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# Are Peer Effects Present in Residential Solar Installations? Evidence from Minnesota and Wisconsin

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**Abstract**: There are geographic differences in the rate of adoption of residential photovoltaic (PV) solar. Are adoption rates in small scale localities (counties and zip codes) influenced by previous, nearby adoptions? This paper adds to the literature on Peer Effects with an analysis of Minnesota and Wisconsin zip codes. I use residential adoption data from the OpenPV Project in an empirical analysis of social interactions. My findings indicate that there is a small but significant effect of nearby adoptions at the zip code level. These peer effects are shown to be nuanced by policy incentives such as the XCEL Solar Rewards Program. I additionally engage in a case study analysis of the relationship of some localities.

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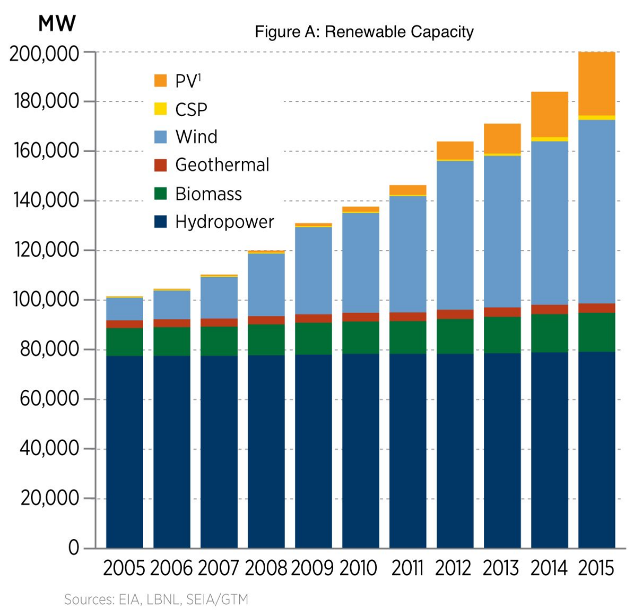
I. Introduction

Renewable Energy development has increased dramatically within the past decade. The total added capacity for renewables has more than tripled since 2008 (Figure A, EIA). Wind and solar energies increased by 500% from 2008 to 2016, attaining more than 120 GW of added capacity (Schiermeier). As of March 2017, solar and wind encompassed more than 10% of total U.S. monthly electricity generation (EIA, 2017[1]). Notably, advancements in renewable energy vary wildly across states and beg the question why. There are significant differences in the factors that affect the adoption of renewable energy across the United States (Maguire et. al. 2016, Schmalensee 2013, Sarzynski et. al. 2011). Ideally, renewables should be installed where they can create the most energy, which would explain why certain locales are most hospitable to wind energy and others to solar. The geographical explanation is not fully convincing, however, as some states with the highest potential for producing wind/solar energy do not necessarily produce the most. Texas is the largest state installer of wind capacity, but North Dakota is currently the state with the most potential for wind energy development (Gass 2013, SEIA).

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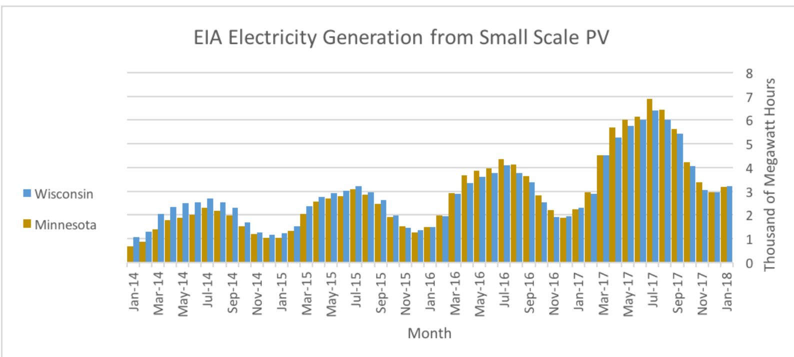
The incentives available to homeowners installing photovoltaic (PV) solar are also important. Despite the lower per-MW cost of wind, solar is more favorable for residential installations than wind for several reasons[2], including the variability of peak load times.[3] Homeowners are also in a position to respond to policy based incentives in their decisions to install renewable energy. Installations are more likely to take place in an area where installers can access income tax credits, solar subsidy programs, and other policy actions that ease the pressure of hefty upfront costs. Additionally, the political leanings of a state may foster an environment that better supports energy development. There are common preconceptions that left-leaning policies favor renewable energy progress, nevertheless, a significant number of “red” states are among the top states for renewable development (Balaraman 2017, Grommet et. al. 2012). Over 36% of Iowa’s electricity comes from wind power, even while the state has typically been regarded as “perennially politically purple,” and seen larger red influence in the 2016 election (Murphy). The policies enacted in each state are significant in their potential to explain the discrepancy between the potential to install and actual installations.

Policy and energy potential alone inadequately predict how PV installations are distributed. Solar installations are more frequent in densely populated areas, which is expected. However, regions with many residential installations also see a greater growth in installations (Walton 2014). Sometimes referred to as “peer effects,”the amount of nearby installations can affect the social inclinations of homeowners to install solar. Unlike most incentives, these are observable at the county and street level (Bollinger 2012). Do policy changes affect the baseline

[2] These reasons include appearance and maintenance preferences, as wind turbines have been found to be disruptive in select neighborhoods (Jones 2007).
[3] Solar Energy was found to be 32% more valuable based on wholesale prices. This may be because Solar is produced mostly during the day, where energy from the grid is more highly demanded, and wind in generally more productive at night(Schmalensee 2013).

level of solar and in turn affect the way consumers are affected by neighboring installations? The Midwest is an interesting study of this phenomenon, as Minnesota and Wisconsin share a similar geographic potential to install solar, but vastly different solar energy portfolios. In 2017, Minnesota was ranked 16th in total added solar capacity, while Wisconsin was 38th. The difference in installed capacity was greater than 500 MW[4] even while the two states have similar solar potential (SEIA).




The difference in solar energy production is less dramatic in an analysis of small scale photovoltaics (Figure B, EIA). This would include residential PV installations. Minnesota and Wisconsin are comparable in this sense, although in recent years Minnesota has generated slightly larger amounts of energy in recent years, but nowhere near the difference in the total amounts of PV energy. Within both states, however, there are differences in PV adoption, as some zip codes install larger amounts of solar continuously, and others never do (Appendix A). This paper examines the potential explanations of this difference. I examine the role of policies and potential of peer effects on the adoption rates in Minnesota and Wisconsin.

## II. Literature Review and Theory

To understand the factors that may cause the cross-sectional differences in past and current rates of residential solar energy adoption, I follow first the framework set in place by

[4] These figures are not solely residential solar installations.

Griliches 1957. Firstly, photovoltaic solar is a technological change with irregular distributions, similar to that of hybrid corn. The likelihood of an agent to adopt a new technology can be expressed by an adoption curve, where the probability is zero for an initial (low) bundle of benefits, and as time increases more people decide to adopt. Griliches finds the adoption curve follows a logistic function, that begins at an origin where someone would conceivably adopt the technological change. The function then follows the probability of adoption (or percent adopted) over time. The model employed is described by the function

$$P = \frac{K}{1 + e^{-(a+bt)}}$$

The growth of solar adoption probability, $P$, tapers off at a certain point, $K$, where the adoption curve approaches the "ceiling" value. At the ceiling, everyone who could possibly install solar does. For solar energy, this maximum is constantly changing in the wake of technological advancements and financial incentives. The slope of the adoption curve importantly represents the rate of adoption and the growth of solar. Like Griliches I examine $b$, the growth rate coefficient, and its dependence on $t$, or the time. The growth rate coefficient can also be read as a measure of acceptance, which is dependant in part on whether the technology is profitable in its adoption. Notably, solar adoption patterns do not have the same "s" shaped adoption curve seen in hybrid corn and other technological innovations. Up to the present period this growth appears almost exponential, and instead looks like the front half of the adoption curve[5] (SEIA 2016).

Griliches found that the primary difference in adoption rates across states was the lags, or differences in origins across states. These lags were the result of the technology (hybrid corn) not

[5] This may be the result of solar not yet achieving grid-parity, or an efficiency greater than that of conventional electricity (Ritchie 2017).

being equally profitable in all locations, and being adopted first in the more profitable areas. This geographic discrepancy also provides a metric by which to examine the relative availability of new technology across states. The potential profitability is an important factor in a solar energy context, as the nature of peer effects lends itself to the analysis of the slopes, or the increasing likelihood of adoption. For the purposes of this analysis, it is assumed that states have very similar access to technological improvements in solar, due to extensive manufacturing of panels from China (Pillai 2015). Thus, the main factor affecting profitability of installing solar panel lies on the solar potential, and cost of the unit. I would expect similar results to Girliches in that areas with high solar potential should yield a equilibrium rate of adoption.

The model set in place by Girliches is one that diagrams the long-term aspects of technological change. The main factors included in the understanding of the growth rate coefficient are the profitability (effectiveness) of the change and time. This is not unusual, as much of the literature following solar energy adoption examines the decision to generate energy independently, as opposed to purchasing energy from the grid. The discussion centers around the inherent cost-benefit analysis of installations- i.e does the money saved from not purchasing energy from the grid (or purchasing less of it) justify the large initial investment?

Bauner 2014 and Brock and Durlauf 2009 attempt to answer this question with the present value model. In this model, the individual homeowner switches from grid energy to solar when their valuations for solar benefits exceed the perceived costs. The valuations of the profitability of the technology reach beyond that of Griliches' profitability, and include preferences for green energy usage, utility from conspicuous consumption, and financial returns (Rai et. al. 2012). Financial returns include the opportunity costs from choosing alternative energy over grid energy and any potential energy savings from doing so. Through this framework, social interactions are considered. If social interactions make it more likely that a consumer evaluates solar energy adoption at a higher rate, then peer effects would be manifested in a steeper, more inelastic demand curve for that consumer's demand for solar energy. I assume that consumers will behave rationally, and that they will choose to adopt when the following is maximized

$$J(t,x) = \ (-\,exp(-\,\sigma t)C + \int_{t}^{\infty} exp(s\alpha\pi(x,\ q(s))ds)$$

A consumer can adopt at any date *s*, but will adopt only at *t* , when the weighted benefit of installing solar, *J,* is maximized. The total costs of the system are included in the term where C is the cost of the installation, and σ is the discount rate. This is subtracted from the perceived benefits, described over the entire duration of the installation. The symbol □ denotes the (discounted) rate of technological progress and $\pi(x,\ q(s))$ is the profit function that is dependant on the type of technology (in this analysis, only photovoltaics are considered). Importantly, the profit is in part from monetary savings based on the energy type, *x*, but on *q(s)*, which denotes, in part, the base level of installations. If *q(s)* increases, it affects the weighted benefit of installing solar, and it may affect the likelihood of adoption.

Brock and Durlauf 2009 model some of the social determinants, factors of *q(s)*, that Girliches does not address in his study. Although I model these social determinants econometrically, my theoretical framework is based on the proof used by Brock and Durlauf. They examine the units by which the adoption curve is made up of (i.e. individual homeowners) before approaching the effect on the aggregate. Brock and Durlauf focus on discontinuities as evidence of peer effects changing the adoption curve. These discontinuities, described as "jumps in the fraction adopting at some particular date," are exceedingly valuable because they indicate a peer effect operating alongside the other determinants of adoption.

What causes these disconsintunites in the adoption curve? Brock and Durlauf point to bunchings in adoption time. Notably, peer effects show a significant lowering of the decision time for installing solar. They implement a hazards model, where the dependant variable is the difference in time between consecutive installations and the clustering of installations occurs throughout time, instead of geographic location (Bollinger et. al. 2012). This would imply that the decision-making process of the potential installer is hastened by the revaluation of the perceived benefits, and that the forward movement to the ceiling is hastened. Discontinuities in the adoption curve are the result of the curve being "steeper" in the presence of social interactions[6] . This analysis does not focus on the distance in time between installations in a neighborhood as utilized by Bollinger et. al. 2010, which demonstrates the decrease in reaction time and only implies a general increase in the number of installations. Instead, I focus on the magnitude of total increases in installations directly. This would indicate a higher ceiling in the adoption curve in the long run, but also may present discontinuities in the current period. I also consider the added capacity, as this both addresses the likelihood that consumers may install, and that their decisions for how much to install are affected.

Social interactions may affect the magnitude of increases in installations in the following way. When social interactions occur, the homeowner may observe these positive externalities toward adopting solar in two ways. First, the homeowner may experience an increase in the value they hold for the "conspicuous consumption" of solar (Bollinger et. al. 2012, Balaraman

[6] Social interactions are defined by Brock and Durlauf as positive spillovers on adoption that result from the feedback of some fraction having already adopted.

2017).[7] This is sometimes referred to as "social utility." While social utility feedbacks are difficult to account for, evidence of higher valuations of houses with installed PV systems points towards either a general preference towards environmental actions, the *perception* of being so and producing green energy, or some combination both (Dastrup et. al. 2011).

Peer effects are not limited to manifestations of social utility. They are also present during "social learning," where social interactions serve as a method of education by which potential installers are called to reevaluate their circumstances based on new information available (Walton 2014, Bursztyn et. al. 2012).[8] The information arises through organizations advocating and providing educational materials on PV solar adoption (Noll 2012). Information on the benefits of installing solar also arrives in less direct, more passive forms that nonetheless could alter the weights homeowners place on factors in their cost-benefit analysis. At present, this analysis is unable to distinguish between social utility and social learning in peer effects. The principles of both social utility and social learning point towards a positive effect on solar adoption, and there is no mechanism by which to separate the effect of awareness from that of conspicuous consumption on the positive decision making of adopting consumers (Brock and Durlauf 2009).

A complete framework of solar adoption involves a critical understanding of how homeowners weigh all the perceived benefits of solar against perceived adoption costs.[9] Much of

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[7] A good that can be conspicuously consumed makes clear to other economic agents that the good is being consumed. In this case, because PV is very visible, either through installer advertising on the property or the inherent visibility of the panels on the home, neighbors and peers are aware of that homeowners consumption.
[8] These effects can take the form of word-of-mouth endorsements of solar, and sequential decisions, wherein the actions of an outside agent are taken into account when the potential installer makes a decision (Bothner 2008).
[9] The perceived hardships associated with installing solar energy are not limited to the upfront costs. Additionally, the forgone goods and savings required to make the purchase are relevant, as well as the uncertainty of significant returns and loss of leisure due to research and evaluation.

the literature focuses on the rate of return as a major determinant of PV profitability, and thus its adoption. Most policies and technological advancements dampen the effect of large upfront costs (Rai et.al. 2012). The predominant present value decision making model indicates that a consumer will adopt when the present value of the savings from the installation is greater than the upfront cost. However, this model does not address social effects on adoption, the inherent uncertainty homeowners face when deciding to install solar (i.e. will they be able to produce enough given their home to cover the expense?) and the hesitance associated with the large capital investment (Ulu and Smith 2009,Bauner 2014)).

These costs include but are not limited to the actual cost of installation, foregone costs of other energy services, research and labor costs, and uncertainty. They also may be tied to social interactions as well[10] (Bollinger et al 2012, Bauner 2014). While all homeowners in a given area may face the same installation and grid energy costs, their decision making processes vary. The sources of variation include differences in environmental preferences[11] and ability to afford solar installations (Ellsworth 1995). A few homeowners would install solar no matter what cost they face, while others are much more dependent on the rate of return they may receive. The likelihood of a homeowner to install owner is dependant on the weights they give certain preferences. Weights placed on the rate of return relative to other factors depend somewhat on the decision maker's ability to afford solar, and their preferences for alternative energy (Dastrup et. al. 2011).

The literature surrounding solar adoption has indirectly focused on the issue of weighting. Kwan (2012) shows that installers place have higher incomes, and are less affected by

[10] See Caveats Section
[11] For the extent of this paper, environmental preferences are the weights placed on ecological concern and/or reducing the impact on the environment by using a renewable energy source (Rai et. al. 2012, Claudy et.al. 2013).

the initial costs than lower-income homeowners. PV solar is thus a luxury good. Higher income households weigh environmental benefits higher, for example, as their basic needs are being met. Thus, factors exist such that the cost benefit analysis associated with the decision to install is not solely based on the wholesale costs of grid/renewable energy. Homeowners additionally consider their own personal preferences for installing solar, and the uncertainty in solar as an investment. Bauner (2014) departs from the basic perception that to install solar, homeowners must "break even," or save more money from installing solar than the cost of implementation. Using the option value model, Bauner determined that the present value of savings must exceed the cost of installation by a factor of 1.6 to result in an current period adoption.[12] However, this model indicates that the preferences of potential installers generate a weight in the decision making process, but offer little insight as to what motivates those preferences.

These weights play an important role in understanding peer effects, and determining where these social interactions would generate the largest effect on adoption. Like Bass 1969, my analysis on policies' relation to peer effects is based on the probability of installation as dependent of the base level of solar. However, I reach beyond the inclination of previous installations affecting the decision making process of current installers, and question what affects the relationship between the number of previous installers and probability of adoption. Complete dependence on Bass' model would imply that the relationship is strictly linear (for which there is little concrete evidence in photovoltaics), and that the size of the market (i.e. the ceiling, or total number of people in an area who could possibly install solar) is quantifiable. The Bass method alone is a principle that results in estimation of the market size, which empirically finds a value

[12] The option value model examines how consumers respond to uncertainty, in that they have the "option" to hold off their investment. In the case of solar, this model would be used to show how much larger the present value of savings must be of offset the uncertainty and result in a consumer to adopt (and not postpone the decision).

more than double the number of households that could adopt solar energy- a problematic finding(Bollinger et. al. 2012).

This paper addresses the effect of previous installations on inducing current installations. I consider nuances in this relationship, as peer effects are found to be minimized in areas where evidence of widespread environmental preferences is evident (Bollinger et. al. 2012). This analysis expands from the peer effects work by Bollinger by replacing the small scale descriptions of incentive removals within administrative regions with zip code and county level analyses, and policy inclusions. I also use data at the zip code-day level, and conduct the fixed effects models used by Bollinger, but do not focus on a realignment of incentives, as the policies I examine affect all relevant households at the same time, with the same degree.

Somewhat unexamined in the literature, effects in policy prove to be an intricate inclusion to this analysis, although the initial passing of policies that provide incentives to potential solar adopters would result in a straightforward impact. Policy adoptions would decrease the perceived costs of installation, and thus more members of the community would find solar profitable to install. I question the possibility that policy changes can result in an initial "shock" to the base level of solar, but that shock will also result in greater peer effects. The effect of the base level on the probability of adoption may thus be affected by policy changes. Essentially, if causal peer effects are present, and a shock to the base level number of adoptions occurs, larger discontinuities will result. I also employ a case-study approach used in the determination of a causal relationship between peer effects and additional installations in select localities.

IV. Empirical Methodology

Modeling the combined effect of social interactions and policy changes requires the adoption of several models. First, I model impact of the base-level of solar on the probability of installation, as described by Bass. The base level is given by the sum of all previous installations in an area *m* up to a time *T*, or;

[1.1] $$b_{zt}= (\textstyle\sum^{T}{}_{t=1}\sum^{z}{}_{z=1}a_{zT})$$

Further analysis of would require knowledge of the differentiation between those whose valuation of solar energy is affected by neighboring adoptions. The Bass Model Equation (1.2) attempts to create a linear model for the probability of the installation depends on the magnitude of innovators (*p*), or those not affected by the conspicuous consumption of others. Installation is also affected by the magnitude of the pressure on imitators on changes to the base level (*q/m*):

[1.2] $$P(T)= p+(q/m)b_{zt}$$

While Bass' model does determine the probability of adoption, it is difficult to estimate. The values of parameters *p* (the magnitude of installations from those not influenced by the install base), *q* (the total installations affected by the base level) and *m* (a magnitude of the market size) are difficult to predict empirically and often inaccurate (Bollinger et. al. 2010). The *q/m* parameter is the *q/m* function, which indicates the pressure homeowners face to install from the installation base. Another model is then considered that captures the likelihood of adoption being nonlinear, and a function of the baseline (*b*), incentives available (*X*) and an error term ($\varepsilon_{zt}$).[13] The value for $\boldsymbol{\alpha}$ is the average number of installations that would occur without knowledge of the base-level of solar or the financial incentives available.

[13] Y(zt) is equivalent to the fraction of owner occupied households adopting at time t in location z. Calculated by $Y_{zt}$= Number of Installations / (Number of Owner-occupied Households- Cumulative Installations)

[2.1] $$Y(zt)= \alpha + B_0 b+ \Lambda X_{zt}+ n_z+u_{zt}+\varepsilon_{zt}$$

I follow Bollinger et al. 2012 in the usage of equation 2.1, and the inclusion of demographic variables to model the variable $u_{it}$, the county-year fixed effects. Bollinger's analysis is even more granular, with the inclusion of zipcode-quarter fixed effects. These demographics (which include GSP, population density, household income, price of natural gas, etc.) are later interacted with the variable for the base level of solar. Interacting the two provides a window by which to observe whether peer effects are constant across all potential installers or if they are influenced by other aspects of the decision making process. The final stage of the analysis addresses whether policy changes affect the variable β, or the effect of base level installations on the decision to adopt. This is determined by an interaction term ($B_3$)

[2.3] $$Y_{zt}= B_o+B_1 S_z+ B_2 B_t+ B_3(S_i*B_i)+\mathcal{C}_z+\mathcal{C}_z*t + \varepsilon_i$$

Additionally, the metric by which Bollinger assessed the effect of temporary shifts in available incentives is given by [2.3], where the adoptions are a function of the base level, the change in incentive indicator for time ($S_i$) and location ($B_i$), and a metric for realignment ($\mathcal{C}$). The realignment term was necessary in Bollinger's analysis because it focused on small subsections of utility administrative regions that saw the same decrease in incentives, but at different times. None of the policies included in this analysis are appropriate for metric, and thus, the realignment term is not considered. Instead, I look for increases in the effect of the base level on the probability of adoption as a result of incentive inclusions.

[2.4] $$Y_{zt}=\alpha+B_0 b+B_1 S_z+B_2 B_t+B_3(S_i*B_i)+\mathcal{C}_z+\mathcal{C}_z*t +B_4 \Upsilon+B_5\pi+B_6\omega+B_7\rho+B_8\tau+B_9\eta+B_{10}\delta+B_{11}\gamma\, n_z+u_{zt}$$

I regress using equation [2.4], where $\alpha$ is the intercept, $b$ is the base level of solar, $B_1$ and $S_1$ are indicators for location and time respectively, $\Upsilon$ represents the cost of the system, $\pi$ is the cost of alternative energy, $\omega$ is the income of the homeowner, $\tau$ is the proximity of other neighbors (housing density), $\delta$ represents the demographics of the homeowner, and $\gamma$ is the energy output of the system. In some parts of the equation, the variables are approximated- for example, solar insolation data is used as a proxy for $\gamma$, and $\omega$ is the average income of a homeowner in that locality that year. I estimate this equation both with and without policy interactions.

By focusing two states with different policy structures in the past decade, Minnesota and Wisconsin, and relatively similar natural endowments, observations of peer effects across counties should be similar within the states, but different across them. A border effect similar to that seen by Bollinger on a large scale is evaluated through state fixed effects.

V. Data

I follow Kwan (2012) in that the primary data is from the National Renewable Energy Lab's OpenPV Project. These data are at the county/zip code level and offers information on the date installed, location, and rebate amount of each installation registered with the program. I use only residential installations less than 20 MW in Minnesota and Wisconsin. There are over 600 zip codes in the data set, which are notably much less than the total number of zip codes in Minnesota and Wisconsin combined. Unlike Kwan, I include installations from 2000-2015, in order to include changes that would result in 2005 from the passage of the Energy Policy Act. Cost of energy data come from the EIA. Additional control variables such as GSP and demographic information at the country level will come from a combination of FRED, the U.S. Census, and Equality of Opportunity Large data. I obtain policy incentives from the DSIRE database, and these include each state's inclusion of RPS structures and solar provisions, loan program initiatives, and statewide rebate programs, as well as a national tax credit policy that is available to potential adopters across both states.

Both Minnesota and Wisconsin were affected by the inclusion of the 2006 Renewable Energy Tax Credit and Xcel's 2013 Solar Rewards Program. Both states experienced general RPS policies from 2000-2015, so an analysis on the inclusion of RPS is not possible. However, Minnesota has included a solar carve-out program in 2013, which can be analyzed. Additional Minnesota-specific policies include the Made in Minnesota Program, SolarSense Rebate Program, and changes to the Net Metering policy.[14] Wisconsin-specific incentives include the 2011 statewide Sales Tax Incentive and the 2011 Net Metering Policy change, further detailed in Table 2. I expect that these policies provide a positive incentive to install solar, and would expect that following their implementation, there would be an increase in the number of installations.

The solar potential variable is the average zipcode solar insolation, at the zip code level, courtesy of the National Laboratory for Renewable Energy. It details the amount of sunlight energy (kWh) a square meter receives in a day, and is thus measured in kWh/m$^2$/day. While there are many measures of solar potential available, solar insolation is ideal. In their decision making process, homeowners would most likely use a measure that would tie in directly to their ability to produce solar- i.e. can they produce enough in the lifetime of the system to warrant the upfront cost of installation and potential maintenance? The greater the value of the solar insolation value, the more likely the consumer is to be able to break even or save money from the installation.

[14] A solar carve-out mandates that a certain amount of renewable energy produced must come from solar. Carve-outs are built into Renewable Portfolio Standards (RPS), which require a certain amount of energy produced by utilities to come from renewable sources.

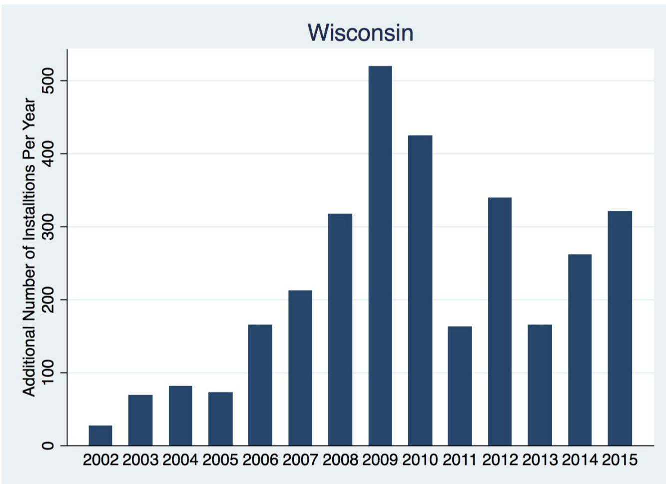
My data is limited in its ability to fully depict the information homeowners take into account when considering solar installation. Bollinger conducts an analysis using both commuting zone data and street level data in California. To my knowledge, no such records exist for Minnesota, and instead, the most granular data I use is zip code level data. Ideally, I would have data on the information each household considered prior to their decision. For example, in my current analysis, I am unable to distinguish social learning from an individual's likelihood to conduct their own research. I also am unable to measure an individual's environmental preferences, which would weigh against peer effects. Lastly, I include time fixed effects, but have no measure of the increasing efficiency of solar panels in the U.S., which also may play a role in the decision.

## VI. Summary Statistics

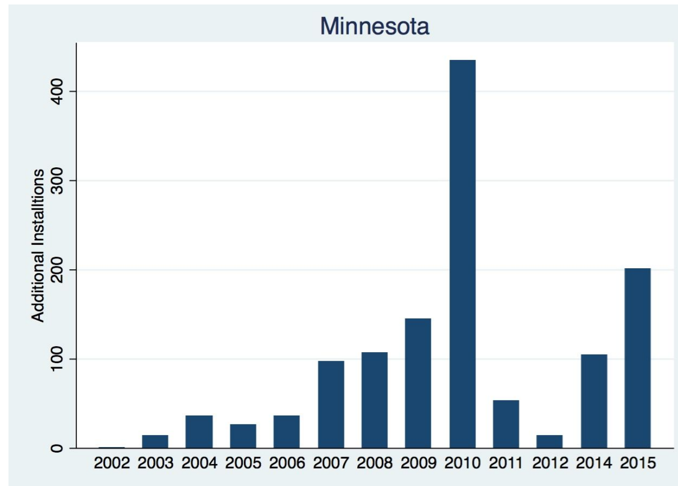
The preliminary analysis of the installations shows rapid growth in both the added capacity and number of installations for both states. According to Table 1.1, Minnesota has much fewer additional installations during the 2000-2015 time period. This isn't necessarily surprising, as the data relates to residential photovoltaic consumption only. Although Minnesota may lead in overall solar photovoltaic capacity, the difference seen here could be due to Minnesota's prominence in community solar programs.[15] Additionally, Wisconsin faces greater prices for natural gas, a substitute for solar, that would increase the likelihood of solar adoption (Table 1.2). Both states face a similar cost per watt for the actual installation of solar, but Minnesota

[15] Community solar programs allow homeowners to purchase solar energy through an agreement with a solar farm. They provide a flexible alternative to the physical installation of solar, while still providing a demand for green energy(Clean Energy Resource).

installers see a greater rebate per watt level, which should favor solar development[16]. The average home value, median income of homeowners, and population per square mile is additionally larger in Minnesota, and would point to a greater propensity to adopt.




Plot 1




Plot 2

Descriptive statistics for the data are detailed in Table 1.2. Notably, the average system size is somewhat close to is reasonable because the average system size is around 5 mW (EIA). For the same reason, there is a large maximum associated with the rebates recorded. Plots 1 and 2 indicate that the additional Installations per year differ wildly, and are not the same across states. Plots 1 and 2 indicates that Minnesota and Wisconsin experience some very large fluctuations in growth of solar, which could be explained by the large stimuluses put in place during this time. more streamlined additions. The plot trends illustrated above are consistent with the "significant (or immediate) growth in investments,installations,and contribution to the energy supply from REsources," that came from the large spending on Green Energy Economy (GEE) areas from the American Recovery and Reinvestment Act of 2009 (ARRA) (Mundaca and Richter 2014).[17] The

[16] Complete Summary Statistics available in Appendix A
[17] As a result of the ARRA, approximately $21 billion was allocated towards renewable energy (RE) development.

majority of this growth occurs during the 2009-2010 period, and aligns with the Great Recession period and shortly following, with a drop shortly afterwards.

However, these plots would not necessarily lead to a determination that peer-effects are present. If peer effects where present and affecting consumer adoption, then the added number of installations should increase over time. This is not the case, and there are fairly large fluctuations in additional adoption. Later analysis deals with how growth is different at a smaller scale- in other words, my paper detracts from the aggregated view of solar installations.

| Table 1.1 | MN | WI |
|---|---|---|
| Total Number of Installations | 1,179 | 3,046 |
| Total Added Capacity(kW) | 11214.5 | 20433.7 |
| Solar Generation Potential(TW) | 15.8 | 19.0 |

| Table 1.3 Summary Statistics at the Zip Code Level | | | | | | |
|---|---|---|---|---|---|---|
| | | MN | | | WI | |
| Variable | **Mean** | Min | Max | **Mean** | Min | Max |
| Base Level | **5.8** | 0 | 54 | **9.47** | 0 | 91 |
| PV Pricing (cost/watt) | **7.2** | 1.83 | 24.3 | **7.2** | .91 | 27.0 |
| Population per sq mile | **1140** | 3.6 | 3342 | **536.47** | 9.1 | 3926 |
| Nat Gas Pricing | **10.61** | 7.12 | 18.76 | **11.27** | 6.85 | 19.93 |
| Solar Potential (kWh/m$^2$/day) | **4.49** | 4.26 | 4.66 | **4.44** | 4.33 | 4.5 |

Additionally, I examine presence of peer effects through clustering. If peer effects are present in Minnesota and Wisconsin zip codes, then there should be clusters of solar installations that grow denser with the passage of time. Using GIS mapping, I detailed the solar installations base level through time. Between the 2002, 2007 and 2012 maps, there is a clear increase in the gross number of installations (Appendix B). Additionally, there is some evidence of clustering, as much of the growth is centered around the bottom zip codes of Wisconsin and the Twin Cities area in Minnesota. Northern Minnesotan zip codes, generally less populous, also have less clustering[18]. The growth in the number of installations is non constant, because although a large amount of growth exists between the 2002, there is an even larger increase in gross installations between 2007 and 2012, which lends support to the presence of clustering solar installations, and peer effects.

Table 2: Policies

| | Affect MN | Affect WI |
|---|---|---|
| Net Metering | 1983(2000,2014) | 1992 (2011) |
| US Residential Renewable Energy Tax Credit | 2006 | 2006 |
| MN Power-Solar Sense Rebate Program | 2004 | -- |
| RPS/(Solar Carve Out) | 1997/(2013) | 1999 |
| Xcel Solar Rewards | 2014 | 2014 |
| Made in MN Incentive Program | 2014 | -- |
| Clean Power Partner Solar Buyback Program | -- | 2007 |

[18] The limited growth in less populated areas may also indicate peer effects, as the observations of a potential installer would most likely occur in denser areas. There are also some notable exceptions near the Canadian border, which see greater clustering. This may be the result of access issues to grid energy or a wealth effect manifested in solar installations on second homes in rural areas.

VII. Empirical Results, Discussion and Caveats

In estimating Equation 2.4, I begin with a random effects model. I expect that there are unobservable differences at the zip code level that would affect the probability of adoption. To address this heterogeneity I then use a fixed effects model that includes both zip code and county level analysis[19] across time. County-time fixed effects would be ideal in this case, as I expect there to be unobserved correlations between counties and my variable of interest. Instead, county fixed effects were used to account for time-independent county-specific differences that are correlated with the probability to install solar. The data is more complete at a county level (i.e. most of the demographic values are at the county level, as zip codes are not evaluated in the Census), but zipcodes are more representative of neighborhoods, and thus the effect of the base level on the probability of installation in a zip code may be more nuanced approach.

I find that while the models are able to predict a good amount of the variation in the data, there are considerable differences between the signs of the models and the expected relationships between independent variables and $Y_{zt}$. Like Bollinger's estimation in California, I find that using zip codes leads to a positive, significant coefficient on the base level of installations. An analysis on the county level does not. Specifically, I find that an additional 1000 solar installations in a zip code would increase the probability of adoption by .47 percentage points (Table 2.1, Appendix A). Therefore, an additional 100 installations in a local zip code will, on average, increase the likelihood of a household adopting PV by .047%. For a zip code with 3,000 homes, an additional installation will increase the probability of installation by 1.4 percentage

[19] A Hausman test indicates that the fixed effects model is preferable to the random effects model.

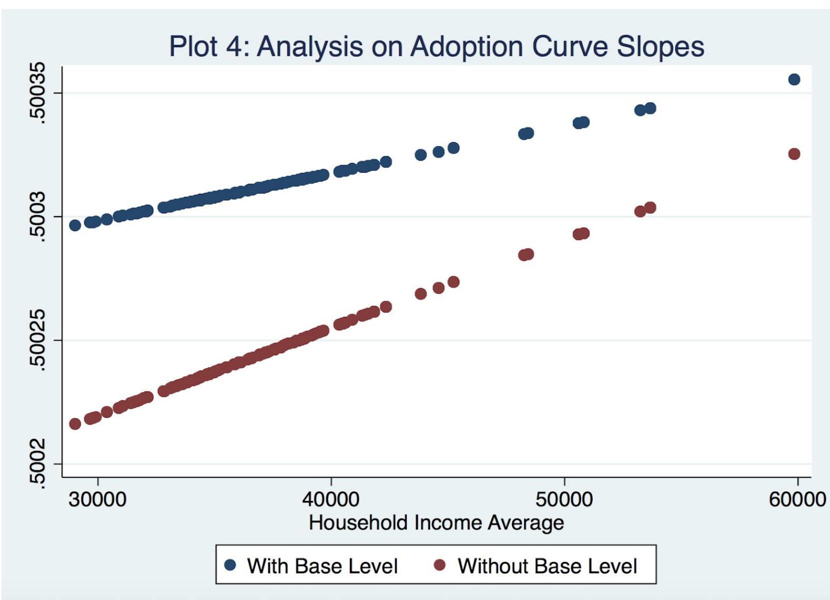
points. In the context of Bollinger's estimations, the power associated with these measures are greater given the smaller sample size.This is consistent with the principle that the observation of neighboring installations influences the perception of adoption uncertainty, and positively impacts solar adoption decisions.

Additionally, I examined how differences in the base level affect the rate by which the probability of adoption increases. For this analysis, I used zipcode and year fixed effects to account for the unobserved time-variant differences in zip codes that would affect the likelihood of adoption. Detailed in 2.2, I find insignificant evidence that Wisconsin homeowners are more affected by peer effects than Minnesota homeowners, and that these peer effects are manifested in the positive relationship between the base level and probability of adoption, $Y_{zt}$. These results are limited by a much smaller sample size, as many zip codes have inconsistent adoption patterns (some years may see many installations, while others may see none).

The largest concern with these results lies in the inability of the model to distinguish the characteristics of counties or zip codes that would already be predisposed to installing solar. While I attempt to curtail this by providing a rich set of fixed effects, I still anticipate the endogeneity of the dependant variable, the likelihood of adoption.

| Table 2.2 Results[20] | County FE | Zip FE 1 | Zip FE 2 |
|---|---|---|---|
| Estimates of $B_3$ | -6.72E-08 | 4.69E-6*** | 4.25E-6*** |
| SE | (-9.73E-7) | (1.49E-6) | (1.5E-6) |
| Number of Obs | 2,119 | 2,090 | 2,090 |
| Policy Dummy | Y | Y | Y |
| Pol. Interaction | N | N | Y |
| Local-Time Dummies | Y | Y | Y |

I have attempted to see whether the base level of solar would influence the slope of the adoption curve empirically through the fixed effects. I do the same visually. I regress with and without the base level variable, and attempt to visualize if the slope is steeper (i.e greater) in the presence of peer effects. The result is seen in Plot 4, where each line represents the relationship between an approximation of the adoption rate ($Y_{zt}$) and explanatory variable of household income. From this analysis, I determine that the presence of a base level does increase the slope of the adoption curve consistently, and there is support to my hypothesis. Additionally, the magnitude to which the adoption curve is steeper is affected by collinearity, as the lines are not parallel. Essentially, the adoption curve may be




[20] This table records only to coefficient of interest. The County and Zip Code Level FE regressions include the variables tabulated in Table 2.1 (Appendix A.3).

steeper in the presence of peer effects, and this steepness is dependant at least in part on the Household's level of income.

A. Policy Interactions

I also examine the effect of policy on the relationship between base level of solar and probability of Installation. In evaluating whether variable $B_3$, I first examine potential sources of stimuli that could create a "shock" to the base level of solar. From there, I can examine whether this shock is accompanied by a change in the relationship between the probability of adoption and the base level of solar. I continue with the zip code fixed effects model, but include an interaction term across several unique policy variables (outlined in Table 2). I then examine both the effect of the policy on the average rate of adoption (the intercept, or $B_2$ variable) and the effect of the policy on the relationship between probability of adoption and the base level (the interaction, or $B_3$ variable). If both $B_2$ and $B_3$ are significantly positive, there would be evidence supporting the narrative that PV policies supply shocks to the base level of solar, and increase peer effects.

From this analysis, I find that there is considerable amount of collinearity between the policy variables. This is potentially due to the close time span in which these policies are implemented. Since most of these policies are active at the same time, and the household level data does not include the rebate source, a homeowner may be influenced by any of those available. Additionally, the Renewable Portfolio Standard was implemented earlier than the start of this analysis, and thus its effects cannot be fully observed in the study. The results of this analysis are detailed in table 3.3. I find that there exists strong support that the Minnesota

Power-Solar Sense Rebate Program increased the magnitude of the peer effect with strong statistical significance, although the effect of a shock to the base level of solar is unobserved. The shock is somewhat unobserved[21] across all policy variables. The coefficients on the XCEL Solar Rewards Program are both negative, indicating that the incentive would decrease both the probability of adoption and the magnitude of peer effects. A potential explanation for this lies in either the relationship between the program and the Made in Minnesota program and the Net Metering policy changes, both of which occurred the year XCEL Solar Rewards began.

The Made in Minnesota program notably does not address the upfront cost, and is instead a performance based incentive similar to net metering (DSIRE). The National ITC policy is an income tax credit meant to address this, and the XCEL Solar rewards is a performance based incentive that offers less per kwh produced than Made in Minnesota. Additionally, since XCEL Solar Rewards began in 2014, and this analysis extends to 2016, there may be a significant lag in the way information on this policy is distributed across residents. The National Income Tax Credit for residential solar installations yields no conclusive results on either trend.

Of course, because these policies occur near the same period of time, it likely that the reason behind the relative insignificant results is due to collinearity across the policy variables. In a somewhat extreme example, both the Made in Minnesota and XCEL Solar Rewards polies occur in 2014. However, Made in Minnesota is dropped due to collinearity while XCEL Solar Rewards shows evidence of affecting $Y_{zt}$. This implies that all of these policies occurring simultaneously may be providing noise, and  distorting the results. Ideally, the data would include the incentives that a homeowner would utilize when making their decision.

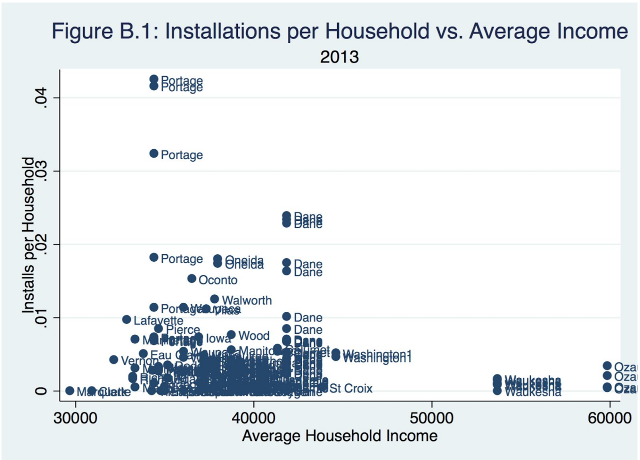
[21] Unobserved refers to either negative or statistically insignificant values of the coefficient.

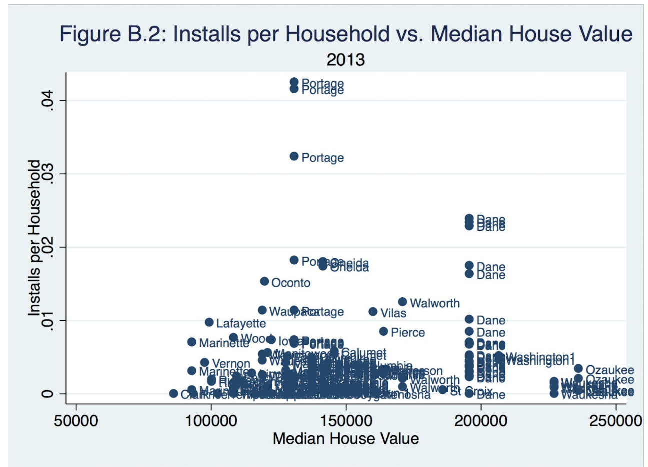
| Table 3.3 Policy Interaction Models[22] | | | | | |
|---|---|---|---|---|---|
| Interaction Model | Base level Effect | Interaction ($B_3$) | Intercept ($B_2$) | $r^2$ | n |
| MN Power | 4.25E-6*** (2.86) | 2.5E-5*** (3.8) | -.003 (.0049) | 0.9564 | 2,090 |
| XCEL Solar Rewards | 7.49E-6*** (4.01) | -3.48E-6** (2.49) | -4.27E-5 (-.91) | 0.9562 | 2,090 |
| National ITC | 1.64E-5 (1.22) | -1.15E-5 (-.88) | 4.18E-5 (.46) | 0.956 | 2,090 |
| *** for p< .01, ** for p< .05, *for p< .2 | | | | | |

B. A Case Study Approach

In my analysis, I also consider counties and zip codes that are either incredibly over performing or underperforming in the adoption of PV solar. From a policy perspective, it may be useful to understand the demographics of these areas, and their responses to policy effects. In order to do so, I take a visual approach. I search for a relationship between demographics factors and a per capita measure of solar adoption. This measure is total number of adoptions up to that year per household. Figures B.1 and B.2 illustrate the results for the year 2013, which I use as an example. Each zip code has been labeled with its respective county for ease of reference. I additionally compile residuals across both states throughout the study in figures B3 and B4 (Appendix D). I do so for ease of reference because Wisconsin generally has greater outliers than Minnesota.

[22] The Made in Minnesota, RPS, and RPS Carve Out policies have been removed due to collinearity. T values for each coefficient are given in parentheses.




Noticeably, several zip codes in Portage County, WI, are over performing in solar installations given, while zip codes in Dane, Hennepin, and Ozaukee counties are relatively underperforming. Portage is below the state average in terms of median house values and average household income. Dane and Ozaukee are both above average in this respect. I examine the relationship between the base level and probability of adoption in these three areas. I use Wood county as a comparison.

First, I examine Dane,Hennepin and Ozaukee counties. Dane and Ozaukee are located in Wisconsin, while Hennepin is located in Minnesota. All three have greater average household incomes and median house values (Table 4.1, Appendix C). Theoretically, these countries should have a generally greater aptitude to install PV systems given these demographics. Of the three, Dane is the only one considerably with a an average base level of solar well above the state average. Hennepin County is slightly above average, and Ozaukee is well below. Alongside this, I run a random effects model across each of the five counties individually.

The results of these regressions are compiled in Table 4.2. I find that across the five individual counties, the coefficient on the base level of solar first increases alongside increases in both household income and house value (from Portage to Wood). This trend noticeably reverse across an analysis of the higher income counties, which see a progressive decline in the relationship between the two. I find that in Dane and Ozaukee, the two richest counties, there is a negative relationship between the probability of adoption and the base level of solar that is statistically insignificant.  This implies that extremely wealthy counties may be less affected by the presence of a peer effect.

Why may Portage be over performing in solar installations? It may be, that like other parts of Minnesota and Wisconsin, that Portage sees an influx of second homes. There is an exceptionally high white percentage living in Portage, at more than 90% (DataUSA). Given that, the relatively high poverty rate, and it's somewhat rural location along the Wisconsin river, Portage WI may be installing solar on many second homes who would benefit from not being connected to the grid.

C. Caveats

My results are limited in several ways. Firstly, my results are unable to fully address endogeneity. My results do not indicate causality- I am unable to determine whether the base level of solar causes an increase in the probability of adoption. Instead, there exists the possibility of simultaneous causality- that areas with high base levels of solar are more likely to adopt solar in the first place.

There is also the potential for omitted variable bias that contributes to endogeneity, due to limitations in my data. I am unable to include covariate shocks such as technological efficiency developments in solar, consumer preferences, and the access of nearby community solar programs in my models. In a way, endogeneity is observational equivalent to peer effects, as peer effects attempt to explain the reason some localities see greater levels of adoption.

A third limitation arises in my methodology. Instead of a predictive model, I use a general fraction of the number of households that have installed solar as my dependant variable. It is likely that different zip codes have varying equilibrium adoption rates, and this cross sectional analysis may consider areas with low ceilings or late origins as underperforming.

Lastly, I am limited by the data. I established earlier that the OpenPV data source did not match the adoption demographics of small scale solar from the EIA. Because the OpenPV project relies on voluntary adoption information, the trends I observe and relate to peer effects may in fact be a measure of the likelihood to provide information. This could bias my results in either direction.

## VIII. Conclusion

The purpose of this analysis was to examine whether there are peer effects present in the adoption of photovoltaic solar in Minnesota and Wisconsin. The presence of these peer effects is expected to expedite solar installations through increased social learning and social utility, I tentatively find that there is a positive, significant relationship between the previous number of installations and likelihood of adoption within a zip code. I tentatively prefer the usage of the zipcode model for its better prediction of more factors in the data, but recognize the value of the county level estimates. I additionally find that policies are found to have a weak effect as a shock to the base level, but a select few (for example, the Made in Minnesota Program) may influence the magnitude of peer effects.

My results are not necessarily conclusive, but point towards an association of peer effects in Minnesota and Wisconsin that could be a reason for the observed clustering of residential PV. Stronger evidence in support of peer effects may be beneficial to policy makers in the allocation of incentives.

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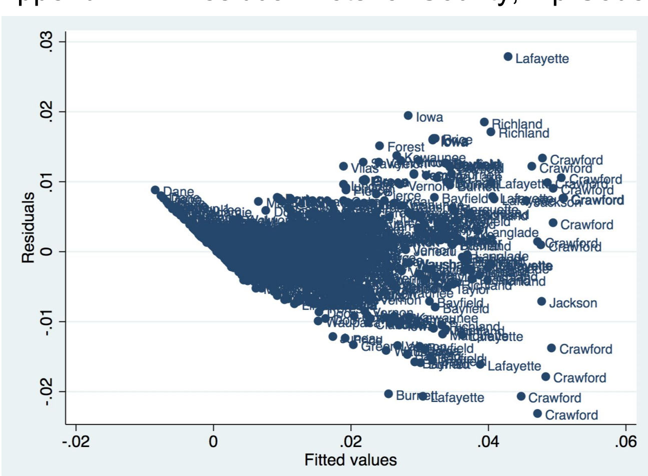
Appendix A1: Complete Summary Statistics for Minnesota and Wisconsin

| Table 1.3 Summary Statistics at the Zipcode Level | | | | | | |
|---|---|---|---|---|---|---|
| | | Minnesota | | | Wisconsin | |
| Variable | **Mean** | Min | Max | **Mean** | Min | Max |
| Base Level | **5.8** | 0 | 54 | **9.47** | 0 | 91 |
| PV Pricing (cost/watt) | **7.18** | 1.83 | 24.28 | **7.2** | .91 | 27.0 |
| Solar Potential (kWh/m/day) | **4.49** | 4.26 | 4.66 | **4.44** | 4.33 | 4.5 |
| Nat Gas Pricing | **10.61** | 7.12 | 18.76 | **11.27** | 6.85 | 19.93 |
| Population per square mile | **1139.654** | 3.6 | 3341.7 | **536.5** | 9.1 | 3926 |
| Median House Value | **159891.5** | 65317 | 226897 | **151932.6** | 86245 | 236340 |
| Median Income | **42404.8** | 29033 | 53249 | **38975.45** | 29676 | 59866 |
| Rebate per watt | **1.89** | 0.37 | 2.25 | **1.24** | 0.09 | 5.06 |
| Gross State Product (GSP) | **343286** | 240282 | 2613895 | **31188.8** | 25124 | 34451 |
| % with Bachelors | **28.8** | 10 | 39.1 | **24.36** | 10 | 40.6 |
| % Hispanic | **2.98** | 0.51 | 15.2 | **2.78** | .33 | 8.76 |
| % Black | **3.94** | 0.07 | 8.84 | **3.41** | 0.06 | 24.3 |
| Number of Households | **185685** | 2494 | 504178 | **106147** | 2494 | 417524 |

Appendix A2: Residual Plots for County, Zip Code Fixed Effects



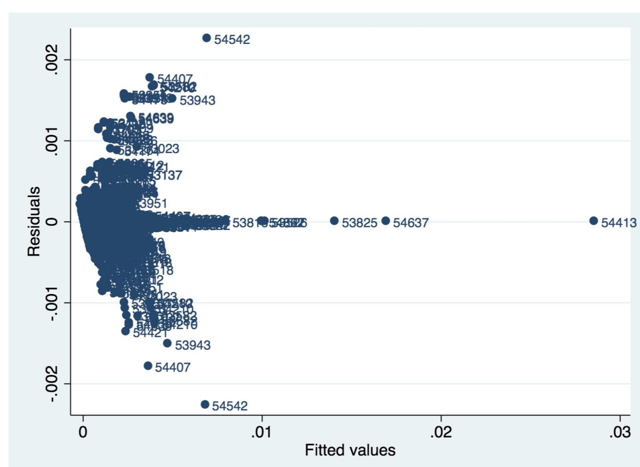




Figure 1: Residuals for County Fixed effects model

Figure 2: Residuals for Zipcode Fixed Effects

Appendix A.3: Fixed and Random Effect Modeling Results

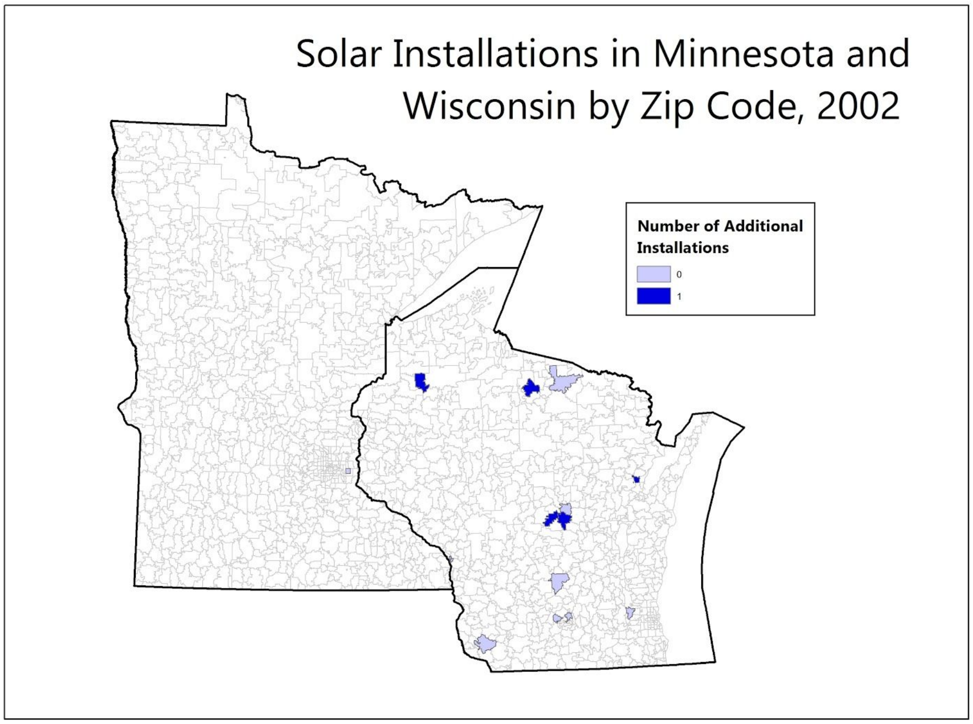
Table 2.1 Probability of Adoption Model ($Y_{zt}$)[23]

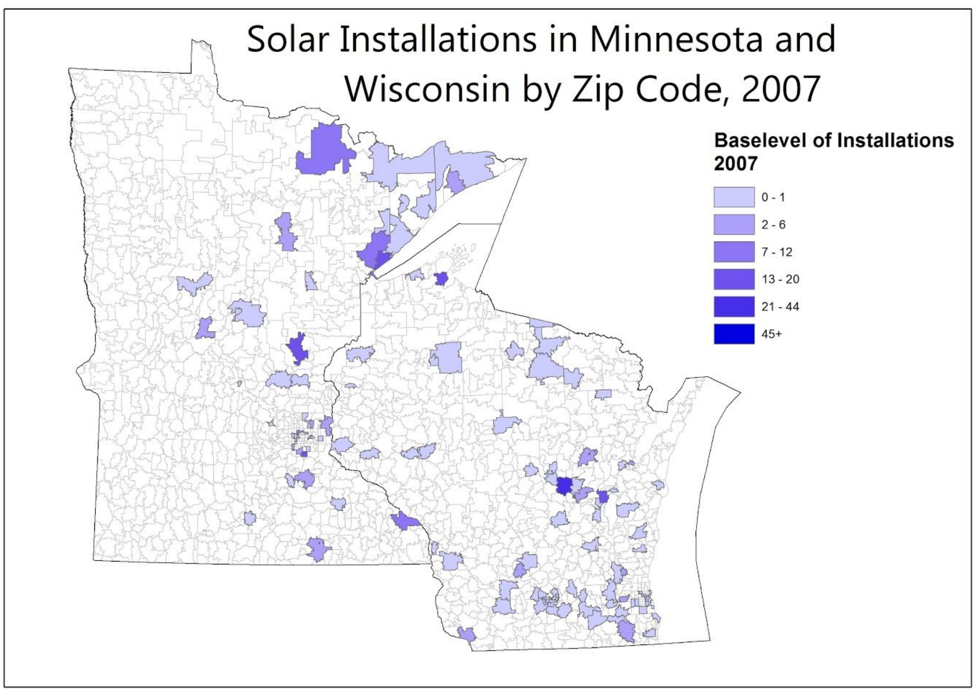
| Variable | OLS(County FE) | OLS Zip(Zip FE) | Zip FE with Interaction |
|---|---|---|---|
| Cost per Watt | .000033*(.0000605) | 2.98E-6(1.49E-6) | 3.39E-6 (1.5E-6) |
| Rebate per Watt | 9.06E-7***(2.39E-7) | -1.38E-8(2.47E-8) | -2.55E-8(2.48E-8) |
| GSP | 1.5E-9***(9.26E-10) | -3.5E-10***(1.02E-10) | -3.64E-10***(1.02E-10) |
| Population/sq. mile | 1.8E-5(5.47E-5) | 2.97E-6(5.01E-6) | 4.21E-6(5E-6) |
| Household Count | -2.39E-8*(3.18E-8) | -2.5E-09(2.8E-9) | -2.98E-9(2.82E-9) |
| Potential | -.119(.273) | .0118(.0122) | .0132(.0122) |
| NG Pricing | -2.87E-4***(4.76E-5) | -1.3E-6(4.25E-06) | -9.44E-7(4.23E-6) |
| Base Level | -6.72E-8(9.73E-07) | 4.69e-6***(5.8E-6) | 4.25E-6***(1.49E-6) |
| Base Level- MN Power Interaction | --- | ---- | .000025***(6.59E-6) |
| Bachelors | -.0056(8E-4)) | -1.5E-5(.0001) | -5.1E-5(.00012) |
| %Black | -.022(0.19) | -.2079(1.13) | .00015(.00047) |
| %Hispanic | .003(.006) | -.00024(.0006) | .00028(.00004) |
| Median Household Value | .000107(.00305) | -1.39E-8(1.17E-8) | -8.87E-9(1.17E-8) |
| Xcel Solar Rewards | .0013***(.00346) | -.0001***(3.91E-5) | -9.02E5**(3.9E-5) |
| Nat ITC | .008***(.0007) | -7.13E-6(7.2E-5) | -1.3E-5(7.18E-5) |
| Milwaukee Shines | -0.0013(.0012) | -3.7E-5(3.91E-5) | -4.29E-5(1.04E-4) |
| WI | -.0062(.018) | .002(.005) | --- |
| Intercept | .594(1.211) | -.0463(.047) | -.0484(.0437) |
| | $r^2$=.819<br>n= 2,119 | $r^2$=.9560<br>n= 2,090 | $r^2$=.9564<br>n=2,090 |

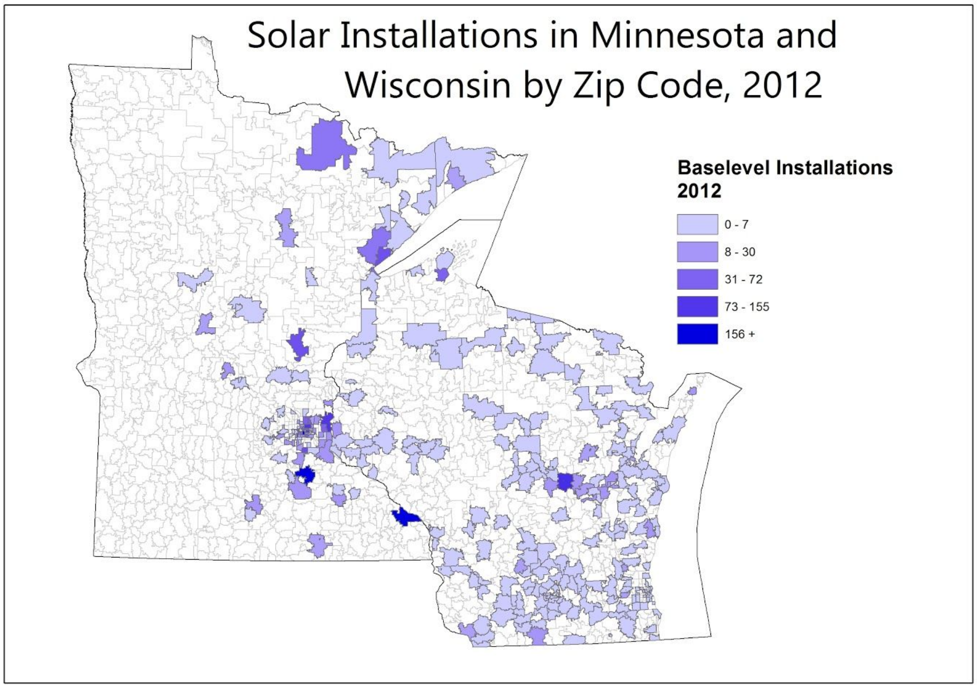
*** for p< .01, ** for p<.05, *for p< .2

[23] Standard errors are expressed in parentheses.

Appendix B: Solar Installation Base level GIS Maps




Solar Installations in Minnesota and Wisconsin by Zip Code, 2012
Baselevel Installations 2012
0 - 7
8 - 30
31 - 72
73 - 155
156 +

Appendix C: Outliers

| Table 4.1 | Summary of Outliers | | | | | |
|---|---|---|---|---|---|---|
| | HH Income | State Average | Median Home Value | State Average | Average Base Level | State Average |
| Portage | 34399.03 | 38975.45 | 131033.9 | 151932.6 | 20.8 | 9.47 |
| Wood | 38763.17 | 38975.45 | 108506.2 | 151932.6 | 3.7 | 9.47 |
| Hennepin | 50631.82 | 42404.8 | 191152.2 | 159891.5 | 6.5 | 5.8 |
| Dane | 41866.38 | 38975.45 | 195817.7 | 151932.6 | 19.6 | 9.47 |
| Ozaukee | 59866.25 | 38975.45 | 236340.9 | 151932.6 | 3.11 | 9.47 |

| Table 4.2 Outlier Coefficients OLS | | |
|---|---|---|
| | Base Level Estimate | t value |
| Portage | 6.25E-06 | 0.67 |
| Wood | 0.0000646 | 0.79 |
| Hennepin | 0.0000213 | 1.19 |
| Dane | -3.55E-07 | -0.21 |
| Ozaukee | -8.43E-06 | -0.36 |
| *** for p<.01, ** for p<.05, *for p<.2 | | |

## Appendix D: Additional Outliers