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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

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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

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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.

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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

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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,

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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.

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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

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female population, and commuter times. represents county fixed effects in the regression. This will control for variables that vary across county but not across time. 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:

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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

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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

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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.

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Tables

Figure 1

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Figure 3

Figure 4

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Figure 6

	(1)	(2)	(3)	(4)	(5)
VARIABLES	N	mean	sd	min	max

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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		

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College	0.00142**	0.00142**
	(0.000619)	(0.000619)
Grad		

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