It’s All Local? How Sub-State Policies Affect Western US Residential Solar Adoption

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Abstract: This paper adds to the literature by investigating whether municipal, county, and utility policies drive residential solar photovoltaic (PV) adoption. While previous studies have investigated the effects of state policies, none have do so while including policies at the sub-state level. I employ spatial econometric techniques, which recently have been used to empirically account for the peer effects and spatial clustering that have been found in residential markets. Results from the largest residential solar market in the US suggest that after controlling for solar resource, environmental preference, and other demographic information, the local policies are an important driver in the residential solar PV market: the average solar policy stimulates a 6.0-7.9% percent increase in installed residential capacity. Further, the residential market exhibits a moderate amount of spatial autocorrelation.

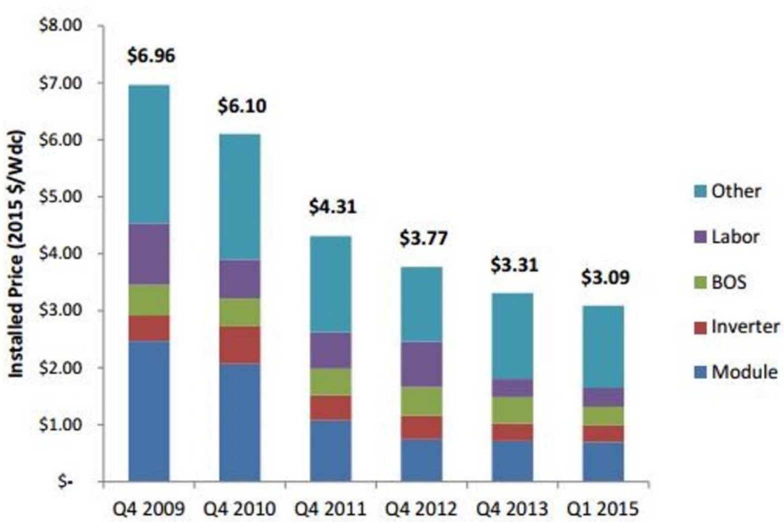
1. Introduction

A market failure exists when the price mechanism fails to account for all associated costs and benefits in the market. The emission of heat-trapping greenhouse gases (GHGs) generated by the production of electricity from non-renewable sources is one such failure. These GHGs represent a significant externality to production. Accordingly, the social costs of production are higher than those felt privately, leading to lower (higher) equilibrium prices (quantities produced) of carbon-based electricity than what would be otherwise realized at the social optimum. With increased understanding of both this market failure and its implications to current and future economic development, policymakers tried to provide incentives to promote renewable energy generation.

Solar is one such option. As a substitute to non-renewable electricity production, it is an attractive non-carbon based option: increased solar generation could help reduce carbon-based generation to socially optimal values while helping meet the predicted increase in consumption levels. Of the three main non-carbon based generation methods, wind, solar, and hydro, only wind and solar have large potential to increase their capacity, as nearly all optimal dam locations have been utilized. While certainly intermittent, solar generation will always have a baseline generation capacity, as even on the cloudiest days some generation is possible. There are trade-offs for large-scale solar generation: large land requirements in potentially sensitive environments have caused some activist groups, otherwise in support of solar generation, to raise concerns. Further, often new or improved transmission lines are required for connecting utility-scale plants to consumption areas. However commercial and residential scale solar are seen by some as more attractive, as the generation infrastructure can fit on existing and available rooftops. In addition to the use of solar energy to heat and light a home or business, there are two main technologies able to harness solar energy: solar photovoltaic (henceforth solar PV) technologies generate electricity, while solar thermal systems provide water heating. While both replace carbon-emitting electricity production, solar PV does so directly, and has generated significantly more interest in individual homeowners, businesses, and policymakers alike.

The installation of a solar PV generation system requires significant upfront financial resources. According to the National Renewable Energy Laboratory (NREL), a residential PV system costs on average $3.09 per watt of installed capacity, or more than $15,000 for a 5 kW system before government and utility financial incentives (Chung et al., 2015). That said, their costs are decreasing. Figure 1 displays the cost reduction in these values: since Q4 2013 the cost of solar has decreased by 7%, since Q4 2009 that reduction is larger than 55% (Chung et al., 2015). These costs have continued their descent into 2015, with the majority of cost reductions coming from declines in soft costs. However some price declines have been offset by falling incentives (Barbose and Darghouth, 2015).

Figure 1: Costs of Residential Solar PV Installations



Source: Chung et al., 2015

Even with this reduction the financial benefits of a system, namely the offset of electricity that would be otherwise purchased from a utility, surpass the upfront costs only years after their installation. While the exact timing depends on the costs and financial incentives available to the homeowner, the difference explains a significant amount of the energy efficiency ‘gap’: the difference between the economically advantageous and actual amount of solar generation installed. A number of third party firms now capitalize on this opportunity by installing and owning entire home systems, while selling the generated electricity either directly to the home or to the connecting utility. Regardless of the financing, the adoption of residential solar is considered a social good, and has received considerable attention recently in the literature.

Borenstein (2015) evaluated the residential solar PV market in California, and found that while it is primarily high-income individuals adopting, that disparity has declined. Further, he finds that adoption is driven by the heaviest electricity-consuming households. California's electricity rate structure is tiered, and adopting households generally pay significantly higher rates for electricity, suggesting that both rate structure and are important considerations. This tiered pricing structure was also found to be significant in California by Dargouth et al. (2011). Bauner and Crago (2015) apply an option value framework to household solar PV decisions, finding that policies that reduce uncertainty could be the most effective stimulants to adoption.

Alongside household financial and personal characteristics, the financial incentives provided are key drivers in the choice of home solar adoption. From individual municipalities to the federal government, political organizations at nearly every level offer varying forms of financial assistance to help spread the diffusion of solar power. The modeling of this policy impact was done differently in the literature. Crago (2014) evaluates the effectiveness of a number of key state policies that have incentivized solar PV adoption, finding significant positive associations between specific policies and capacity addition. Borchers et al. (2014) find similar effects between specific policies and wind and solar adoption on US farms, however using a different set of state policies. Kwan (2012) also models residential PV adoption, however he measures the effects of an average level of state incentives. None of the preceding study models the effects of federal policy, as those effects are felt everywhere in their study area. Similarly, none measure the impact that sub-state regulatory processes create. This may be an important omission: Two studies (Burkhardt et al., 2015, Dong and Wiser, 2013) highlight how local permitting and regulations can greatly influence both adoption prices and development times.

However the choice to adopt solar power is not strictly a financial choice. The understanding of solar technology is an important predictor of residential adoption, leading Islam and Meade (2013) to recommend education policies to stimulate solar adoption. Noll et al. (2014) demonstrate how Solar Community Organizations have been an effective means of reducing barriers to adoption. Peer effects are also demonstrated to impact adoption at the zip code level (Bollinger and Gillingham, 2012 and Snape and Rynikiewicz, 2012).

There have been recent attempts to quantifying these peer effects. Marcello and Gillingham (2015) find notable clustering in the solar PV adoption, patterns that do not merely follow intuitive spatial patterns of either income of population. Richter (2013) empirically demonstrates small but significant social spillovers in UK installations at the neighborhood level. Balta-Ozkan et al. (2015) further quantify these spatial spillovers in UK solar PV adoption by utilizing spatial econometric methods, which this study follows builds upon looking at the western US market.

The goal of this paper is to investigate whether sub-state policies have an influential impact on residential solar PV adoption. Using a unique dataset created to geographically locate relevant incentivizing policies, this paper improves the literature by estimating their effect on the solar PV market, while at the same time accounting for the empirically demonstrated spatial patterns of residential adoption. Finding suggest that after controlling for relevant demographic, environmental, and solar potential variables, local policies are found to have a positive and significant impact on the residential market. Further, solar PV adoption is estimated to have a weak but significant spatial dependence. Interestingly after the inclusion of state fixed-effects, state-level solar incentivizing policies do not have a significant effect in the market, suggesting that other differences at the state level have a larger effect in the market than the particular adoption policies.

2. Hypothesized Model

The main empirical goal of this paper is to accurately model the key drivers of solar adoption in the Western United states. Given the cited literature above, I create equation (1) as a hypothesized linear model of the market:

$$y_{i,t} = \alpha + X_{i,t}\beta + P_{\mathrm{i,t}}\gamma + E_{i,t}\delta + H_{i,t}\phi + Po_{i,t}\zeta + S_{i,t}\kappa + St_{i,t}\psi + \epsilon_{i,t} \qquad (1)$$

The dependent variable $y_{i,t}$ represents the total amount of solar PV capacity in county i in year t. In the WECC there are 405 counties, and for the data available t denotes years 2009-2014. X_t is an (n*t) by k matrix of k county-level demographic characteristics such as income, age, race, and population and homeownership. Nearly all empirical studies have suggested that income and solar adoption have a strong positive correlation. There is some evidence that racial background is an important determinant of environmental concern. I choose the percent Hispanic ($H_{i,t}$) designation for the western US states as other racial designations (i.e. Black, Asian, etc) are heavily skewed towards California, and would possibly capture other California-specific effects. However in western US states, the Hispanic population is more evenly distributed[1]. The level of homeownership is likely an important predictor of residential solar adoption. Similar to other home improvements, renters have little incentive and likely less ability to pay the large up-front costs of solar installations. Further, landlords will have significantly less incentive to add solar PV to rental units, especially given the high opportunity cost they would face: those resources could otherwise be spent in ways that would quickly and reliably increase rent, such as newer appliances, better heating, etc.

P_t is an (n*t) by 1 vector of electricity prices. Solar installations are a substitute to purchasing electricity from a utility. A positive relationship, with higher prices incentivizing greater adoption, is both intuitive and empirically demonstrated in Borenstein (2015) and Dargouth et al. (2011). However this relationship could exhibit a degree of endogeneity, as greater share of electricity generated by solar PV could also

[1] Results are qualitatively similar when using percent Black or percent non-white.

impact prices. In fact, utilities often make the argument increased solar PV integration raises prices, as it takes increased effort to manage its intermittent generation. E_t represents an (n*t) by 1 vector of environmental preferences. There are a number of important positive environmental outcomes from large-scale adoption of solar power, mainly the reduction of GHG emission and improvements in air and water quality caused by a reduction in coal or natural gas emissions. Capturing these preferences likely helps explain the household decision[2]. Po_t is an nxr matrix of solar policies that residents in county *i* at time *t* face, where r is equal to the number of geographic levels of policy. For example, a household in Oakland will receive the incentives from any policy run by the city, Alameda County, their electric utility (PG&E), the state of California, and by the US federal government, and each will vary given they year. Finally, St_t represents a vector of state fixed effects that would capture any additional differences between states affecting solar adoption (e.g. labor costs, construction and connection standards, etc). The states in this sample area likely have significant difference in permitting, labor, and safety regulations. While the impact of each individual regulatory difference on the solar PV market is likely small, aggregated these could make non-trivial differences.

3. Data

3.1 Solar Installations

Data for residential solar capacity was obtained from the Open PV Project[3]. Produced by the National Renewable Energy Lab (NREL), the Open PV project is a comprehensive dataset of solar PV installations, with data contributed by utilities, installers, and the general public. Data is validated by NREL through a variety of ways, in part based on the trust NREL gives to the reporter. I used data from

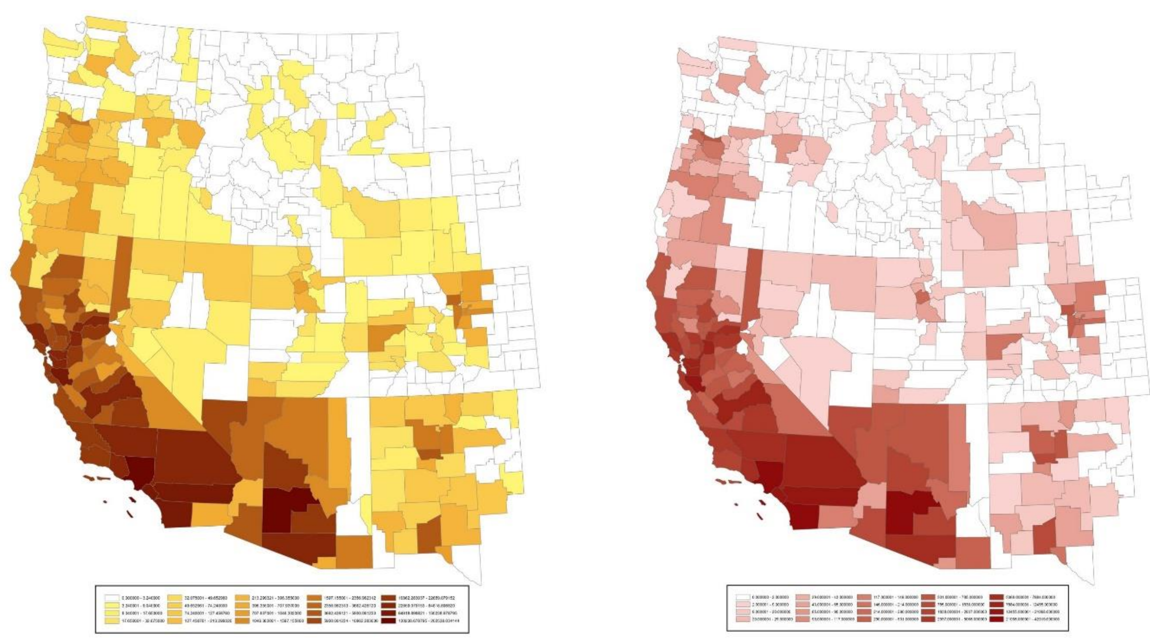
[2] However strict environmental preference may not be the best explanatory variable: while there is a strong correlation between environmental preference and the political left, energy independence is a trait shared across the political spectrum. There are some for example with strongly divergent views about the importance of air quality who nevertheless support the increase in solar generation

[3] For more information about data methodology, see https://openpv.nrel.gov/about.

counties in the Western Electricity Coordination Council (WECC) region of Oregon, Washington, California, Utah, Nevada, Colorado, Wyoming, Arizona, and parts of New Mexico, Montana, Texas, and South Dakota (see figure # for study area). Individual home installation data are aggregated to the county level. Following Kwan (2012), I limit the upper range of individual solar installations to 10 kW to ensure that the solar installations included are in fact residential systems (n=230,152)[4]. The distribution of installed solar capacity in 2016 (Figure 2, Panel A) and number of solar PV installations (Figure 2, Panel B) is highly concentrated in the Southwest part of the WECC. Given both the large number of zeros and the right-skewedness of the distribution of county kW installed capacity, I use an inverse hyperbolic sine transformation, which accommodates zero values but otherwise is directly interpretable as a log transformation (see Burbidge et al., 1988, MacKinnon and Magee, 1990).

Figure 2: Residential Solar PV Capacity and Number of Installations, 2016

Panel A   Panel B



[4] As of 4/15/2016

3.2 Policy Variables

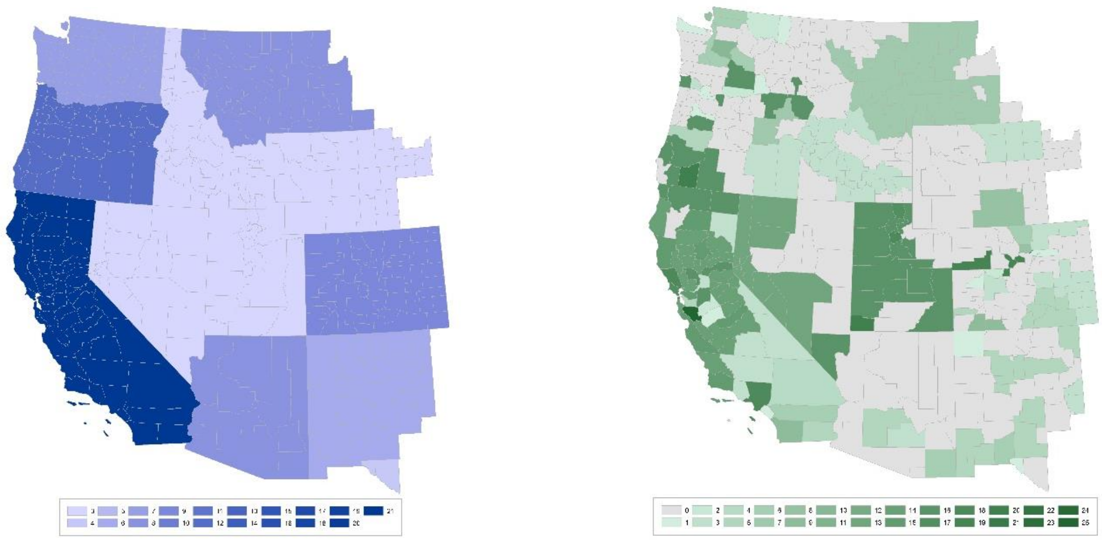
State, utility, county, and municipality policies are collected from the North Carolina Clean Energy's Database of State Incentives for Renewables and Efficiency (DSIRE, 2015). The DSIRE database is a comprehensive collection of policies and incentives that involve renewable energy and energy efficiency growth in the US. There are 43 categories of renewable policy; everything from corporate tax credits to feed-in tariffs. From these categories, I select from all but the corporate and utility categories those designated with as solar technologies. While many of these policies are at the state level, a significant number are enacted by cities, counties, and utilities. Dong and Wiser (2013) provide evidence that city-level permitting tangibly affects both the price and development time of residential PV installations. With this in mind, I include both municipality and county policies. However given that demographic data is only available at the county level, I aggregate municipal policies to the county level. Only policies in the county's dominant population center are included, however there were only a small number of municipal policies in a county that were not included at the county level, as in general municipal policies are enacted in larger cities that dominate the majority of the county.

Renewable policies from utilities are important to include in the analysis as well. Investor-owned utilities (IOUs) are generally not interested in measuring and/or correcting for social costs. Further, they have some disincentive for the increase of solar energy: Solar PV is both distributed and intermittent, making their job of providing electricity at all hours difficult and often more expensive. However, there are some reasons for IOUs to promote residential solar PV capacity additions: Evidence. Further, municipal utilities and electric cooperatives are generally more attuned to both customer preferences as well as larger problems, and more insulated from the pressure to increase profit. Thus I include solar policies at the utility level. Assigning them to a particular county can be difficult, as their boundaries often do not align perfectly with county jurisdictions. I follow the similar path with that of city-level policies: counties whose main population centers within a utilities coverage area are said to be affected by this policy, and vice versa. Utility coverage areas for most states in the WECC are available through individual states'

Public Utility Commissions, with varying degrees of resolution. Only California has utility coverage areas available in shapefile formats: for the rest utility coverage images were georeferenced and interpolated using ArcGIS. I combine these sub-state policies from the utility, county, and municipality level into one ‘Local’ value for each county, and another reflecting the policies for the state in which the county resides. The distribution of state solar policies are displayed in panel A of figure 3. As can be seen, significant variation happens at the state hole. Non-state policies are displayed panel B, which displays a much smaller amount of variation between counties.

Figure 3: Number of Solar Incentivizing Policies

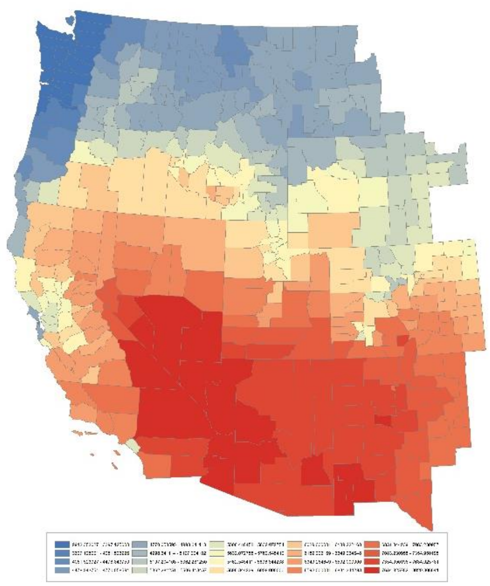
Panel A Panel B



3.3 Solar Insolation

To measure the amount of potential a given county has to generate electricity from solar radiation, I use annual solar insolation, the cumulative kilowatts per square meter per day. This data is collected and distributed by NREL[5] and produced by the State University of New York/Albany satellite radiation model. This data is available at 10 kilometer resolution, and each county's annual average values are calculated using ArcGIS's spatial statistics toolbox. These averages are displayed in figure 4.

Figure 4: Average Solar Insolation



3.4 Environmental Preference

To capture county residents' environmental preferences, I use results from the US Presidential elections. Coan and Holman (2008) demonstrate how there has been a long established and intuitive correlation between Democratic Party voting and environmental concern. Further, in his first presidential term and during the 2012 election campaign, President Obama frequently made mention of themes of climate

[5] Available: http://www.nrel.gov/gis/data_solar.html

change, energy independence, renewable resources, and a ‘green’ economy. While the decision for a single office will be a selection of a number of non-policy issues, and thus provide a weaker proxy for a single preference, given the recent rise in political polarization in the US the difference in voting record from individual elections will likely matter less.

In the cross-sectional analysis, I include the number of Whole Foods locations in each county to further capture environmental preference is. Whole Foods is an upscale food retailer, specializing in food certified as natural and/or organic. It caters to a population with a willingness to pay higher prices for food perceived to be healthier and more ethically produced, which I assume is highly correlated with the environmental preferences that would drive solar adoption. To my knowledge, this is the first time Whole Food locations have been used to measure environmental performance. However many similar measures have been used, such as organic food sales and hybrid and electric vehicle penetration.

3.5 Electricity Prices, County Demographics

Average residential electricity prices come from EIA’s form 861, which provide average electricity prices at the residential level from each utility, which are averaged at the state level. County demographic information comes from US Census’ American Community Survey, using the American FactFinder website[6]. Using their five year ACS estimates, I use income per capita[7], percent identifying as Hispanic, and county median age. Summary statistics for demographic information and all other variables are displayed in Table 2.

Table 1: Summary Statistics

[6] Available: http://factfinder.census.gov/faces/nav/jsf/pages/searchresults.xhtml?refresh=t

[7] 2014 dollars

Variable	Obs	Mean	Std. Dev.	Min	Max
Year	2430	2011.5	1.708177	2009	2014
LocalP	2430	3.756379	4.766848	0	25
StateP	2430	8.1893	5.399439	3	21
ResCapkW	2430	2418.246	11647.16	0	202219.9
tr(ResCapkW)	2430	3.016599	3.431741	0	12.91026
lnPers	2430	10.54842	0.2309342	9.758636	12.17811
PctDem	2430	40.69779	16.29271	5.772967	93.38633
MedAge	2430	39.98428	6.768037	21.7	61.2
HmeOwn	2430	69.85514	7.924824	36.59945	94.7254
Hisp	2430	17.22641	17.36023	0	85.17928
wBach	2430	24.4986	10.02818	2.4	67.8
StateE	2430	10.73388	2.280217	7.58	16.25
SolPot	2430	5783.208	1133.905	2912.353	8020.807
lnNumOwd	2430	8.954802	1.712668	4.867535	14.25511
Detached	2430	70.5549	9.642919	18.1	98.3

4. Empirical Model

A limitation of the model in equation (1) is that it ignores any spatial influence on the adoption of solar power. As explained in the previously cited literature, there are likely strong spatial influences in an empirical model estimating the adoption of residential solar, from peer effect causing industry and/or adoption clustering. Failing to include influential explanatory variables into the model would create omitted variable bias. To test the spatial effects presented in equation (1), I generate a Moran's I statistic, and in comparing it to a chi-squared distribution with 1 degree of freedom, I strongly reject the null hypothesis of no spatial autocorrelation.

4.1 Spatial Methodology

Given this significant presence of spatial autocorrelation, I follow Balta-Ozkan et al. (2015) in applying spatial econometric methods to solar PV market, modeled in equation (1). I do this in three ways: First, I evaluate the market using a cross sectional approach. Second, to better address questions of identification, I adopt a simple fixed-effects panel approach. And third, I incorporate the covariates the cross sectional analysis to evaluate their impact in a panel setting. Overall, results suggest that sub-state policies hae been an important driver in the choice to adopt residential solar PV.

In a cross-sectional setting, there are a number of methods that account for the presence of spatial dependence (for detailed background, see LeSage and Pace 2009). The most common form is the Spatial Autoregressive (SAR) model:

$$y_i = \rho W y_i + X_i\beta + \epsilon_i \tag{2}$$

where W represents a known nxn spatial weights matrix, and the scalar ρ is estimated to describe the degree of spatial dependence in the model. When $\rho = 0$, there is no spatial dependence, and the model reduces to a standard OLS model, as in equation (1). Every model considered here and below uses a spatial-weights W matrix, which has a number of ways to model, such as assigning neighbors based on distance or shared borders. However the marginal effect estimates produced by the model are generally not sensitive to W's specification (LeSage and Pace, 2014). In this study I build a contiguity-based weights matrix.

Another common form of spatial modeling is the Spatial Error Model, or SEM, which models the error terms to follow some spatially weighted process:

$$y_i = X_i\beta + u_i, \;\; u = \lambda W u_i + \epsilon_i \tag{3}$$

where λ describes the degree of spatial dependence in the error term. Like the SAR, a λ value of 0 reduces the model to standard OLS. The SEM is unique in that its estimates of the marginal effects are similarly interpretable as those from OLS.

The interpretation of non-SEM spatial econometric models requires more care than is generally given. Producing the marginal effects from the SAR requires simple algebra to generate its reduced form:

$$y_i = \rho W y_i + X_i\beta + \epsilon$$

$$y_i - \rho W y_i = X_i\beta + \epsilon$$

$$y_i(I_n - \rho W) = X_i\beta + \epsilon$$

$$y_i = (I_n - \rho W)^{-1} X_i \beta + (I_n - \rho W)^{-1} \epsilon \quad (4)$$

Partially differentiating the reduced form equation with respect to $x_{i,t}$ produces:

$$\frac{\partial y_i}{\partial x_i} = S(W) = (I_n - \rho W)^{-1} X_i \quad (5)$$

where $S(W)$ is an nxn matrix displaying the all marginal effects on y_i from a change in x_i. The diagonal elements in this matrix are the marginal effects from county i on the dependent variable in county i, known as the direct effects. The off-diagonal elements in $S(W)$ are the effects on the dependent variable in county i from a change in the independent variable in county j, called the indirect effects. Total effects sum direct and indirect. While each individual effect can be calculated, LeSage and Pace (2009) recommend presenting the average total, direct, and indirect effects. Accordingly, the marginal effects are presented following this method below.

4.2 Cross Sectional Model

To select the most appropriate model for cross sectional data, I follow Florax et al.. (2003) in using Lagrange Multiplier (LM) tests to evaluate the results from the SEM and SAR relative to OLS. Both tests strongly reject their individual null hypotheses (no omitted spatial lag, no spatial correlation in residuals). A strong limitation is that they both assume no spatial autocorrelation in the form in which they did not test: LM lag tests assumes no spatial autocorrelation in the error, and LM error assumes no spatial autocorrelation in the variable being measured (Burnett and Lacombe, 2012). Robust LM Lag and Error models have been developed to address these concerns. Results of these tests also confirm spatial dependence. I follow Ellhorst (2010) by using Likelihood Ratio (LR) tests to determine whether either the SAR or SEM is preferable to the Spatial Durban model (SDM):

$$y_i = \rho W y_i + X_i \beta + W X_i \Theta + \epsilon_i \quad (6)$$

The two null hypothesis for the LR tests are that in the SDM,

$$1)\ H_o\colon \Theta = 0 \quad , \quad 2)\ H_o\colon \rho\beta + \Theta = 0 \tag{7}$$

If the first null hypothesis is correct, a SAR model is preferable, if the second is correct the SEM should be used. In the event of rejection of both null hypotheses, the SDM is the best fit for the cross sectional model (Ellhorst, 2010).

Results for the Moran's I, LM, and LR tests are provided in table 2. Both LM tests are significant at the 1% significance level, supporting the Moran's I results and strongly rejecting the null hypothesis of no spatial dependence, and point towards the use of either the SAR or SEM. The robust versions of the LM Lag tests are also highly significant, however the LM Error test is only significant at the 10% level. LR tests evaluate the two null hypotheses in (7), which are both strongly rejected. These results both suggest that the SDM is the preferable model. As the SDM nests both the SAR and SEM, it will produce unbiased coefficients even if the true DGP is the SAR or SEM. Conversely, using a SAR or SEM when the true DGP is an SDM will lead to either omitted variable bias or a loss in efficiency, or both (Ellhorst, 2010).

Table 2: Spatial Specification Tests

	Statistic	P-value
Moran's I	5.1026	0.000000
LM Lag	34.3008	0.000000
LM Lag Robust	23.9787	0.000001
LM Error	13.9770	0.000001
LM Error Robust	4.2833	0.038480
LR Spatial Lag	22.4361	0.032900
LR Spatial Error	39.6550	0.000082

Regression coefficients of each model considered are presented in table (3). Here it can be seen that each spatial model estimates highly significant values of both ρ. This value of spatial dependence is considered moderate: Pace et al. (2012) find much higher ρ values in many economic factors such as income and production. That said, at the county level, spillovers are an important part of the market (ρ=.44-.54), suggesting that in this time-period when a county increased its solar PV capacity by 10kW, neighboring counties will increase theirs by an average of 4.4-5.4 kW. This lends weight to the arguments put forth above about the importance of both peer effects and spatial clustering.

Table 3: Cross Sectional Regression Coefficients

	SDM	SDM-W	SAR	SEM	OLS
consta	-9.550	.	-4.734	-8.000*	-5.052
	(0.279)	.	(0.245)	(0.069)	(0.313)
LocalP	0.0358**	1.1403	0.0290**	0.0222	0.0447***
	(0.016)	(0.254)	(0.022)	(0.109)	(0.004)
StateP	-0.003	2.1552**	0.0536*	0.0549	0.1494***
	(0.957)	(0.031)	(0.062)	(0.208)	(0.000)
lnPers	-0.021	0.4183	-0.245	-0.365	-0.621
	(0.960)	(0.675)	(0.520)	(0.377)	(0.185)
PctDem	-0.013*	-0.144	-0.010	-0.004	-0.014*
	(0.092)	(0.884)	(0.100)	(0.528)	(0.058)
Age	0.0539***	-0.923	0.0290**	0.0398***	0.0559***
	(0.001)	(0.355)	(0.017)	(0.006)	(0.000)
Hisp	0.0236***	-1.576	0.0154**	0.0249***	0.0259***
	(0.007)	(0.114)	(0.010)	(0.001)	(0.000)
Educ	0.0501***	-1.289	0.0143	0.0224*	0.0107
	(0.000)	(0.197)	(0.154)	(0.050)	(0.383)
StatEl	0.2930	-1.577	-0.091	0.1472	-0.102
	(0.150)	(0.114)	(0.282)	(0.285)	(0.327)
SolPot	0.0000	1.3312	0.0003***	0.0004**	0.0007***
	(0.766)	(0.183)	(0.001)	(0.020)	(0.000)
Detach	-0.006	-1.938*	-0.005	0.0004	-0.022**
	(0.508)	(0.052)	(0.529)	(0.956)	(0.030)
lnNOwn	0.9764***	-2.282**	0.5953***	0.6963***	0.8796***
	(0.000)	(0.022)	(0.000)	(0.000)	(0.000)
rho	0.4709***	.	0.5709***	.	.
	(0.000)	.	(0.000)	.	.
lambda	.	.	.	0.688***	.
	.	.	.	(0.000)	.
R-Squared	0.818	.	0.6651	0.7585	0.6376

As noted previously, the marginal effects of the spatial econometric models are not the regression coefficients. The marginal effects the preferred SDM model in three specifications are properly reported in table 4. The average direct effects are highly significant for the local policy variable in each specification listed (and for all that I ran). These positive marginal effects suggest that an addition solar polices at the city, county, and utility level between 2009-2014 lead to an increased in installed residential solar PV capacity by 6-7.9%.

Table 4: Cross Sectional Marginal Effects

	SDM			SAR		
	Average Direct Effects	Average Indirect Effects	Average Total Effects	Average Direct Effects	Average Indirect Effects	Average Total Effects
LocalPol	0.0409***	0.0877*	0.1286***	0.0321***	0.0363**	0.0685**
	(0.005)	(0.051)	(0.007)	(0.018)	(0.033)	(0.022)
StatePol	0.0121	0.3029***	0.3150***	0.0603*	0.0672*	0.1276**
	(0.823)	(0.004)	(0.000)	(0.051)	(0.055)	(0.049)
lnPersInc	0.0228	0.7143	0.7371	-0.260	-0.290	-0.551
	(0.959)	(0.612)	(0.626)	(0.532)	(0.539)	(0.534)
PctDem	-0.014	-0.015	-0.029	-0.010	-0.012	-0.023
	(0.063)	(0.554)	(0.273)	(0.106)	(0.125)	(0.112)
Age	0.0540***	-0.000	0.0538	0.0307***	0.0345**	0.0653***
	(0.000)	(0.996)	(0.269)	(0.017)	(0.026)	(0.019)
Hisp	0.0226***	-0.018	0.0044	0.0167***	0.0188***	0.0356***
	(0.007)	(0.388)	(0.825)	(0.009)	(0.015)	(0.010)
wBach	0.0494***	-0.011	0.0378	0.0150	0.0169	0.0319
	(0.000)	(0.759)	(0.332)	(0.171)	(0.188)	(0.176)
ElectPr	0.2709	-0.514	-0.243	-0.099	-0.113	-0.212
	(0.156)	(0.131)	(0.360)	(0.290)	(0.302)	(0.293)
SolPot	0.0001	0.0010**	0.0011***	0.0004***	0.0004***	0.0008***
	(0.643)	(0.023)	(0.000)	(0.001)	(0.002)	(0.001)
Detached	-0.010	-0.069	-0.080	-0.006	-0.006	-0.013
	(0.263)	(0.027)	(0.016)	(0.492)	(0.509)	(0.499)
lnNumOwn	0.9897***	0.2451	6.3414***	0.6433***	0.7255***	1.3689***
	(0.000)	(0.204)	(0.000)	(0.000)	(0.000)	(0.000)

In the preferred SDM model, the average direct effect of state policies have no statistically significant effect, however the indirect effects of state policies are highly significant. The significance of the indirect effects is intuitive: the majority of neighboring counties will be subject to the same state policies as a given county. In this model, the state effects then are captured by the indirect and total effects. That the magnitude of these effects is so much larger than the local policies is also intuitive: states have significantly more financial resources available then do municipal or county governments. Their inventive programs likely offer higher subsidies, thus are able to incentivize larger amounts of adoption.

While the number of owned houses in a given county is highly significant, the percent detached is not, suggesting that the total number of houses owned in a county is a much better predictor of solar adoption. In the west, the row houses common to areas like Washington DC are rare. It is likely that only few populous counties have significant large percentages of attached housing units, while the majority of the rural counties in the WECC have smaller values. Education is found to have a positive and significant impact on adoption, lending weight to earlier research that suggests knowledge of renewable systems is a strong driver of adoption.

4.2 Panel Model

A limitation of this model is that of identification: there is no guarantee the policies came before the installation of solar PV systems. The scenario where incentive policies were enacted after the capacity was installed could also produce those exact coefficients. To partly mitigate this, I consider a spatial model using panel data

$$y_{i,t} = \rho W y_{i,t} + X_{i,t}\beta + \mu_i + \eta_t + \epsilon_{i,t} \tag{8}$$

where μ_i represents a kx1 vector of county indicators and η_t represent an Tx1 indicator for years in the sample (where T=6, with the sample running from 1999-2014). In similar specification tests as in table 2, the SDM is preferred to the SAR. Hausmann tests suggest that pooled-OLS models are preferred to ones adding time, county, or time and county fixed effects. The marginal effects from this model (Table 5) suggest similar conclusions as the cross sectional model: an additional sub-state policy increased installed capacity in this time period of 7.15%.

Table 5: Panel Marginal Effects

	SDM: Pooled OLS			SDM: Time and Spatial Fixed Effects		
	Average Direct Effects	Average Indirect Effects	Average Total Effects	Average Direct Effects	Average Indirect Effects	Average Total Effects
LocalPol	0.0445***	0.0271	0.0715***	0.0292***	0.0368	0.066***
	(6.794)	(1.284)	(3.089)	(2.719)	(1.476)	(2.649)
StatePol	-0.0009	0.3127***	0.3117***	0.0076	-0.099	-0.092
	(0.000)	(7.667)	(10.26)	(0.127)	(0.000)	(0.000)
lnPersInc	0.0121	1.3477**	1.3597**	-0.781	-4.812	-5.593
	(0.063)	(2.263)	(2.119)	(0.000)	(0.000)	(0.000)
PctDem	-0.010	-0.009	-0.019	-0.037	0.0546***	0.0166
	(0.000)	(0.000)	(0.000)	(0.000)	(2.459)	(0.704)
Age	0.0506***	-0.065	-0.014	-0.000	0.0799**	0.0793**
	(8.817)	(0.000)	(0.000)	(0.000)	(2.116)	(1.978)
Hisp	0.0174***	-0.020	-0.003	0.0118	-0.034	-0.022
	(4.552)	(0.000)	(0.000)	(0.871)	(0.000)	(0.000)
wBach	0.0493***	0.0025	0.0517***	0.0067	0.0037	0.0104
	(9.397)	(0.136)	(2.724)	(0.665)	(0.107)	(0.254)
ElectPr	0.2134***	-0.187	0.0261	0.0916	-0.223	-0.131
	(2.730)	(0.000)	(0.354)	(1.324)	(0.000)	(0.000)
SolPot	0.0003***	0.0006***	0.0009***	.	.	.
	(2.453)	(3.719)	(7.585)	.	.	.
Detached	-0.213	-2.651	-2.865	-0.183	-2.120	-2.303
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
lnNumOwn	1.127***	2.6424***	3.7695***	0.0255	-3.369	-3.343
	(5.367)	(3.328)	(4.880)	(0.045)	(0.000)	(0.000)

This lends support to the arguments put forth in Burkhardt et al. (2015) and Dong and Wiser (2013) that local policies are an important driver of solar adoption. An important distinction is that this study only considers renewable policies, whereas these earlier studies use a more comprehensive set of local construction, connection, and permitting policies. Nevertheless, these results should help direct attention of local municipality and county policies as a main driver of solar PV adoption. There is no significant effect in the change of neighboring counties, which suggests that the clustering found in Bollinger and Gillingham (2012) is likely limited to within county effects. These results provide robust evidence that sub-state policies at the municipal, county, and utility level are important drivers of residential solar adoption.

The impact of average solar insolation is positive and significant in each direct and indirect total estimate, This relationship seems intuitive, and indeed potentially overshadowing other relationships, especially in the WECC region, as greater amounts of solar insolation would decrease the time required to pay off the upfront investment. However these results suggest that while it is an important consideration, there are other salient factors. Consider the case of Germany: with the solar potential roughly of Seattle, Germany leads the world in installed solar PV capacity. Even in cold and cloudy areas, electricity can be generated using solar PV. With sufficient interest, policy incentive and financial resources, a household could still be willing to install a PV system even with relatively limited solar insolation. The value of solar insolation is time invariant, and thus is not included in the third model with both time and spatial fixed effects.

Income has expected significant and positive effects on adoption, confirming earlier studies' assertions that adoption is concentrated among wealthy households. The percentage of voters who chose democratic candidates is insignificant in every effect measure, suggesting that either the percent voting democrat is an inaccurate measure of environmental preference or more likely that other covariates such as income and solar potential have a much greater impact on the decision to adopt solar PV.

6. Conclusions

This paper has contributed to the literature by empirically demonstrated how sub-state policies are important drivers of residential solar PV adoption. Focusing on the largest residential solar market, I created a unique dataset identifying the location of utility, county, and municipality solar incentive policies, and exploit their variation to examine their effects on known residential installations. I also utilize spatial econometric methods to evaluate the spatial spillovers in the market, which while modest are significant.

There are a number of important policy considerations from this study. First, a larger focus on local policies and regulations is warranted when considering residential markets. Potential consumers may have a better familiarity of local incentive policies available to them, and those on the margin are likely more influenced by the policies they know. Second, proponents of policies to promote residential solar PV adoption may do well to focus their efforts towards sub-state governments. There the potential to enact policy change might be significantly lower than at the state level, as county commissioners are likely more accessible and amenable to lobbying efforts. Third, residential solar firms may do well to focus their marketing efforts in areas with already high levels of installed capacity, where they could capture the peer-effects and spatial clustering of residential systems. Given the significant spatial autocorrelation displayed in the market, they may well already be doing so.

This study is limited in a number of ways. As mentioned above, this research design is unable to capture the effect of tiered electricity prices and may be omitting an important driver. This study treats all policies as homogeneous, which is unlikely to be the case. One net-metering policy may be more favorable than another, whereas PACE financing might offer more incentives in some areas. This variation within and between policy categories is not captured, but could be part of future work. Further, this study was not able to incorporate local permitting or regulatory process efficiency, which may explain a large share of solar PV adoption. However even with these limitations, this study presents new evidence that local renewable policies are a significant driver of solar PV adoption.

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