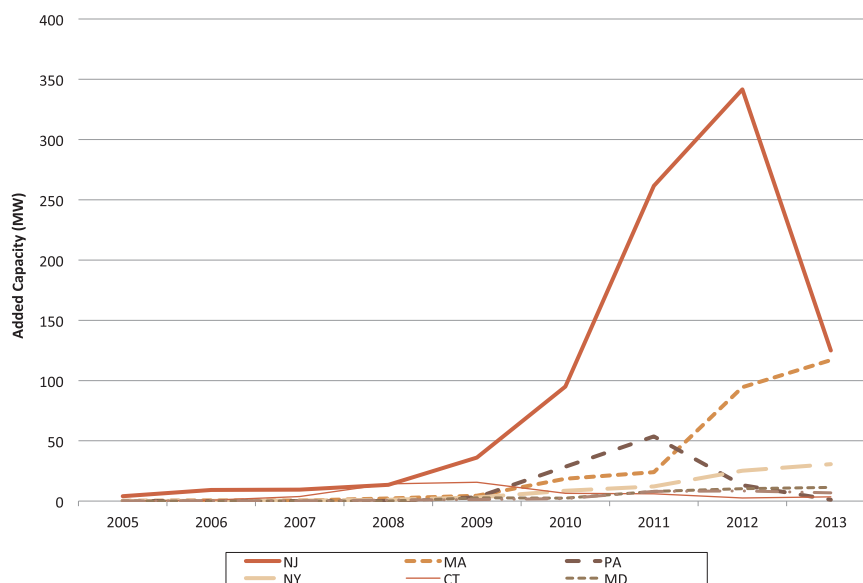


Fig. 1. Annual PV capacity additions of selected states, 2005–2013.

Rebates are cash incentives given on the basis of the system's capacity rating. Rebate programs typically obtain funding through surcharges on electricity. Electricity customers pay surcharges per kilowatt hour which provides renewable energy programs with funding. Between 2005 and 2013, eight of the thirteen states in our study used a renewable energy surcharge. The charges range from 0.01 cents per kilowatt hour in Pennsylvania to 0.1 cent per kilowatt hour in Connecticut. State tax exemptions or waivers apply a waiver on the sales tax of all or part of the cost of equipment for a solar installation. Waivers likely appeal to customers because they are simple to understand and scale to the size of the installation.

Renewable Portfolio Standards (RPSs) are general mandates for renewable energy, and as such do not incentivize solar directly. The renewable mandates require load serving entities (LSEs) to acquire a certain amount of renewable energy (typically measured in MWh). Each state determines what renewables can participate, and how they qualify under the RPS. LSEs can produce their own energy or obtain renewable energy credits (RECs) from other producers. The existence of a RPS gives local stakeholders experience with deploying renewable energy sources like solar and wind. Although RPSs include solar power, the policy's effect on solar deployment has been small in the presence of lower cost options like wind (Wiser et al., 2011). Many states have put in place solar-specific mandates known as solar carve-outs, which led to the creation of markets for solar renewable energy credits (SRECs). LSEs receive an SREC for producing a certain amount (typically 1 MWh) of electricity from solar energy. LSEs can also buy SRECs from other electricity producers, including owners of solar PV systems. If LSEs do not have enough SRECs to meet regulatory requirements, they can instead pay the Solar Alternative Compliance Payment (SACP). The SACP schedule is typically set by state regulatory agencies several years in advance.<sup>1</sup>

Performance based incentives (PBIs) provide payments based on electricity produced by a solar PV installation. This incentive is based on actual production, as opposed to other incentives that are based on installed capacity. Net metering standards provide legal rights for solar PV customers to be compensated for energy fed back into the grid, and

increases the value of a solar installation beyond the electricity that is directly used by its owners. In some cases, a “solar adder” provides additional payments in excess of the retail rate, such as in Vermont. Loan programs allow solar PV adopters to pay back the high upfront costs with below-market interest rates. An example is the PACE loan program, which collects payments through annual assessments on property tax bills.

### 3. Data sources

Data on annual installations of commercial solar PV were obtained from the Open-PV database of the National Renewable Energy Lab (NREL) (National Renewable Energy Laboratory, 2015a).<sup>2</sup> We use a lower bound of 10 kW-capacity and an upper bound of 10 MW-capacity to identify commercial installations. This 10-kW lower bound is consistent with the National Renewable Energy Lab's definition of commercial systems (Goodrich et al., 2012; Barbose et al., 2012) as well as residential studies that use 10-kW as the upper bound for residential systems (Crago and Chernyakhovskiy, 2017; Kwan, 2012). We chose 10 MW as the upper bound since this was the largest capacity of systems identified in the data set as “commercial” except for five outliers, which were removed from the final data set used for estimation. In addition to systems identified as “commercial” in the database, commercial installations also include installations for nonprofit and public organizations (such as school buildings), although non-businesses constitute a small portion (at most 7% for the years in our study) of total installations. The data from Open-PV identify the zipcode where installations are located. To generate county level observations, we use a zipcode-to-county crosswalk file from the Missouri Data Center. We obtain 9274 observations of solar PV installations identified by their month, day, and year of installation. These observations are aggregated across 300 counties for every year from 2005 to 2013.

Data on solar incentives are obtained from the Database of State Incentives for Renewables and Efficiency (DSIRE, 2015). Appendix Fig. A.1 gives information on the years different incentives are present in each state in our study. Data on incentives such as net metering, loan programs, and performance based incentives are obtained from DSIRE

<sup>1</sup> Since one purpose of the SACP is to set a ceiling price for SRECs, state governments typically publish SACP rates many years in advance. For example, MA state legislature sets a 10-year forward schedule, while New Jersey's recent rates cover 15 years from 2014 to 2028. An exception is the state of PA whose SACP rates are set after the SREC market clears.

<sup>2</sup> Open PV is a voluntary submission database, and as such does not include every solar installation in the United States. As of April 2018, cumulative capacity in our study area reported by Open PV was 72.3% of that reported in the Solar Energy Industries Association website (OpenPV 2018, SEIA 2018).

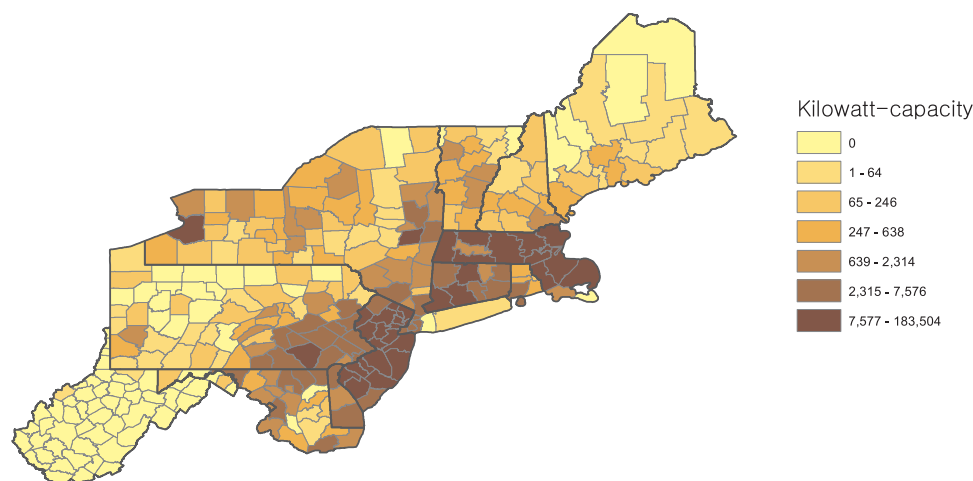


Fig. 2. Cumulative solar PV capacity in the Northeast, 2013.

and are represented by binary variables which indicate whether or not the incentive was available in a given state for a particular year. Other incentives are measured using specific amounts. The sales tax waiver variable is the sales tax rate for each state. Several states increased the rate during our study period. All of the states in our study have a single tax rate except for New York state, which has a 4% state tax in addition to county-specific tax rates. To represent the impact of Renewable Portfolio Standards, we include a RPS trend variable, similar to that used by [Menz and Vachon \(2006\)](#). This variable indicates how many years the RPS program has been in place.

The rebate variable gives the dollar rebate amount per watt of installed capacity. To supplement information obtained from DSIRE, we obtain annual rebate rates for states with active rebate programs from state administration agencies either by request or by using information from published state regulations. States like Delaware, New Jersey and New York were first to offer rebates, and rates started relatively high at over \$4 per watt. States that offered rebates later in the study period had initial rebate offerings that were no more than \$2.5 per watt. [Fig. 3](#) shows that for the different states with active rebate programs in the study period the annual rebate rates have been generally decreasing since its peak in 2008. (We do not show Rhode Island which only had a rebate in 2013.) The average rebate was \$2.12 per watt in 2008, falling to an average of \$0.88 per watt in 2013.

The price of SRECs is measured as the average yearly price of SRECs in a state. These prices were obtained from Flett Exchange, a leading trader of SRECs in New England ([Flett Exchange, 2015](#)). [Fig. 4](#) shows the trend in SREC prices for states with active SREC markets. A common trend for a majority of SREC markets is high prices at inception of the market, and prices trending downward toward the end of our study period, suggesting increasing supply of credits relative to demand. Data on SACP rates, which is the amount LSEs have to pay if they do not have sufficient SRECs, were obtained from DSIRE.

Retail commercial electricity prices were obtained from the Energy Information Administration (EIA) ([U.S. Energy Information Administration, 2015b](#)). We use the annual average of each state. EIA collects data on retail rates from different electricity providers including municipal utilities and cooperatives to obtain an annual average. Solar insolation is a measure of solar radiation energy received by an area at a given time, and is expressed as kilo-watt hours per square meter per day (kWh/sqm/day). We use the annual average of daily solar radiation received for each county, obtained from [National Renewable Energy Laboratory \(2015b\)](#). Data from NREL is based on finer-scale data from the State University of New York/Albany satellite radiation model which measures hourly insolation at a 10-km resolution. As a control variable for the size of the market (i.e. number of potential adopters) we include the number of businesses in a county

with more than 10 employees. We obtain data on businesses from the [U.S. Census Bureau \(2016b\)](#). The number of businesses with more than 10 employees is likely to be an underestimate of the true market size since non-profits and government agencies are also potential PV adopters, and businesses with less than 10 employees can adopt commercial-scale PV. Nonetheless, this variable is a reasonable indicator of potential market size to the extent that there are more larger businesses in counties with a greater number of organizations that can potentially adopt commercial-scale solar PV systems.

We also control for demographic characteristics likely to affect adoption of solar PV, including income, unemployment and population density. Household income acts as a proxy for discounting preferences and the ability of households and businesses to invest in solar projects, while unemployment is a measure of the strength of the local economy. Data on income and unemployment are obtained from the [U.S. Bureau of Labor Statistics \(2015\)](#). It is not clear how population density will affect commercial PV capacity. Population density has been found to be negatively related to changes in residential PV capacity ([Crago and Chernyakhovskiy, 2017](#)). It is possible that a highly dense area will have less available space for large solar projects. However, it is also possible that more dense areas will have a greater number of businesses that can choose to put up a solar installation. In addition, dense areas may be more conducive to peer effects such as that studied by [Bollinger and Gillingham \(2012\)](#), in which the visibility of solar panels in neighboring properties encouraged adoption. Population density combines population data from the American Community Survey and land area from the Census Tiger/Line database ([U.S. Census Bureau, 2016a, 2016c](#)).

Prior literature on residential solar PV adoption also suggests that pro-environmental preferences are an important driver of solar PV adoption. Therefore, we include measures of this in our empirical model. To capture environmental preferences, we use the percent of voters who voted for a Democratic House of Representatives candidate. Democratic Party affiliation has been linked to pro-environmental beliefs and actions such as support for climate legislation ([Cragg et al., 2013](#)), energy conservation ([Costa and Kahn, 2013](#)), and residential solar PV adoption in particular ([Crago and Chernyakhovskiy, 2017](#); [Dastrup et al., 2012](#)).<sup>3</sup> Voting data are obtained from the [U.S. Federal Election Committee \(2016\)](#). Since representatives are voted for every other year we interpolated the value for odd numbered years. Finally, as a measure of familiarity with and preference for solar technology we also include

<sup>3</sup> Although Democratic Party support has been statistically linked to pro-environmental attitudes in many settings, a reviewer pointed out that the solar market has recently found support among Republicans and is seeing growth in Republican leading states (Murawski2017, Merchant2018).

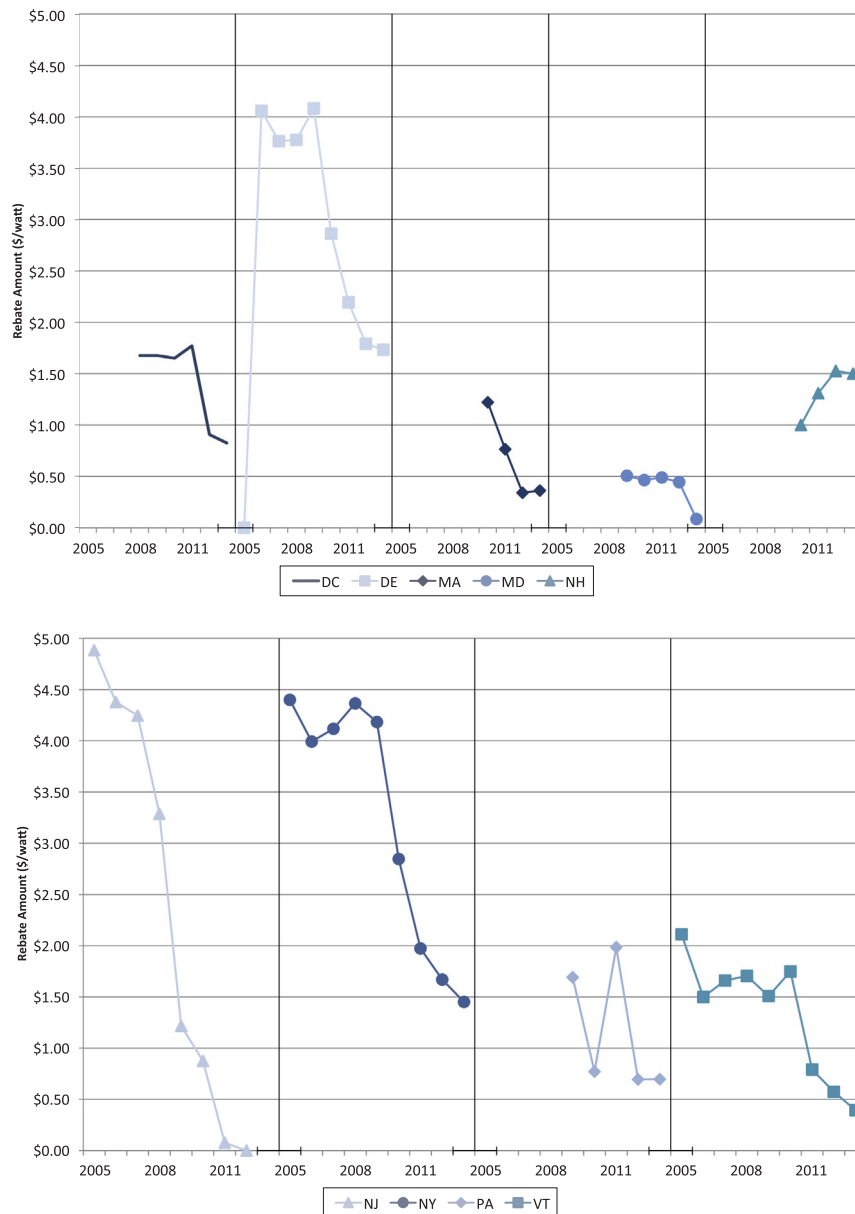


Fig. 3. Changes in rebate rates over time, 2005–2013.

lagged count of new commercial installations, which are obtained from the [National Renewable Energy Laboratory \(2015a\)](#).

A detailed summary of the variables in our study is provided in Appendix [Table A.1](#).

#### 4. Estimation and empirical results

The model we estimate is given by:

$$\ln Y_{it} = \alpha_0 + \beta P_{it} + \delta D_{it} + \gamma M_{it} + \eta E_{it} + \xi C_{it-1} + \kappa_t + t + \epsilon \quad (1)$$

where  $i$  denotes county  $i$ ,  $t$  gives the year and  $\epsilon$  is the error term. The dependent variable is the log of  $Y$ , the amount in kilowatts of PV capacity added in year  $t$ . The explanatory variables include vectors of policy incentives  $P_{it}$ , demographic characteristics  $D_{it}$ , market factors  $M_{it}$ , and an indicator of environmental preferences,  $E_{it}$ .<sup>4</sup> We include year fixed effects,  $\kappa_t$  where  $\kappa_t = 1$  if year =  $t$  and 0 otherwise, to

account for changes in market conditions and federal policy over time. The time trend,  $t$  where  $t = 1$  for 2005.... $t = 13$  for 2013, captures decreasing cost of solar installation. Finally, the lagged count of annual commercial installations,  $C_{it-1}$ , serves as a control for changes in solar market trends that vary by county over time. These include changes in preferences for having solar panels and familiarity with solar technology (for example, through peer effects), that are not captured by demographic or environmental preference variables.

We estimate Eq. (1) using a Tobit estimator.<sup>5</sup> The Tobit model is appropriate for settings in which the dependent variable is zero for a significant number of observations but is continuous over positive values ([Wooldridge, 2010](#); [Cameron and Trivedi, 2010](#)). This aptly describes our data: 66% of observations for county-year capacity additions of commercial solar PV systems are zero.

A linear estimator such Ordinary Least Squares (OLS) is simpler to implement but does not take the restriction on the dependent variable

<sup>4</sup> Some variables do not vary over time or vary only at the state level (See Appendix [Table A.1](#)).

<sup>5</sup> The Tobit estimator belongs to a class of estimators for limited dependent variables, in which the range of the dependent variable is restricted in some form.



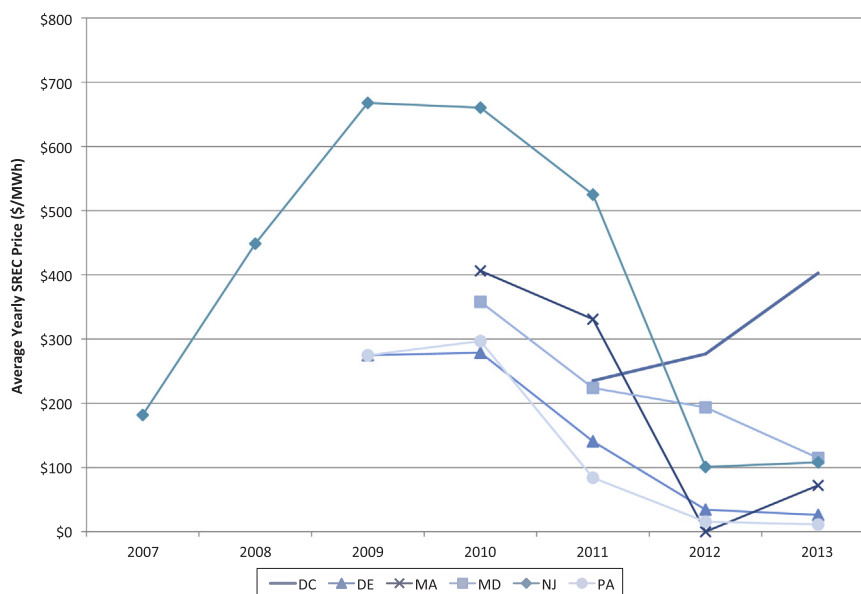


Fig. 4. SREC prices in states with active SREC markets, 2005–2013.

into account. To see if there is a gain in using the Tobit estimator, we compare results of estimating (1) using OLS and Tobit. Results are shown in Appendix Table A.2. The results show a sharp difference in the significance and magnitude of coefficients, confirming the need to use a non-linear estimator.

A key issue in our estimation is the possible endogeneity of policy incentives, particularly the SREC price. Policy variables can be endogenous if there are omitted variables that are correlated with these variables. We mitigate the omitted variables problem by including a broad set of controls that capture key factors affecting changes in PV capacity. In addition to control variables, we include year fixed effects and a time trend to capture unobserved variables that vary over time, as well as lagged count of new solar installations to account for other unobserved variables that vary by time and county. We address the possible endogeneity of the SREC price using instrumental variables, which we describe below.

We first estimate Eq. (1) using a pooled Tobit estimator. The pooled estimator assumes that regressors are exogenous. The SREC price is determined in the SREC market depending on supply and demand of SRECs. Since contemporaneous PV capacity may affect the supply of SRECs, the SREC price could be endogenous. To account for possible endogeneity of the SREC price, we instrument the SREC price with the Solar Alternative Compliance Payment (SACP), which is the dollar amount that LSEs have to pay the state government if they do not have sufficient credits to meet the solar power generation mandate. The first stage regression of the SREC price on SACP and other covariates show that SACP is highly significant, and is therefore a good candidate for an instrument (See Appendix Table A.3). While we cannot test that our instrument meets the exclusion restriction, we know that SACP rates are typically set well in advance by state administrators, and unlike the SREC price, is not determined by supply and demand of solar generation credits in a given time period. Thus, it is likely to meet the exclusion restriction.

To account for possible county-specific effects, we also estimate the model using a random effects (RE) Tobit estimator.<sup>6</sup> The RE Tobit model also assumes that regressors are exogenous. We cannot simultaneously include county-specific effects and the instrumental variable in our model because there is currently no available estimator

that can estimate a Tobit model with both individual-specific effects and endogenous regressors (Cameron and Trivedi, 2010).

The Pooled Tobit is the most straightforward Tobit estimator. The RE Tobit accounts for county-specific effects and allows us to take into account random unobserved heterogeneity at the county level. However, both Pooled Tobit and RE Tobit assume exogenous regressors. The instrumental variables (IV) Tobit is similar to the Pooled Tobit in that there are no county-specific effects, but it accounts for possible endogeneity of SREC prices by instrumenting SREC prices with SACP rates. Since different estimators have their own advantages (and limitations) we present results from all three estimators. Table 1 presents the estimated beta coefficients for Pooled Tobit, IV Tobit and RE Tobit estimators.

Table 1 shows that the time trend, electricity price, insolation, and number of businesses are significant across the different estimators. Whereas the number of businesses is primarily a control variable for the size of the market, the other three non-policy variables are key determinants of financial returns from a solar PV installation. Insolation and price of electricity jointly determine the total value of electricity output from a solar PV installation, while the time trend represents the cost of installation. Population and income are significant in the Pooled Tobit and IV Tobit, but not in RE Tobit. This contrasts with residential studies by Crago and Chernyakhovskiy (2017) and Kwan (2012) who find these variables to be statistically significant drivers of growth in PV capacity in a wide range of estimators including RE Tobit, IV Tobit, and OLS. Unemployment has a negative and significant effect, which is expected since low unemployment signals a strong local economy and greater ability on the part of businesses to invest in solar PV.

The share of Democratic party votes (an indicator of pro-environmental preference) is only significant in the RE Tobit, while the lagged count of commercial PV installations, which captures solar technology familiarity and preference, is only (weakly) significant in the pooled Tobit. The lack of broad significance of these two variables contrasts with findings in the residential solar market that pro-environmental preferences and peer effects are statistically significant determinants of PV capacity (Crago and Chernyakhovskiy, 2017; Bollinger and Gillingham, 2012).

In terms of policy variables, the rebate, sales tax waiver, SREC price, and RPS trend are significant across estimators. The policy variables that are not significant across estimators are loan programs, PBI, and net metering. The presence of net metering is critical to financial returns of a commercial solar installation. However, it is likely that the

<sup>6</sup> A fixed-effects Tobit estimator yields biased estimates so we do not use that particular estimator.

**Table 1**  
Regression results across Tobit estimators: beta coefficients.

	Pooled Tobit	IV Tobit	RE Tobit
Time Trend	1.484*** (0.231)	1.588*** (0.234)	1.605*** (0.262)
Electricity Price	0.916*** (0.159)	1.008*** (0.171)	0.849*** (0.195)
Lagged Count of New PV Installations	0.0389* (0.0212)	0.0310 (0.0217)	– 0.00951 (0.0227)
Insolation	9.561*** (1.668)	9.361*** (1.664)	9.822*** (2.742)
ln(Business)	4.189*** (0.388)	4.168*** (0.388)	4.452*** (0.699)
ln(Population)	– 0.789** (0.312)	– 0.790** (0.312)	– 0.690 (0.561)
Income	– 0.000106*** (0.0000280)	– 0.000107*** (0.0000280)	– 0.0000942 (0.0000576)
Unemployment	– 0.875*** (0.200)	– 0.930*** (0.202)	– 0.623*** (0.304)
Democrats	0.00429 (0.0393)	0.0226 (0.0400)	0.132** (0.0642)
Loan Program	0.909 (0.898)	0.562 (0.903)	1.972 (1.345)
Sales Tax Waiver	1.094*** (0.120)	1.010*** (0.130)	1.010*** (0.164)
Rebate	2.465*** (0.247)	2.390*** (0.255)	2.881*** (0.263)
PBI	1.131 (0.901)	1.472 (0.905)	2.637** (1.076)
SREC Price	0.00713*** (0.00182)	0.0130*** (0.00343)	0.00509** (0.00198)
Net Metering	4.575*** (2.024)	4.634*** (2.027)	0.704 (2.165)
RPS Trend	1.057*** (0.172)	0.960*** (0.181)	0.814*** (0.170)
Constant	– 110.4*** (8.400)	– 111.0*** (8.360)	– 119.9*** (13.19)
Log-Likelihood	– 3898.9	– 19271.6	– 3814.4
Observations	2700	2700	2700

Standard errors in parentheses. Year fixed effects are included in regressions. Standard errors for the RE estimator are bootstrapped standard errors, clustered at the county level.

For the Pooled Tobit and IV Tobit, standard errors are cluster-robust.

\*  $p < 0.1$ .

\*\*  $p < 0.05$ .

\*\*\*  $p < 0.01$ .

effect of net metering can not be identified in our regressions because almost all states have allowed net metering since 2003.

#### 4.1. Marginal effects

In addition to information about which variables significantly affect growth in solar PV capacity, the magnitude of the effect of a change in these variables on new capacity is also of interest. In this section, we discuss marginal effects of variables that are significant across estimators. The estimated marginal effects can be interpreted as semi-elasticities (proportional change in PV capacity for a one unit change in the independent variable).<sup>7</sup> In the discussion below, we focus on the results of the IV Tobit model since it addresses the endogeneity of SREC price. The estimates from Pooled Tobit and RE Tobit estimators are shown in the tables for comparison. Table 2 shows that a one dollar increase in electricity price increases capacity by 38%. A one unit change in insolation will increase capacity by 368%. The difference in insolation of the sunniest county and least sunniest county in our sample is 1, so all else equal the sunniest county will have over three times more solar PV than the least sunny county. The marginal effect of the

**Table 2**  
Effect of non-policy variables on new solar PV capacity: marginal effects.

	Pooled Tobit	IV Tobit	RE Tobit
Time Trend	0.571*** (0.0887)	0.580*** (0.0899)	0.623*** (0.0965)
Electricity Price	0.353*** (0.0611)	0.384*** (0.0651)	0.329*** (0.0761)
Insolation	3.682*** (0.647)	3.688*** (0.647)	3.813*** (1.091)

Standard errors in parentheses.

\*\*\*  $p < 0.001$ .

**Table 3**  
Effect of Rebate on new solar PV capacity: marginal effects.

Rebate (\$/kW-Capacity)	Pooled Tobit	IV Tobit	RE Tobit
0.1	0.768*** (0.0617)	0.756*** (0.0649)	0.881*** (0.0638)
0.5	0.817*** (0.0709)	0.803*** (0.0741)	0.946*** (0.0740)
1	0.880*** (0.0829)	0.863*** (0.0861)	1.029*** (0.0874)
2	1.010*** (0.108)	0.987*** (0.111)	1.200*** (0.116)
3	1.144*** (0.135)	1.116*** (0.138)	1.377*** (0.147)

Standard errors in parentheses.

\*\*\*  $p < 0.01$ .

time trend shows that each additional year sees an increase in capacity of 58%. This increase is likely related to decreasing solar installation costs over time.

For policy variables, it is more informative to present marginal effects at different levels of the incentive. Table 3 shows that a one dollar increase in the rebate offered increases new PV capacity by 76–112%, depending on the prevailing rebate rate. The marginal effect is larger as the rebate rate increases. This is because the total incentive to be received is larger the greater the rebate rate is. This suggests that larger rebate rates are appropriate to jump start the market and encourage more adoption. This result is consistent with many states' strategy to begin with larger rebate rates and taper off the rebate rate as the market expands. The marginal effect of SREC price is roughly the same across SREC values with a \$1 increase in the SREC price leading to a roughly 0.15% increase in solar capacity added (Table 4). Table 5 shows that if the sales tax is at 5%, increasing the sales tax waiver from 5% to 6% will increase new capacity by 51%. Similar to the rebate, if the initial waiver rate is high, the marginal effect is also larger. If the sales tax is at 7%, increasing the sales tax waiver from 7% to 8% will increase added capacity by 56%. The effect of one additional year of having a RPS policy ranges from a 29% increase in capacity in the early years of the RPS to 46% when the RPS policy has been in place for 10 years (Table 6). The RPS variable reflects growing expertise in deploying renewable energy sources. The trend in marginal effects suggests that these effects are cumulative over time, and greater expertise in a state encourages more solar adoption.

The empirical analysis presented here has number of caveats. First, we assume that after instrumenting for SREC prices, incentives are exogenous. It is possible that omitted variables related to support and preference for solar remain. In this case, endogeneity of incentives will lead to bias in estimated impacts. We have attempted to minimize this potential for bias by including controls for support of renewable energy (Democratic Party votes) and preference for solar technologies (lagged count of PV installations). Bias from omitted variables is likely to be small if we have adequately controlled for the key drivers of growth in solar PV capacity. To the extent that some bias remains, effects of

<sup>7</sup> Marginal effects are average partial effects, which give the average of partial effects across the different values of the independent variables, while holding the covariate of interest at a constant value, usually the mean.

**Table 4**  
Effect of SREC Price on new solar PV capacity: marginal effects.

SREC Price (\$/MWh)	Pooled Tobit	IV Tobit	RE Tobit
50	0.00274*** (0.000693)	0.00144 (0.00131)	0.00197** (0.000746)
100	0.00279*** (0.000721)	0.00146 (0.00134)	0.00200** (0.000767)
250	0.00296*** (0.000805)	0.00150 (0.00142)	0.00208** (0.000830)
400	0.00312*** (0.000889)	0.00155 (0.00151)	0.00216** (0.000892)

Standard errors in parentheses.

\*\*  $p < 0.05$ .

\*\*\*  $p < 0.01$ .

**Table 5**  
Effect of sales tax waiver on new solar PV capacity: marginal effects.

Sales Tax (%)	Pooled Tobit	IV Tobit	RE Tobit
5	0.503*** (0.0642)	0.509*** (0.0694)	0.457*** (0.0857)
6	0.530*** (0.0702)	0.536*** (0.0759)	0.479*** (0.0929)
7	0.557*** (0.0761)	0.563*** (0.0823)	0.501*** (0.100)
8	0.584*** (0.0819)	0.590*** (0.0886)	0.523*** (0.107)

Standard errors in parentheses.

\*\*\*  $p < 0.01$ .

**Table 6**  
Effect of RPS trend on new solar PV capacity: marginal effects.

RPS Year	Pooled Tobit	IV Tobit	RE Tobit
1	0.339*** (0.0434)	0.294*** (0.0499)	0.277*** (0.0504)
5	0.445*** (0.0798)	0.367*** (0.0812)	0.336*** (0.0765)
10	0.580*** (0.126)	0.460*** (0.121)	0.411*** (0.109)

Standard errors in parentheses.

\*\*\*  $p < 0.01$ .

incentives should be seen as upper bound estimates.

Second, we have not accounted for spatial spillovers across state lines. It is possible that knowledge and expertise in one state's solar market will affect other states' solar markets if installers operate across state lines. If these spillovers are driving some of the increase in PV capacity, the true effect of in-state incentives will be smaller than our estimates. However, the influence of out-of-state solar market growth on in-state capacity additions is likely to be second order to the effects of incentives and other factors within a state that are included in our estimated model.

#### 4.2. Policy cost and CO2 savings from solar rebates

A welfare evaluation of solar incentives is beyond the scope of this paper. However, based on our results we can provide a rough estimate of the social benefits of solar electricity in relation to the cost of funding solar incentives.

For social benefits, we focus on CO2 savings, since a key benefit of solar electricity is its lower GHG emissions relative to electricity produced from fossil fuels. For this analysis, we focus on the rebate incentive since it is highly significant in our regressions. Furthermore, the rebate is a direct financial incentive which makes our calculations

below transparent.

We define a baseline scenario based on the mean annual kW-capacity installed in the states during our study period, which is roughly 1500 kW as well as the mean rebate rate of \$1 per watt (or \$1000 per kW). Based on our regression results (see Table 3), increasing the rebate by a dollar per watt will increase capacity by 86%, which means there will be 2790 kW of capacity instead of 1500 kW. The total cost of funding the rebate increase can be calculated as:  $2,790 \text{ kW} * \$2,000/\text{kW} - 1,500 \text{ kW} * \$1,000/\text{kW} = \$4,080,000$ .

To calculate CO2 savings, we take the increase in PV-capacity (1290 kW) and calculate CO2 savings assuming a 30-year lifespan for the solar panels. To calculate CO2 savings, we need information on how much electricity a kW of capacity is expected to generate, and how much CO2 is saved when solar electricity displaces electricity from the grid. Using the median solar insolation for the Northeast of 4.5 kWh per square meter per day, annual production of solar electricity is about 1200 kWh per kW capacity (National Renewable Energy Laboratory, 2017). Solar panels may degrade over time, causing a decrease in electricity production. Using a degradation rate of 0.5% per year (Branker et al., 2011; Jordan and Kurtz, 2013), we calculate that over 30 years, 33,390 kWh of electricity will be produced from a kW of capacity. Multiplying 33,900 kWh with 1290 (the additional capacity due to the increase in rebate) gives 43,731,000 kWh of electricity produced from additional solar installations. The amount of CO2 savings varies by location depending on the mix of electricity sources. Based on electricity production in the Northeast, we use a value of 1.44 lbs CO2 per kWh electricity produced (Baker et al., 2013). Using this figure, we find that the additional capacity due to the rebate saves 31,012.6 tons of CO2 over thirty years. Comparing this with the cost of increasing the rebate by one dollar (\$4,080,000) shows that 0.0076 tons of carbon is saved per dollar of rebate expenditure. Alternatively, we can say that the cost of CO2 savings through the solar rebate program is \$131.5/ton of CO2. Policy makers can use this figure to compare public expenditures in the solar program with other CO2-saving alternatives. We should note though that incentivizing solar energy has other benefits in addition to carbon mitigation such as increasing diversity of energy sources and spurring technological advances that can reduce the cost of clean energy.

#### 5. Conclusion

We find strong evidence that factors that directly effect financial viability and returns on investment have the most impact on capacity growth in the commercial solar PV market. These include electricity price, solar insolation, and installation cost. Among policy variables, incentives that either reduce cost or provide revenue such as rebates, sales tax waivers, and SREC price are significant. The importance of financial considerations is not surprising since most installers of commercial solar systems are businesses, whose decisions are presumably guided by profitability.

Unlike residential installations, which can be partly motivated by pro-environmental attitudes and solar technology preferences, commercial installations appear to be unmotivated by these factors as evidenced by the lack of significance of variables such as Democratic Party votes and lagged count of PV installations.

The significance of policy incentives suggests that the continued availability of these incentives will be important to the future growth of the commercial market segment. Public funding to support expansion of the solar market raises questions about the cost of financing incentive programs. Many states have steadily decreased or even eliminated rebates over time due to cost concerns. States can continue to encourage growth in commercial PV capacity by improving the effectiveness of existing incentives. For example, states can put in place mechanisms to reduce the uncertainly related to SREC prices, given that the volatility in SREC prices may be dampening its ability to encourage new installations (Bauner and Crago, 2015). Steps in this direction can stimulate growth in the commercial segment without imposing additional financial burden on public funds or ratepayers.



## Appendix A

Net Metering										
	2005	2006	2007	2008	2009	2010	2011	2012	2013	
CT	*	*	*	*	*	*	*	*	*	
DC	*	*	*	*	*	*	*	*	*	
DE	*	*	*	*	*	*	*	*	*	
MA	*	*	*	*	*	*	*	*	*	
MD	*	*	*	*	*	*	*	*	*	
ME	*	*	*	*	*	*	*	*	*	
NH	*	*	*	*	*	*	*	*	*	
NJ	*	*	*	*	*	*	*	*	*	
NY	*	*	*	*	*	*	*	*	*	
PA	*	*	*	*	*	*	*	*	*	
RI	*	*	*	*	*	*	*	*	*	
VT	*	*	*	*	*	*	*	*	*	
WV	*	*	*	*	*	*	*	*	*	

Loan Program										
	2005	2006	2007	2008	2009	2010	2011	2012	2013	
CT		*	*	*	*	*	*	*	*	
DC						*	*	*	*	
DE						*	*	*	*	
MA						*	*	*	*	
MD	*	*	*	*	*	*	*	*	*	
ME						*	*	*	*	
NH						*	*	*	*	
NJ					*	*	*	*	*	
NY					*	*	*	*	*	
PA					*	*	*	*	*	
RI						*	*	*	*	
VT						*	*	*	*	
WV										

PBI										
	2005	2006	2007	2008	2009	2010	2011	2012	2013	
CT										
DC										
DE										
MA										
MD										
ME					*	*	*	*	*	
NH										
NJ										
NY						*	*	*	*	
PA										
RI										
VT										
WV										

Sales Tax Waiver										
	2005	2006	2007	2008	2009	2010	2011	2012	2013	
CT		*	*	*	*	*	*	*	*	
DC										
DE										
MA	*	*	*	*	*	*	*	*	*	
MD				*	*	*	*	*	*	
ME										
NH										
NJ	*	*	*	*	*	*	*	*	*	
NY										
PA										
RI	*	*	*	*	*	*	*	*	*	
VT	*	*	*	*	*	*	*	*	*	
WV										

RPS										
	2005	2006	2007	2008	2009	2010	2011	2012	2013	
CT		*	*	*	*	*	*	*	*	
DC			*	*	*	*	*	*	*	
DE			*	*	*	*	*	*	*	
MA	*	*	*	*	*	*	*	*	*	
MD		*	*	*	*	*	*	*	*	
ME			*	*	*	*	*	*	*	
NH			*	*	*	*	*	*	*	
NJ	*	*	*	*	*	*	*	*	*	
NY		*	*	*	*	*	*	*	*	
PA			*	*	*	*	*	*	*	
RI			*	*	*	*	*	*	*	
VT			*	*	*	*	*	*	*	
WV										

Rebate										
	2005	2006	2007	2008	2009	2010	2011	2012	2013	
CT				*	*	*	*	*	*	
DC	*	*	*	*	*	*	*	*	*	
DE		*	*	*	*	*	*	*	*	
MA				*	*	*	*	*	*	
MD				*	*	*	*	*	*	
ME					*	*	*	*	*	
NH					*	*	*	*	*	
NJ	*	*	*	*	*	*	*	*	*	
NY	*	*	*	*	*	*	*	*	*	
PA				*	*	*	*	*	*	
RI				*	*	*	*	*	*	
VT	*	*	*	*	*	*	*	*	*	
WV										

SREC										
	2005	2006	2007	2008	2009	2010	2011	2012	2013	
CT							*	*	*	
DC					*	*	*	*	*	
DE					*	*	*	*	*	
MA					*	*	*	*	*	
MD					*	*	*	*	*	
ME										
NH										
NJ			*	*	*	*	*	*	*	
NY					*	*	*	*	*	
PA					*	*	*	*	*	
RI										
VT										
WV										

Fig. A.1. Timing of implementation of solar incentives.

**Table A.1**  
Summary statistics.

Variable	Varies By <sup>a</sup>	Min	Max	Median	Mean	Std deviation
Dependent Variable						
Added Capacity (kW/year)	C,Y	10	75,716	193	1591	4867
Solar Market Policies						
Net Metering (b)	S,Y	0	1	1	0.91	0.28
Loan (b)	S,Y	0	1	0	0.46	0.5
Performance-Based Incentive (b)	S,Y	0	1	0	0.12	0.32
Sales Tax Rate (%)	S,Y	0	7	0	1.69	2.74
Rebate (dollars/watt)	S,Y	0	4.88	0.36	1.1	1.49
SREC Price (dollars/MWh/year)	S,Y	0	668	0	51	128.17
RPS Trend (Number of years)	S,Y	0	11	2	2.89	2.86
Instruments						
SACP (\$/MWh/year)	S,Y	0	711	0	104	209.33
Controls						
Electricity Price (cents/kWh)	C,Y	5.53	17.11	11.61	11.55	3.23
Insolation (kWh/sqm/day)	C	4.08	5.01	4.47	4.48	0.2
Number of Businesses	C,Y	42	166,050	2805	8592	15,115
Population Density(pop/sq. mile)	C,Y	2.77	72,006	140	1138	5304
Income (\$)	C,Y	17,275	121,632	36,037	38,348	11,528
Unemployment (%)	C,Y	2	17.1	7	6.77	2.21
Democratic votes (%)	S,Y	30.16	97.34	56.35	56.61	0.09

<sup>a</sup> S denotes state, C denotes county, and Y denotes year. (b) denotes binary variables.

**Table A.2**  
Tobit versus OLS: beta coefficients.

	Pooled Tobit	OLS
Time Trend	1.484 <sup>***</sup> (0.231)	0.310 <sup>***</sup> (0.0914)
Electricity Price	0.916 <sup>***</sup> (0.159)	0.0131 (0.0712)
Lagged Count of PV Installations	0.0389 <sup>*</sup> (0.0212)	0.0896 <sup>***</sup> (0.0167)
Insolation	9.561 <sup>***</sup> (1.668)	2.939 <sup>***</sup> (1.080)
ln(Business)	4.189 <sup>***</sup> (0.388)	1.075 <sup>***</sup> (0.232)
ln(Population)	− 0.789 <sup>**</sup> (0.312)	0.0825 (0.179)
Income	− 0.000106 <sup>***</sup> (0.0000280)	− 0.0000305 (0.0000275)
Unemployment	− 0.875 <sup>***</sup> (0.200)	− 0.260 <sup>**</sup> (0.0972)
Democrats	0.00429 (0.0393)	0.00886 (0.0179)
Loan Program	0.909 (0.898)	− 0.680 (0.491)
Sales Tax Waiver	1.094 <sup>***</sup> (0.120)	0.467 <sup>***</sup> (0.0759)
Rebate	2.465 <sup>***</sup> (0.247)	0.697 <sup>***</sup> (0.137)
PBI	1.131 (0.901)	2.078 <sup>**</sup> (0.648)
SREC Price	0.00713 <sup>***</sup> (0.00182)	0.00572 <sup>***</sup> (0.00110)
Net Metering	4.575 <sup>**</sup> (2.024)	− 0.171 (0.486)
RPS Trend	1.057 <sup>***</sup> (0.172)	0.585 <sup>***</sup> (0.0939)
Constant	− 110.4 <sup>***</sup> (8.400)	− 30.13 <sup>***</sup> (5.117)
Log-Likelihood	− 3898.9	− 8036.9
Observations	2700	2700

Standard errors in parentheses.

<sup>\*</sup>  $p < 0.1$ .

<sup>\*\*</sup>  $p < 0.05$ .

<sup>\*\*\*</sup>  $p < 0.01$ .

**Table A.3**  
First stage IV regression.

SACP	.453*** (0.0116)
F(23, 2676)	253.23
Observations	2700

Standard error in parentheses. Only the coefficient on SACP is shown.

\*\*\*  $p < 0.01$ .

## References

- Baker, E., Fowle, M., Lemoine, D., Reynolds, S.S., 2013. The economics of solar electricity. *Annu. Rev. Resour. Econ.* 5, 387–426.
- Barbose, G., Darghouth, N., Wiser, R., 2012. Tracking the Sun V an historical summary of the installed price of photovoltaics in the United States from 1998 to 2011. Environmental Energy Technologies Division, Lawrence Berkeley National Laboratory.
- Bauner, C., Crago, C.L., 2015. Adoption of residential solar power under uncertainty: implications for renewable energy incentives. *Energy Policy* 86, 27–35.
- Bollinger, B., Gillingham, K., 2012. Peer effects in the diffusion of solar photovoltaic panels. *Mark. Sci.* 31, 900–912.
- Branker, K., Pathak, M., Pearce, J.M., 2011. A review of solar photovoltaic levelized cost of electricity. *Renew. Sustain. Energy Rev.* 15, 4470–4482.
- Cameron, A.C., Trivedi, P.K., 2010. *Microeconometrics Using Stata*. Stata Press College Station, TX.
- Costa, D.L., Kahn, M.E., 2013. Energy conservation? Nudges? And environmentalist ideology: evidence from a randomized residential electricity field experiment. *J. Eur. Econ. Assoc.* 11, 680–702.
- Coughlin, J., Grove, J., Irvine, L., Jacobs, J.F., Phillips, S.J., Moynihan, L., and Wiedman, J., 2016. A guide to community solar: utility, private, and non-profit project development. Report prepared for the National Renewable Energy Lab.
- Cragg, M.I., Zhou, Y., Gurney, K., Kahn, M.E., 2013. Carbon geography: the political economy of congressional support for legislation intended to mitigate greenhouse gas production. *Econ. Inq.* 51, 1640–1650.
- Crago, C.L., Chernyakhovskiy, I., 2017. Are policy incentives for solar power effective? Evidence from residential installations in the Northeast. *J. Environ. Econ. Manag.* 81, 132–151.
- Dastrup, S.R., Graff Zivin, J., Costa, D.L., Kahn, M.E., 2012. Understanding the solar home price premium: electricity generation and green social status. *Eur. Econ. Rev.* 56, 961–973.
- DSIRE, 2015. Database of state incentives for renewables and efficiency. Available at <<http://www.dsireusa.org>>.
- Flett Exchange, 2015. Market data SREC prices. Available at <<http://www.flettexchange.com>>.
- Goodrich, A., James, T., Woodhouse, M., 2012. Residential, commercial, and utility-scale photovoltaic (PV) system prices in the United States: current drivers and cost-reduction opportunities. Working paper, National Renewable Energy Laboratory (NREL), Golden, CO.
- GTM Research and Solar Energy Industries Association, 2017a. Solar Market Insight Report 2010 Year in Review (Executive Summary). <<https://www.seia.org/sites/default/files/us-solar-market-insight-report-q1-2011-120627093305-phpapp01.pdf>>.
- GTM Research and Solar Energy Industries Association, 2015. Solar Market Insight report 2015 Q4. Available at <<https://www.seia.org/research-resources/solar-market-insight-2015-q4>>.
- GTM Research and Solar Energy Industries Association, 2016. Solar Market Insight report 2016 Q4. Available at <<http://www.seia.org/research-resources/solar-market-insight-report-2016-q4>>.
- GTM Research and Solar Energy Industries Association, 2017b. Solar Market Insight report 2017 Q2. Available at <<http://www.seia.org/research-resources/solar-market-insight-report-2017-q2>>.
- GTM Research and Solar Energy Industries Association, 2014. US Solar Market Insight 2013 Year in Review (Executive Summary). Available at <<http://www.seia.org/research-resources/solar-market-insight-report-2013-year-review>>.
- Hart, D., Birson, K., 2016. Deployment of solar photovoltaic generation capacity in the United States. Prepared for the Office of Energy Policy and Systems Analysis, US Department of Energy.
- Hitaj, C., 2013. Wind power development in the United States. *J. Environ. Econ. Manag.* 65, 394–410.
- Hughes, J.E., Podolefsky, M., 2015. Getting green with solar subsidies: evidence from the California solar initiative. *J. Assoc. Environ. Resour. Econ.* 2, 235–275.
- Jordan, D.C., Kurtz, S.R., 2013. Photovoltaic degradation rates – an analytical review. *Prog. Photovolt. Res. Appl.* 21, 12–29.
- Krasko, V.A., Doris, E., 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 local environmental, social, economic and political variables on the spatial distribution of residential solar PV arrays across the United States. *Energy Policy* 47, 332–344.
- Menz, F.C., Vachon, S., 2006. The effectiveness of different policy regimes for promoting wind power: experiences from the states. *Energy Policy* 34, 1786–1796.
- National Renewable Energy Laboratory, 2015a. Open PV Project. Available at <<http://openpv.nrel.gov>>.
- National Renewable Energy Laboratory, 2017. PVWatts Calculator. Available at <<http://pvwatts.nrel.gov>>.
- National Renewable Energy Laboratory, 2015b. Solar maps development: how the maps were made. Available at <<http://www.nrel.gov/gis/solar-map-development.html>>.
- PACENation, 2017. Commercial PACE near you. Available at <<http://pacenation.us/pace-programs/commercial>>.
- Sarzynski, A., Larrieu, J., Shrimali, G., 2012. The impact of state financial incentives on market deployment of solar technology. *Energy Policy* 46, 550–557.
- Steward, D., Doris, E., Krasko, V., Hillman, D., 2014. The Effectiveness of State-Level Policies on Solar Market Development in Different State Contexts. National Renewable Energy Lab technical report. Available at <<http://www.nrel.gov/docs/fy14osti/61029.pdf>>.
- U.S. Bureau of Labor Statistics, 2015. Local area unemployment statistics. Available at <<http://www.bls.gov/lau>>.
- U.S. Census Bureau, 2016a. American community survey. Available at <<http://factfinder2.census.gov/faces/nav/jsf/pages/index.xhtml>>.
- U.S. Census Bureau, 2016b. County business patterns. Available at <<http://www.census.gov/econ/cbp>>.
- U.S. Census Bureau, 2016c. Geography. Available at <<http://www.census.gov/geo>>.
- U.S. Energy Information Administration, 2015a. Direct federal financial interventions and subsidies in energy in fiscal year 2013. Available at <<https://www.eia.gov/analysis/requests/subsidy/>>.
- U.S. Energy Information Administration, 2015b. Electric power annual. Available at <<http://www.eia.gov/electricity/data/state/>>.
- U.S. Federal Election Committee, 2016. U.S. Federal election committee. Available at <<http://www.fec.gov/press>>.
- Wiser, R., Barbose, G., Holt, E., 2011. Supporting solar power in renewables portfolio standards: experience from the United States. *Energy Policy* 39, 3894–3905.
- Wooldridge, J.M., 2010. *Econometric Analysis of Cross Section and Panel Data*. MIT Press.