College of the Holy Cross, Economics Department
Advisor: Professor Kiel

Measuring Political Affiliation's and Peer Effects' Impact on Solar Panel Adoptions in New York State

Tavish McNulty
April 15, 2023

I Introduction

As climate change continues to become an immediate threat, the discussion around renewable energy has become increasingly critical. The Industrial Revolution radically increased our productive capabilities but has rapidly increased greenhouse gas emissions into the atmosphere. Figure 1 with data collected from the U.S. Department of Energy illustrates the rapid rise of Carbon emissions since the start of the Industrial Revolution in the 1760s. These gasses have contributed to global warming by trapping ultra-violet rays from the sun and steadily heating the earth's surface over time (NASA.gov). Figure 2 displays data from the World Bank on global GDP growth and CO2 emission damages as a percent of global GNP. Since the 1970s damages from CO2 emissions have slowly inclined reaching almost 2% while global GDP growth seemes to have greatly fluctuated. Based on these figures, it appears that despite rapidly rising carbon emissions, global GDP growth over the last 50 years has not grown correlatively as it did in the Industrial Revolution. Rising carbon damages only adds to this observation. This insight drives the incentive for policymakers to push renewable energy technologies. As people start to experience the impacts of global temperature changes, there is a greater reliance on renewable energy sources. Beyond understanding the science of renewables, it is important to understand what prompts their adoption. Technology adoption rates have been studied extensively across several fields. Implementing new technology is often seen as difficult since adoption often comes with some sort of risk and uncertainty. In terms of renewable energy technologies, the inability to see their future benefits and relative novelty may create a risk factor for consumers.

However, the idea that renewable energy sources are new inventions is actually a misconception. For centuries, civilizations have used waterwheels and windmills for mechanical energy. It wasn't until the industrial revolution where production was taken to a global scale, we saw huge increases in non-renewable energies. At the time, renewables simply couldn't compete with the efficiency of non-renewables. Today, they have become both available and affordable to consumers across the U.S. making up about 19.8% of U.S. energy generation (EIA.gov). Out of these, solar panels, or photovoltaic panels (PVs) have become the most viable option for the residential sector. Home solar installation costs have dropped by nearly 20% from 2010, and the market now reaches all 50 states (SEIA). Despite this, solar only makes up about 2.8% of energy generation in the U.S. (EIA.gov). This begs the question as to why consumers aren't adopting solar panels at a faster rate. Loan programs, grant programs, research subsidies, net metering, and the Renewable Portfolio Standard brought about a roughly 70% decrease in solar panels costs over the decade. As these technologies become more efficient, policymakers and the utility industry are particularly interested in what drives peoples' adoption decisions for PVs. I will be looking specifically into how peer effects drive adoption decisions among consumers. Peer effects in the context of technological diffusion are ways that a neighborhood or group influence other's decisions to adopt a technology. There is a lack in the current literature on finding new variables that can measure peer effects among PV diffusion. This presents an opportunity to study how social factors may influence PV adoption rates and to leverage that knowledge to increase adoptions. This paper expands on this idea by looking into how political parties may play a role as a peer effect in PV adoption.

II Literature Review

Research in consumer decisions behind renewable energies has generally focused on solar panels. Their wide availability across the US have made data much more readily available.

Despite New York, New Jersey, and the New England states having relatively lower solar irradiation compared to the west coast, they have some of the highest levels of solar electric capacity (SEIA). This distinguishes solar energy from renewables that are more restricted to the environment such as geothermal, wind power, and hydropower. The circumstances around solar panels create an atmosphere where consumers have a unique decision between a cost-effective renewable energy technology and non-renewables with negative externalities making them a great source to study peer effects.

Demand for solar panels can change based off more than just price. Peer effects and other forms of social pressures have been studied extensively across the literature (Bollinger and Gillingham, 2012; Barnes et al, 2022; Graziano et al, 2019; Balta-Ozkan et al, 2021). In the study of PVs, peer effects are defined as the impact individuals from a common group have on other group members' decision to adopt a PV (Barnes et al, 2022; Xiong et al., 2016). An example of a peer effect would be if a potential adopter had neighbors who had strong feelings against anything pro-environment and that potential adopter now feels less inclined to purchase solar panels despite the benefits they know exist. The peer effect here is the influence the neighbors' opinion has on others on potential adopters. Several newer studies break down these peer effects into active and passive peer effects (Barnes et al, 2022; Balta-Ozkan et al, 2021). Active peer effects are generally studied as adoption spread by word-of-mouth. Researchers often use word-of-mouth when referring to adoptions caused by spread of information across neighbors whether it be at a social gathering, work, or in passing. Passive peer effects are based on an adoption that indirectly affects others' decision to adopt in the group. For example, a person driving through their town may be more inclined to adopt if they see several of their neighbors with rooftop PV installations. The quintessential difference I will use to distinguish between active and passive peer effects is whether the original adopter influenced a potential adopters' decision intentionally or unintentionally.

As Bollinger and Gillingham (2012) discuss, the challenge in studying peer effects is that they are notoriously difficult to measure. Across most PV research many studies use geospatial data and proximity of adoptions to represent peer effects. This data can recognize geographical trends but there is no way to prove that local adoption decisions were based off their neighbors. I argue that the main concern with geospatial patterns when studying peer effects is that you cannot distinguish if they were based off active peer effects (word-of-mouth), passive peer effects (visibility or other indirect influence), or neither. To get around this, some researchers use commute time as a measure for passive peer effects. The idea is that longer daily commute times increase the likelihood of one being exposed to solar panels. Bollinger and Gillingham (2012) find evidence of individuals in the San Francisco Bay Area with over 30-minute commutes being associated with higher adoption rates. When it comes to active peer effects many researchers do not have an alternative to geospatial data. Bollinger and Gillingham (2012) also ran a fixed effects using using geographical installation data in California controlling for various demographic variables. They find that an additional installation in a zip code increases the probability of additional adoptions by .78 percentage points, which they attribute to peer effects. Barnes et al (2022) use a mixed methods analysis combining geospatial and survey data in the Las Vegas Valley to seek evidence of active peer effects. They leverage geographical data with a survey analysis of 193 respondents to distinguish whether consumers' adoption decision was based on passive or active peer effects. Their work reveals evidence of active peer effects having a significant effect increasing PV adoption rates among early adopters. Barnes et al's (2022) mixed methods analysis was possibly one of the best ways to distinguish between active and passive peer effects. Being able to combine the geospatial dataset with survey data allowed the authors to determine exactly how adoptions spread. However, with 193 observations, it is still questionable whether the sample size is reflective of the total population. There is a consensus that proximity and clustering of PV installations are attributed to peer effects. However, the data doesn't give a complete story as to exactly what social factors are prompting this increase in adoptions.

More recent research has attempted to resolve the issue of identifying variables that represent active peer effects by analyzing how community programs stimulate adoptions. Programs such as Solarize Connecticut have been proven effective in increasing adoption rates (Gillingham and Bollinger, 2020). Solarize Connecticut spread solar awareness through community programs, provided $0 down financing, and introduced solar panels as an investment with net metering (SmartPower, 2013). Balta-Ozkan et al (2021) studied the spatial differences in PV adoptions in areas weighted on proximity to environmental and energy related charities. The idea is that the closer an adoption is to one of these organizations the more likely that they were influenced by them. Hence, it is an active peer effect in the sense the organizations intentionally influenced potential adopters' decision via outreach or other proactive methods. They found that these charities have a positive impact on PV adoption rates in the United Kingdom. Another study analyzes 228 solar community organizations across the U.S. from 1970 to 2012 and found that solar community organizations' (SCO) ability to leverage trusted community networks have made them extremely successful at increasing adoptions (Noll et al, 2014). They recommended that further statistical research involving PVs and peer effects should not disregard these organizations. Studies that incorporate some measure of the exposure from these SCOs may be able to get a more accurate measure of the effect of active peer effects in a community.

Why make this distinction between active and passive peer effects? As states begin to increase their solar capacity, prices will continue to drop and make PVs available to more of the population. Finances will be less important in the adoption equation and policymakers will be more interested in how peer effects can continue to promote renewable energies. Differentiating the impact active and passive peer effects have on consumers can help government officials determine where to allocate resources to maximize adoption in different areas. For example, if active peer effects are shown to have a strong impact on increasing adoption rates in one area, then the local government may need to provide more solar funding for solar community organizations. However, if it is the case the adoptions are being attributed to passive peer effects, then these resources can be allocated elsewhere. Matisoff and Johnson (2017) find that 67% of the money allocated toward PV incentives supported consumers who would have adopted PVs without the incentives. Policymakers can leverage their understanding of active and passive peer effects to avoid further misallocations of taxpayer dollars.

This paper expands on this idea by looking into how political parties may play a role in stimulating active peer effects in PV adoption. It is possible that promoting certain political ideologies are positively or negatively correlated with PV installations. Solar panels are associated with environmentalism and global warming. These terms have been highly politicized over recent years. Mildenberger (2019) conducted a survey amongst republicans and democrats across all U.S. states. He found that although both parties support renewable energy research, democrats support increasing funding more by about 10% in almost every state. Crago and Chernyakhovskiy (2014), also incorporated political data into their analysis. They found a strong relationship between adoption rates and democratic-leaning individuals as well as areas with more hybrid vehicles in California. Sunter et al (2018) use a LOWESS model to measure the number of PV installations in each census tract in New York and Texas. They find that despite the partisan division on solar panels republicans adopt the same if not more solar panels than democrats. These studies show mixed results on the question of identity politics in PV technological promotion. Since the publishing of these studies solar panels have continued to grow and new datasets have become available, so there is still more work to be done.

In extension to previous research, I will interpret political affiliation and adoption rates in the context of peer effects and diffusion theory. Diffusion theory is essentially a roadmap of technological adoption among consumers and explains what kinds of consumers are more likely to adopt in certain periods of the diffusion process. Most of the literature uses proximity of installations as a measure for an active peer effect, however, in this paper I use political affiliation as a measure of an active peer effect. Political affiliation represents evidence of active peer effects under the assumption that people generally socialize with those of the same party and discuss common thoughts. The goal is to try and isolate political affiliation and determine whether it serves as an active peer effect in solar panel adoption patterns in New York. The state has solar panel installation data from 2010 to 2020. I have not found any previous studies that use this dataset in their analysis of peer effects and PV adoptions. This data should give me an accurate analysis of counties that have undergone the effects of peer effects. I will attempt to answer whether political affiliations act as SCOs and drives consumers' decision to adopt solar panels in NY. If true, I argue that political parties are promote active peer effects in New York neighborhoods.

III Data

All data I gathered is on the county level from the years 2010 to 2020 in New York state (NYS). This data is available on NYS' government website and is collected by the New York State Department of Public Service, the NYS Independent System Operator, and the NYS Energy Research and Development Agency (NYSERDA). The dataset includes all registered solar panel projects in NYS by county. Since I am interested in only consumer solar panel adoptions, I set a ceiling on solar panel size of 10kwh. The average household solar panel installation size in the U.S. about 6kwh so 10 allows for some error. Voter registration data was also gathered from New York's government website. The voter data I gathered represents the number of "active" registered republicans, democrats, and independents. Presidential election results were gathered from the MIT Election Data and Science Lab. Finally, demographic data such as age, gender, population, household information, employment, education, and income were be gathered from the U.S. Census Bureau. The dependent variable PVperHouse is calculated by taking the number of PV projects below the 10kwh threshold and dividing that by the number of houses in the solar market. I quantified the solar house market by only including resident-owned households built after the year 2000 in a county. The reason for doing only including resident-owned houses is to isolate adoptions based off consumer decisions. I only included houses built after the year 2000 because houses with a roof that is 15 to 20 years old typically cannot sustain solar panels unless the roof is replaced. The remaining variables, their meanings, and sources are represented in Figure 9 with summary statistics in Figure 6.

IV Theoretical Model

The approach used to understand consumers' adoption decision around PVs will be analyzed via traditional consumer choice economic theory in the context of diffusion innovation theory. Many scholars have previously used diffusion innovation theory to explain consumer adoption of PVs (Barnes et al, 2022). The theory was developed by E.M. Rogers in 1962 and explains how products becomes incorporated into a group. The theory breaks consumers into five categories: Innovators, Early Adopters, Early Majority, Late Majority, and Laggards (Figure 4). As you can see by the NY dataset (Figure 5), NY consumers have gone through the stages of Innovators, Early Adopters, and are just on the cusp of Early Majority. Diffusion theory tells us that this makes New York a relevant location for studying active peer effects, since information of a product an early stage typically comes from information being actively spread by neighbors or sellers (Barnes et al, 2022). With limited rooftop PV adoptions, early adopters would not be as exposed to seeing them. Thus, active peer effects would be the primary way information about the technology is spread amongst consumers. So, if there are any kind of other active peer effects in NY, they should be prominent in the data according to diffusion theory.

V Two-Way Fixed Effects Regression Model

This study will use the following regression model:

$$Y_{ct} = \beta_0 + \beta_1(political\_affiliation_{ct}) + \beta X_{ct} + \alpha_c + \delta_t + \epsilon$$

Y_{ct} represents the dependent variable, the number of installed solar panels per number of households in a given county and year. Political affiliation is the variable of interest representing the number of active democrat, republican, and independent voters in a given county and year. X represents the remaining control variables such as age, education level, house size, male and female population, and commuter times. α_c represents county fixed effects in the regression. This will control for variables that vary across county but not across time. δ_t represents year fixed effects.

VI Difference-in-Differences Regression Model

I also adopt a similar methodology to a paper by Dahl et al (2022). They analyze how republican and democratic counties' fertility rates responded to changes in political leadership using a difference-in-differences regression. I will use a similar model to assess how republican and democratic counties' PV adoption rates responded to the 2016 election using this equation:

$$Y_{ct} = \beta_0 + \beta_1 treat_{Year\geq 2017} + \beta_2 treated_{rep,dem\ county} + \beta_3 did_{rep,dem} + \beta X_{ct} + \epsilon$$

I generate a dummy variable "treat" for observations in 2017 and after, then a dummy variable "treated" for counties whose votes were 50% or more democrat leaning. Interacting the two creates the difference-in-differences estimator, "did", which should capture the effect the election had on democratic leaning counties' adoption rates after President Trump was elected. Similar to the previous regression X represents all the control variables.

VII Results

The first regression results are displayed in Figure 7. The (1), (2), and (3) results represent an OLS regression, County-fixed effects regression, and two-way fixed effects regression respectively. Contrary to the theoretical model, TravTime, average commuter time per county, which is supposed to be representative of passive peer effects is significant throughout each regression. NY is in the early stages of PV adoption. According to Diffusion Theory, we would expect passive peer effects to not be as prominent in promoting adoption. However, the coefficient in regression (3) is statistically significant at the 1% level and is interpreted as a one-minute increase in average travel time increases adoptions by 0.00775 PVs per household. This is also economically significant because it would mean for every thousand households 7.75 solar panels will be installed by increasing average commute time by one minute. This is a large number considering NY is still in the early adopter period.

The variable of interest PERDEM, which represents percent of active voters registered as democrat, is not statistically significant amongst any of the regressions. This supports the hypothesis that political affiliation does not play a role in PV adoptions. Interestingly, going from the county fixed effects to county and year fixed effects regression changes the sign and magnitude of the coefficient going from 0.00156 to -0.000480. This indicates that adding the time fixed effects may be interacting strongly with the coefficient. Observing the year dummy variables, yr14 through yr20 have statistically significant and large coefficients relative to the other variables. This result makes the difference-in-difference regression more of interest since it appears certain events in time may be driving adoption rates. Applying the difference-in-difference model to the 2016 election may give hidden evidence of political affiliation playing a role in adoptions.

The results of the difference-in-differences regression are displayed in Figure 8. Regression (1) uses counties that voted more than 50% democrat in the 2016 election as the treated group while regression (2) is the exact same but uses counties that voted more than 50% republican as the treated group. The two election results do not exactly add to 100 since there is a small percentage of voters in other parties which is why I ran two regressions. Contrary to what diffusion theory tells us which is that passive peer effects aren't as relevant to early adopters, TravTime is positive and statistically significant. The "did" estimator is not statistically significant in the regression. The coefficient is negative -0.00362 for democrats and positive 0.00362 for republicans. This indicates that after the election in 2017, democratic voting counties decreased PV adoptions by 0.00362 PVs per household and Republicans increased PV adoptions by the same magnitude. This result may be evidence that PVs are not as politicized by party as previously thought but voters are still responding to changes in future expectations caused by political events. Democrats may have been concerned for the future and responded to the election by adopting less solar panels while republicans had the opposite effect. This would mean political affiliation is some form of an active peer effect, however, the coefficients still are not statistically significant, so I cannot reject the null hypothesis and come to this conclusion.

VIII Conclusion

As a result, this study adds to the current literature on peer effects and diffusion theory in the context of solar panel adoption rates. Previous work has not considered the possibility that political affiliation acts as an active peer effect in PV adoption. These results have not allowed me to state with confidence that this is true. However, this research provides a new approach to measure of peer effects and their causality in technological diffusion processes. Further research could be done to identify different social groups that promote PV adoption. Being able to take advantage of this understanding would allow policymakers to not overcommit resources to solar incentives when unnecessary. Some concerns I have with this work are that PVs tend to have a lag period between installations and the actual consumer decision by about 2-6+ months, which I did not consider. Also, certain states may have different political attitudes toward solar panels. Different states may then reveal different results if this study was done using other states' data. Finally, my R-squared values in Figure 7 regressions (2) and (3) are 0.186 and 0.333

respectively. These values are relatively low indicating there may be some variables that I did not capture in my regression. Adding in variables for weather conditions and policies may yield more accurate results as opposed to my model that attempts to capture them via time and county fixed effects. All in all, this work shows that consumers' decisions surrounding solar panels are a complex function. More research needs to be done to understanding societies' preferences toward renewable energy technologies to create a sustainable future.

Tables

Figure 1

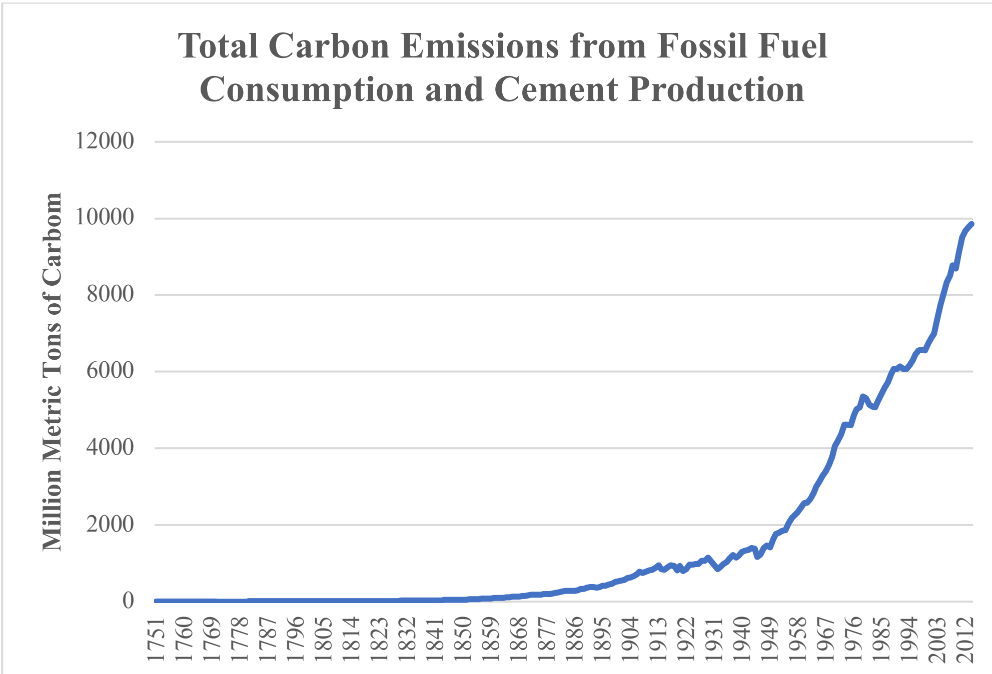


Figure 2

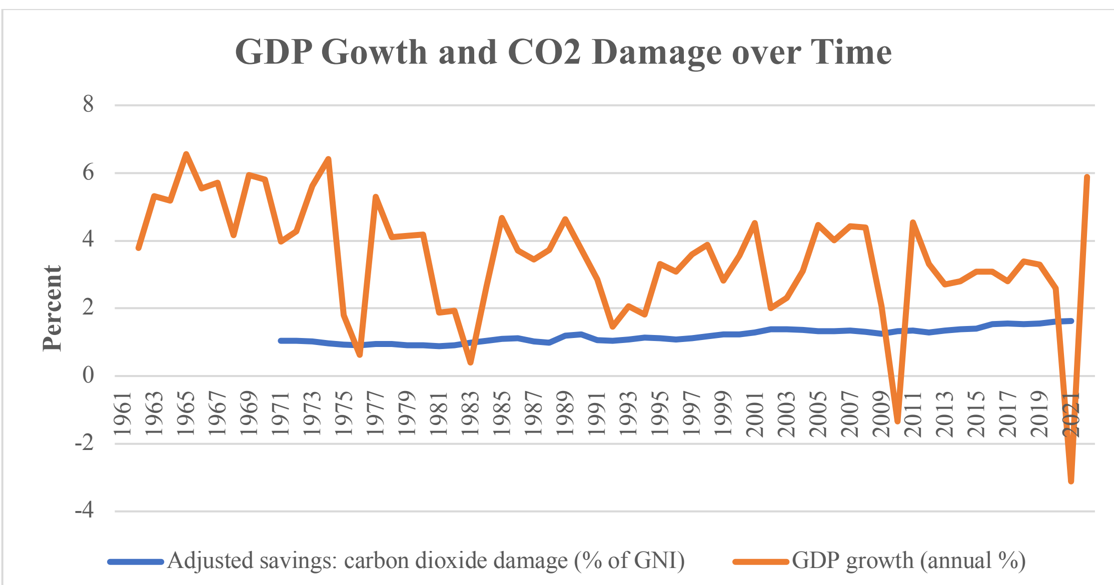


Figure 3

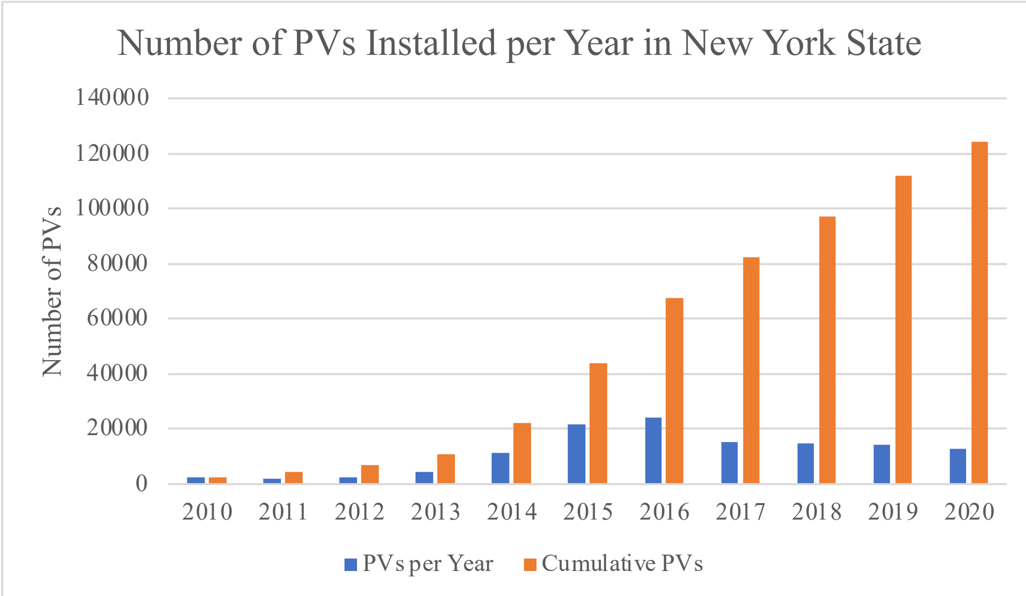
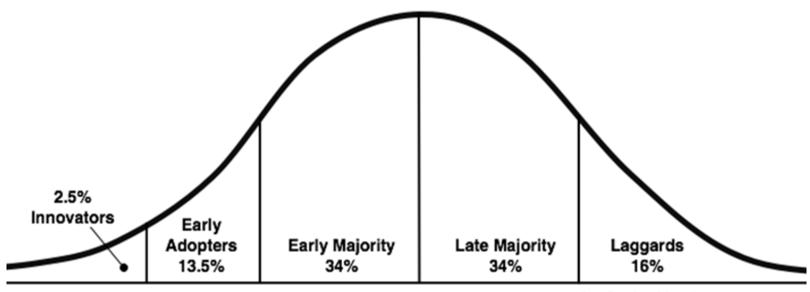


Figure 4



Source: http://blog.leanmonitor.com/early-adopters-allies-launching-product/

Figure 5

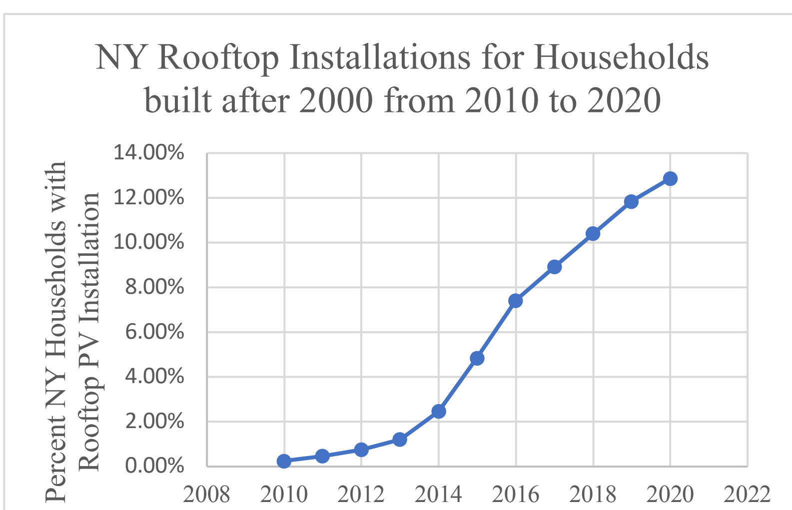


Figure 6

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
County	682	31.50	17.91	1	62
SolarHousMarket	682	4,552	5,441	93.50	34,246
PV	682	182.3	602.4	0	5,752
PVperHouse	682	0.0246	0.0386	0	0.382
PERDEM	682	45.71	14.51	24.36	91.13
PERREP	682	47.39	13.62	6.638	70.55
PERIND	682	6.898	1.676	2.138	13.01
TravTime	682	25.40	6.303	17.40	45.40
HSIZE	682	2.489	0.234	2.020	4.130
Pop	682	315,082	537,808	4,454	2.635e+06
PMALE	682	49.74	1.465	46.85	55.21
PFEM	682	50.26	1.465	44.79	53.15
AGE	682	40.85	3.599	29.50	55.50
HUnder	682	44.48	7.354	24	61.40
College	682	43.68	3.593	32.50	52.40
Grad	682	11.85	4.801	5.200	30.80
INC	682	73,912	20,845	47,325	163,997

Figure 7

VARIABLES	(1) PVperHouse	(2) PvperHouse	(3) PvperHouse
PERDEM	-0.000133	0.00156	-0.000480
	(0.000319)	(0.000940)	(0.000883)
PERIND	0.00852***	0.0255***	0.000789
	(0.00209)	(0.00570)	(0.00633)
TravTime	0.00149*	0.00751**	0.00775***
	(0.000845)	(0.00294)	(0.00276)
HSIZE	0.0372*	0.00728	-0.00179
	(0.0209)	(0.0162)	(0.00999)
Pop	1.94e-08*	8.89e-07***	5.96e-07**
	(1.17e-08)	(2.98e-07)	(2.78e-07)
PMALE	-0.000245	-0.00407	-0.00441
	(0.00120)	(0.00571)	(0.00487)
AGE	-0.000202	-0.00118	-0.00323
	(0.000661)	(0.00200)	(0.00204)
College	-0.000436	-0.00226*	-0.00271*
	(0.000564)	(0.00121)	(0.00136)

Grad	0.00200***	-0.00251	-0.00350
	(0.000677)	(0.00231)	(0.00257)
yr11			-9.05e-05
			(0.00252)
yr12			0.00178
			(0.00547)
yr13			0.00644
			(0.00726)
yr14			0.0220**
			(0.00931)
yr15			0.0491***
			(0.0121)
yr16			0.0498***
			(0.0127)
yr17			0.0250**
			(0.0101)
yr18			0.0215**
			(0.0103)
yr19			0.0204*
			(0.0102)
yr20			0.0181*
			(0.00976)
Constant	-0.148	-0.313	0.165
	(0.102)	(0.321)	(0.274)
Observations	671	671	671
R-squared		0.186	0.333
Number of County	61	61	61

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 8

	(1)	(2)
VARIABLES	PVperHouse	PVperHouse
TravTime	0.00132*	0.00132*
	(0.000798)	(0.000798)
HSIZE	0.0330	0.0330
	(0.0202)	(0.0202)
Pop	8.56e-09	8.56e-09
	(1.07e-08)	(1.07e-08)
PMALE	0.00257**	0.00257**
	(0.00122)	(0.00122)
AGE	0.000991	0.000991
	(0.000749)	(0.000749)

	(1)	(2)
College	0.00142**	0.00142**
	(0.000619)	(0.000619)
Grad	0.00213***	0.00213***
	(0.000783)	(0.000783)
treat	-0.00653	-0.0101***
	(0.00911)	(0.00247)
treated1	0.00388	
	(0.00739)	
did1	-0.00362	
	(0.00892)	
treated2		-0.00388
		(0.00739)
did2		0.00362
		(0.00892)
Constant	-0.348***	-0.344***
	(0.118)	(0.114)
Observations	671	671
Number of County	61	61

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 9

Variable	Definition	Source
PVperHouse	Number of solar panel projects in a county 10kwh and under divided by the number of resident-owned households built after 2000 in a county	NYS Government website and ACS 5-year estimates
HSIZE	Average number of people per household in a county	ACS 5-year estimates
PERIND, PERDEM, PERREP	Percent of active voters registered as independent, democrat, and republican respectively	NYS Government website
PDEM, PREP, POTHER	Percent of votes a democrat, republican, or other candidate received in each county in 2012, 2016, and 2020 elections	MIT Election Data and Science Lab

Pop	Total population in a county	ACS 5-year estimates
PFEM, PMALE	Percent of total population in a county that are female and male respectively	ACS 5-year estimates
AGE	Average age in a county	ACS 5-year estimates
INC	Average income in a county	ACS 5-year estimates
College, Grad, HUnder	Percent of population in a county that completed received a high school diploma or less, college degree, or graduate degree respectively	ACS 5-year estimates
TravTime	Average minutes of commute time in a county	ACS 5-year estimates
treat	Dummy variable indicating an observation occurred in 2017 or after	
treated1	Dummy variable indicating a county voted greater than 50% democrat in the 2016 election	
treated2	Dummy variable indicating a county voted greater than 50% republican in the 2016 eleciton	
did1	Difference-in-differences interaction variable between treat and treated1	
did2	Difference-in-differences interaction variable between treat and treated2	

References

Araújo, Kathleen, Jean Léon Boucher, and Omkar Aphale. "A Clean Energy Assessment of Early Adopters in Electric Vehicle and Solar Photovoltaic Technology: Geospatial, Political and Socio-Demographic Trends in New York." *Journal of Cleaner Production* 216 (2019): 99–116. https://doi.org/10.1016/j.jclepro.2018.12.208.

Balta-Ozkan, Nazmiye & Yildirim, Julide & Connor, Peter & Truckell, Ian & Hart, Phil. (2021). Energy transition at local level: Analyzing the role of peer effects and socio-economic factors on UK solar photovoltaic deployment. Energy Policy. 148. 112004. 10.1016/j.enpol.2020.112004.

Barnes, Jesse & Krishen, Anjala & Chan, Alexander. (2022). Passive and active peer effects in the spatial diffusion of residential solar panels: A case study of the Las Vegas Valley. Journal of Cleaner Production. 363. 132634. 10.1016/j.jclepro.2022.132634.

Barton-Henry, Kelsey & Wenz, Leonie & Levermann, Anders. (2021). Decay radius of climate decision for solar panels in the city of Fresno, USA. Scientific Reports. 11. 8571. 10.1038/s41598-021-87714-w.

Boden, T.A., G. Marland, and R.J. Andres. 2017. Global, Regional, and National Fossil-Fuel CO2 Emissions. Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, U.S. Department of Energy, Oak Ridge, Tenn., U.S.A. doi 10.3334/CDIAC/00001_V2017.

Bollinger, Bryan, and Kenneth Gillingham. “Peer Effects in the Diffusion of Solar Photovoltaic Panels.” *Marketing Science* 31, no. 6 (2012): 900–912. https://doi.org/10.1287/mksc.1120.0727.

Crago, Christine Lasco, and Chernyakhovskiy Ilya. “Solar PV Technology Adoption in the States: An Empirical Investigation of State Policy Effectiveness” Agricultural & Applied Economics Association’s 2014. https://ageconsearch.umn.edu/record/169939/?ln=en.

D. A. Sunter, J. Dees, S. Castellanos, D. Callaway and D. M. Kammen, "Political Affiliation and Rooftop Solar Adoption in New York and Texas," *2018 IEEE 7th World Conference on Photovoltaic Energy Conversion (WCPEC) (A Joint Conference of 45th IEEE PVSC, 28th PVSEC & 34th EU PVSEC)*, Waikoloa, HI, USA, 2018, pp. 2426-2429, doi: 10.1109/PVSC.2018.8548257.

Dahl, Gordon & Lu, Runjing & Mullins, William. (2022). Partisan Fertility and Presidential Elections. American Economic Review: Insights. 4. 473-490. 10.1257/aeri.20210485.

De Groote, Olivier, and Frank Verboven. “Subsidies and Time Discounting in New Technology Adoption: Evidence from Solar Photovoltaic Systems.” *American Economic Review* 109, no. 6 (2019): 2137–72. https://doi.org/10.1257/aer.20161343.

"Frequently Asked Questions (Faqs) - U.S. Energy Information Administration (EIA)." *Frequently Asked Questions (FAQs) - U.S. Energy Information Administration (EIA)*, https://www.eia.gov/tools/faqs/faq.php?id=427&t=3.

Gillingham, Kenneth, and Bryan Bollinger. "Social Learning and Solar Photovoltaic Adoption." *SSRN Electronic Journal*, 2020. https://doi.org/10.2139/ssrn.3657970.

Graziano, Marcello, Maurizio Fiaschetti, and Carol Atkinson-Palombo. "Peer Effects in the Adoption of Solar Energy Technologies in the United States: An Urban Case Study." *Energy Research & Social Science* 48 (2019): 75–84. https://doi.org/10.1016/j.erss.2018.09.002.

Howe, Peter & Marlon, Jennifer & Mildenberger, Matto & Shield, Brittany. (2019). How will climate change shape climate opinion?. Environmental Research Letters. 14. 10.1088/1748-9326/ab466a.

Labay, Duncan G., and Thomas C. Kinnear. "Exploring the Consumer Decision Process in the Adoption of Solar Energy Systems." *Journal of Consumer Research* 8, no. 3 (1981): 271. https://doi.org/10.1086/208865.

Letzelter. "Residential Solar Power in Upstate New York : An Analysis of the Key Drivers of Adoption," n.d. https://doi.org/10.17760/d20293296.

Matisoff, Daniel C., and Erik P. Johnson. "The Comparative Effectiveness of Residential Solar Incentives." *Energy Policy* 108 (2017): 44–54. https://doi.org/10.1016/j.enpol.2017.05.032.

Noll, Daniel & Dawes, Colleen & Rai, Varun. (2014). Solar Community Organizations and active peer effects in the adoption of residential PV. Energy Policy. 67. 330–343. 10.2139/ssrn.2305790.

Ostlund, Lyman E. "Perceived Innovation Attributes as Predictors of Innovativeness." *Journal of Consumer Research* 1, no. 2 (1974): 23. https://doi.org/10.1086/208587.

Schelly, Chelsea. "What's Political about Solar Electric Technology? the User's Perspective." *Engaging Science, Technology, and Society* 1 (2015): 25–46. https://doi.org/10.17351/ests2015.002.

"Solar Generation Was 3% of U.S. Electricity in 2020, but We Project It Will Be 20% by 2050." *Homepage - U.S. Energy Information Administration (EIA)*, https://www.eia.gov/todayinenergy/detail.php?id=50357.

"Solar Industry Research Data." *SEIA*, https://www.seia.org/solar-industry-research-data.

"Solarize Connecticut." *SMARTPOWER*, https://www.smartpower.org/solarize-connecticut.html.

Strum, Harvey, and Fred Strum. "American Solar Energy Policy, 1952–1982." *Environmental Review* 7, no. 2 (1983): 135–54. https://doi.org/10.2307/3984497.

Umit, Resul. "Solar Panels and Political Attitudes." *Political Studies Review*, 2021, 147892992110448. https://doi.org/10.1177/14789299211044868.

Vasseur, Michael. “Incentives or Mandates? Determinants of the Renewable Energy Policies of U.S. States, 1970-2012.” *Social Problems* 63, no. 2 (2016): 284–301. https://www.jstor.org/stable/26370870.

Xiong, Hang & Payne, Diane & Kinsella, Stephen. (2016). Peer Effects in the Diffusion of Innovations: Theory and Simulation. Journal of Behavioral and Experimental Economics. 63. 10.1016/j.socec.2016.04.017.

Yu, Jiafan, Zhecheng Wang, Arun Majumdar, and Ram Rajagopal. “DeepSolar: A Machine Learning Framework to Efficiently Construct a Solar Deployment Database in the United States.” *Joule* 2, no. 12 (2018): 2605–17. https://doi.org/10.1016/j.joule.2018.11