Exploring the Role of Race and Place in Residential Solar Photovoltaic (PV) Adoption

by

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Abstract

The urgency of addressing climate change and grid decarbonization in the United States necessitates the rapid deployment of clean energy technologies at scale. Residential solar photovoltaic (PV) technologies have emerged in the past decade as one such technology as a result of substantial cost declines, though market penetration remains low. New government initiatives and policy incentives have been enacted to encourage the uptake of these technologies, however recent research has documented distributional challenges related to their deployment. Building on emerging studies focused the racial equity implications of residential solar PV deployment, this research implements a series of regression models on two, national solar installation datasets, controlling for market, policy, and demographic variables. The primary goal of this work is to systematically evaluate the effect of race and ethnicity on 1) the probability of a community having at least one solar installation and 2) the diffusion of solar PV technologies, defined as the total number of installations in a community. Results indicate strong evidence that communities classified as majority-Black are associated with decreased likelihood of having any solar at all, and fewer installations overall, in most of the specified models. The results vary for majority-Hispanic communities, with observed disparities present in some of the models. Controlling for certain demographic variables has differentiated effects for different racial and ethnic majority classifications, due to the cumulative impacts of socioeconomic disadvantage for those groups. The study concludes with a discussion of policy implications, methodological limitations, and avenues for future policy research to support an equitable clean energy transition.

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Joseph—once a dingus, always a dingus. But now we are coastal elite dinguses.

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Contents

Introduction

Mounting pressures from the rapidly changing climate require rapid deployment of new technologies at scale and policies to accelerate the clean energy transition (Hanna and Victor 2021; Meckling, Sterner, and Wagner 2017; Geels et al. 2017; Bumpus and Comello 2017; Åhman, Nilsson, and Johansson 2017; Holmes et al. 2021). Over the last decade, many of these technologies have rapidly matured (e.g. wind and solar), leading to decreased costs and—in theory—greater accessibility to broader populations in the United States. Residential solar PV technology costs, in particular, have fallen dramatically, from approximately $4/W in 2007 to $0.35/W in 2017 (Comello, Reichelstein, and Sahoo 2018). While lower costs and government incentives for solar drive adoption, distributional challenges related to its equitable deployment across different groups (e.g., income, race and ethnicity) remain (Darghouth et al. 2022; Carley and Konisky 2020; Sovacool, Barnacle, et al. 2022; Sovacool, Newell, et al. 2022; O'Shaughnessy, Barbose, Wiser, Forrester, et al. 2021; Brockway, Conde, and Callaway 2021; Goldstein, Reames, and Newell 2022; Lukanov and Krieger 2019; Castellanos, Sunter, and Kammen 2021; Hanke, Guyet, and Feenstra 2021; Si and Stephens 2021). This research focuses on how residential solar photovoltaic technology adoption may be influenced by the racial and ethnic composition of communities in the United States. Using two, national datasets disaggregated to the census-tract level, I construct a series of regression models to examine the role that race and ethnicity plays in the likelihood and extent of residential solar photovoltaic (PV) adoption. To begin, I take stock of primary barriers to solar adoption, before examining specific racial equity considerations, the primary focus of this work.

Barriers to Residential Solar PV Adoption

Barriers to residential solar PV adoption documented in prior work include lack of energy efficiency and renewable energy policy generally; lack of information and low consumer awareness; inadequate workforce capacity; lack of stakeholder/community participation in projects; political polarization of climate and energy issues; the growing need for energy storage for variable renewable technologies; and high, often unanticipated "soft costs" of solar related to labor, permitting, and interconnection, among others (Corrado, Holt, and Schambach 2022; Margolis and Zuboy 2006; Ramasamy 2022).

Moving beyond these higher-level barriers, several studies have examined individual-level perspectives that factor into the decision to adopt solar (Palm 2018; Schulte et al. 2022; Scheller et al. 2021). Income is often cited as a key difference in the ability of households to install solar. Regardless of income, households tend to be motivated by environmental norms and perceived financial benefits (Wolske 2020), and social networks play a sizeable role in the spread of information regarding the benefits of solar (Wolske, Stern, and Dietz 2017; Graziano and Gillingham 2015). The presence of the aforementioned barriers mean that even if a household is knowledgeable about residential solar PV, motivated to adopt and has the financial means to adopt, accessibility of installers, incentives, and institutional support may ultimately prevent them from doing so particularly if adoption among peers is low or non-existent.

With these baseline barriers and motivations identified, it is critical to consider the disparate impacts they may pose to different demographic groups. For example, people of color are more likely to be renters, have lower household incomes, and higher populations of limited English-proficiency individuals, all of which may impact their access to and ability to adopt solar PV technologies (Reames 2020). Consequently, there is a need to better understand the distributional effects that these barriers may pose to the equitable adoption of these technologies.

Equity and Solar PV Adoption

Just as income is considered a highly influential constraint on a household's decision to adopt, it has often been the main dimension through which researchers have considered the notion of "equity" in studies of residential solar PV deployment to date; this may be the result of policy developments that have focused on increasing market penetration of residential solar PVs among low-to-moderate income (LMI) households (Crago, Grazier, and Breger 2023; Si and Stephens 2021; O'Shaughnessy, Barbose, Wiser, and Forrester 2021; "Bringing the Benefits of Solar Energy to Low-Income Consumers" n.d.; Paulos et al. 2021; O'Shaughnessy 2022). While studies relating income and solar PV deployment have increased, the literature focused on quantifying the relationship between race, ethnicity, and residential solar deployment is relatively sparse. As of writing, I identified three, peer-reviewed articles that explicitly consider the role of racial and ethnic equity and residential solar PV adoption, all published within the last several years.

First, Sunter, Castellanos, and Kammen (2019) combine data from Google's Project Sunroof data with 2009-2013 demographic data from the American Community Survey (ACS) to conduct a non-parametric analysis of adoption trends across different racial and ethnic majority groups. Plotting a state-normalized solar deployment metric against the proportion of renters and income level at the tract-level, they observe trends in deployment across different races and ethnic groups. They conclude that after controlling separately for these two variables, Black, Hispanic, and Asian communities experience less solar deployment, relative to areas with no racial or ethnic majority.

Next, Reames (2020) analyzes solar potential and penetration across four U.S. cities with a focus on LMI communities. Leveraging DeepSolar, a national-level dataset on solar installations disaggregated to the census tract level (also featured in this analysis), he finds that race/ethnicity does not have a statistically significant correlation with total rooftop solar penetration in Washington, DC, Riverside, CA, or Chicago, IL; in San Bernardino, CA, he finds a statistically significant, positive association between the percent of the non-white population and solar penetration.

Finally, Gao and Zhou (2022) adopt Sunter, Castellanos, and Kammen (2019)'s approach to segmenting groups based on racial and ethnic majority classification to examine correlations between the effects of "solar justice" policies on residential solar PV adoption. Relying on a pre-processed, census tract-level dataset from the Lawrence Berkley National Lab, they run regressions on annual residential solar installations from 2012 to 2019 (at the census tract level), finding evidence of a negative correlation between of race/ethnicity and annual installations, for majority-Black, majority-Asian, majority-Hispanic, and no majority tracts.

Each of these studies provides evidence of disparities across racial/ethnic groups, but do not come without limitations. Sunter, Castellanos, and Kammen (2019)'s non-parametric approach does not quantify the effects of race and ethnicity and presents results only at the national level. Reames (2020) samples census tracts within four U.S. cities, but few estimated parameters reach statistical significance at that sample size; he also uses a simplified classification of race/ethnicity, using "percent of non-white population" as a catch-all grouping for nonwhite racial groups. Gao and Zhou (2022)'s underlying dataset is not demographically representative at the national-level (due to overrepresentation of Hispanic and Asian populations and underrepresentation of Black and White populations, compared to national averages), which may result in biases in the estimated coefficients for each racial or ethnic group. Moreover, conflicting results across these three studies warrant a more systematic approach to studying disparities in race and ethnicity in residential solar PV adoption.

This work contributes to the existing literature by 1) conducting parametric modeling on a demographically representative, national-level solar dataset at the census tract level, 2) comparing the results across two datasets using remote sensing to assess residential solar adoption, 3) quantifying the associations between different racial and ethnic group classifications and residential solar installations and 4) using a national-level analysis to inform case study selection of a specific locality through lenses of both race and place. The results provide evidence of racial disparities in the initial "seeding" of residential solar installations and quantifies the magnitude of the associations between race/ethnicity and residential solar installations in the U.S. I conclude by discussing the limitations of the research and suggest avenues for future policy-relevant research.

Data and Methods

The primary goal of this research is to aid in answering the following research questions:

- Is there a relationship between a census tract's racial and ethnic composition and the likelihood of it containing at least one residential solar PV installation ("seeding")?
- To what extent is solar deployment, defined as the total number of installations in a census tract, characterized by disparities across race and ethnicity?

To do so, I employ a combination of statistical modeling and qualitative policy analysis of specific geographies to analyze the explanatory variables of interest and their relationship with residential solar photovoltaic adoption for census tracts in the United States. I compile and analyze data on demographic, market, and policy variables from different sources at the tract-level, where available, and combined them with national datasets on residential solar PV installations. The final dataset serves as the input to a series of logistic and ordinary least squares (OLS) regression models, implemented using R programming language; a link to the full set of scripts is included in the Appendix ("The Comprehensive R Archive Network" n.d.). Information on the data sources and models used in this analysis are described in the remainder of this section.

Data Sources

Table 1 summarizes the definitions and data sources for each variable included in the analysis presented in this work; this also corresponds to Model 5 in the logistic and OLS regressions that follow.

Residential Solar PV Installations. I use data on the total number of residential solar PV installations from two sources: the DeepSolar database, produced by researchers at Stanford University, and Google's Project Sunroof. DeepSolar uses machine learning to identify solar installations using satellite imagery, while Project Sunroof uses 3D digital elevation models to extract key building features (e.g. presence or absence of solar panels) and models building suitability for solar installations. Both datasets are national in scope, with spatial resolution at the census tract level. The DeepSolar dataset includes an estimated 1,277,794 residential solar installations, and Project Sunroof includes 650,494 total estimated installations. The year of comparison for the dependent variable, total residential solar PV installations, is 2015. This was the most recent data available at the start of this project.

Racial and Ethnic Composition. I include several variables on race and ethnicity at the Census-tract level from the 2011 – 2015 American Community Survey (ACS) to capture racial and ethnic compositions across communities. Following Sunter, Castellanos, and Kammen (2019) and Gao and Zhou (2022), I classify tracts based on the proportion of different races and ethnicities present in each tract in the dataset. "Majority-Black" tracts are those with a non-Hispanic Black population that exceeds 50%, "Majority-Asian" tracts have a non-Hispanic Asian population greater than 50%, and "Majority-Hispanic" tracts are those with a Hispanic population greater than 50%. Tracts where no racial or ethnic group exceeds 50% are classified as "No Majority" tracts. All others are majority non-Hispanic white.

Table 1. Definitions and Data Sources.

Variable	Definition	Source
Dependent Variables		
Total Solar Installations	Total number of residential solar installations in a census tract	DeepSolar, Project Sunroof
Solar Installations (Binary: Yes = 1, No = 0)	Yes, if ≥ 1 residential solar installation is present in a census tract	DeepSolar, Project Sunroof
Explanatory Variables		
Majority Black (Yes = 1, No = 0)	Yes, if >50% of respondents in a census tract self-identify as non-Hispanic, Black	2015 ACS
Majority Asian (Yes = 1, No = 0)	Yes, if >50% of respondents in a census tract self-identify as non-Hispanic, Asian	2015 ACS
Majority Hispanic (Yes = 1, No = 0)	Yes, if >50% of respondents in a census tract self-identify as Hispanic	2015 ACS
No Majority (Yes = 1, No = 0)	Yes, if none of the target groups achieves a majority of the racial/ethnic composition	2015 ACS
Control Variables		
Average Daily Solar Radiation	Daily solar radiation averaged from 1983 to 1993 (kWh/m^2/d)	DeepSolar/NASA
Average Residential Electricity Price	Average residential electricity price, by state (cents/kWh)	EIA 2015
State-Level Incentives	Total number of state-level, residential solar PV incentives available in 2015	DSIRE
Housing Units*	Total number of housing units in a tract	2015 ACS
Age	Median age of individuals in a census tract	2015 ACS
Income*	Median income in a census tract	2015 ACS
Educational Attainment	Percent of population in a census tract with a bachelor's degree or higher	2015 ACS
Detached, single-family homes	Percent of housing stock that consists of detached, single-family housing in a census tract	2015 ACS
Limited English Proficiency Population	Percent of households in a tract that speak English less than "very well"	2015 ACS

**These variables are log-transformed in the regression models.*

Daily Solar Radiation. Data on average daily solar radiation are included in the DeepSolar database at the tract level, sourced from NASA's Surface Meteorology and Solar Energy product, which has a spatial resolution of 1 x 1 degrees (Chandler, Whitlock, and Stackhouse 2004). Daily solar radiation is expressed as the average daily solar radiation, in kilowatt-hours per square meter per day (kWh/m^2/day), over a ten-year period from 1983 to 1993. Solar radiation accounts for a key physical constraint on the viability of solar PV development across geographies (Yu et al. 2018). Prior studies have identified strong positive relationships between higher levels of solar irradiance and total residential installations (Wang et al. 2022; Kwan 2012).

Average Residential Electricity Rate. To control for potential differences in the effect of electricity costs on residential solar PV installation, I use average residential electricity costs in cents per kilowatt-hour (cents/kWh) derived from Energy Information Administration (EIA) estimates from 2015; consequently, every tract within a state shares the same value (EIA 2015). While this field is included in the original DeepSolar database, I cross reference those values with the EIA data from 2015 as a quality check.

State-Level Incentives. Leveraging the DeepSolar database and the North Carolina Clean Energy Technology Center's Database of State Incentives for Renewables & Efficiency (DSIRE), I extract the total number of state-level residential solar incentives available in the contiguous United States, as of 2015, and use it as a proxy for access to state-level resources to aid in solar deployment ("Database of State Incentives for Renewables & Efficiency").

Data Compilation

Table 2. Comparison of Average Tract-Level Characteristics in DeepSolar and Project Sunroof Compared to ACS Estimates.

	Tracts in the 2011-2015 ACS	DeepSolar	Project Sunroof
% White	62.8%	62.9%	56.9%
% Black	13.4%	13.5%	15.7%
% Asian	4.6%	4.5%	5.8%
% Hispanic	15.9%	15.9%	18.6%
% Limited English Proficient	4.7%	4.7%	5.8%
Median Income	$57,752	$57,655	$60,174
Median Age	38.9	38.9	37.9
% with a Bachelor's Degree or Higher	28.6%	28.6%	31.5%

After compiling the final dataset, I conduct a series of preliminary descriptive analyses. First, I examine the two datasets in terms of their representation of the general population, as estimated by the 2015 ACS data. Table 2 provides an overview of that comparison, across several demographic variables. I perform several t-tests on the DeepSolar and Project Sunroof data, comparing their average values for these variables to the ACS (see Appendix). From them, I conclude that there is not a statistically significant difference between the mean values of these variables in DeepSolar and the ACS. DeepSolar is therefore more closely aligned with national-level demographics, compared to Project Sunroof. Consequently, many of the tables and figures presented in this work use DeepSolar as the data input; corresponding figures using the Project Sunroof data are presented in the Appendix.

In the DeepSolar database, I found that the authors' tabulation of the census data did not isolate Hispanic and non-Hispanic ethnicities from the racial groups. To address that, I extracted the race and ethnicity variables from the ACS in R using tidycensus to ensure that those groups are mutually exclusive in my analysis (Walker, Herman, and Eberwein 2023). Formally, the race and ethnicity explanatory variables correspond to non-Hispanic, Black-majority; non-Hispanic, Asian-majority; and Hispanic-majority tracts. No majority tracts have neither a racial nor ethnic majority.

Additionally, I randomly selected 10 observations and manually calculated each of the variables described above. This provided a quality check on the overall data compilation process and enabled the correction of any errors that arose during the merging process.

Model Specification

Dependent Variable Transformation

After compiling the data, I ran a preliminary version of the final OLS model on both the DeepSolar datasets and analyze the residuals with a Quartile-Quartile (Q-Q) plot; the output was characterized by non-normality of the model's residuals and heteroskedasticity, violating two OLS assumptions. To correct for the former, the dependent variable for the OLS models is transformed using equation (1) below, where $\hat{Y}_i$ is the natural log-transformed dependent variable in the OLS models and n is the total number of residential solar installations detected in census tract i. For the latter, the estimated coefficients described in the Results section are presented with heteroskedastic-robust standard errors.

$$\hat{Y}_i = \ln(n_i + 1) \tag{1}$$

Log-transforming the dependent variable in this manner retains the zero values, which are of particular relevance to this analysis. Following this transformation, I re-ran the preliminary OLS model and observe that the residuals more closely resemble normal distribution. Following Kwan (2012), the number of housing units, and median income are also log-transformed. As a robustness check I also run the models using the inverse hyperbolic sine (IHS) transformation, another data transformation commonly used in econometric and social science applications. With the IHS transformation, the estimated coefficients can be interpreted in the same manner as a log-transformed variable (Aihounton and Henningsen 2021). The output from those models are included in the Appendix.

Handling Multicollinearity

Because this analysis uses several highly correlated variables as controls I calculate the variance inflation factor (VIF) for the fully specified model. "Median income" and "the percent of the population living in owner-occupied housing units" are highly correlated, with VIF values greater than four. The owner-occupied fraction is also highly correlated with the percent of the population living in "detached single-family unit" housing, so the latter is excluded from the model specifications. Median income and the percent of the population with a bachelor's degree or higher are also highly correlated. As an additional sensitivity check and to mitigate against potential errors arising from multicollinearity I also test models that include only median income, only the percent of the population with a bachelor's degree or higher, and both variables together. All of the specified models are documented in the Appendix.

Model Selection

The first portion of the statistical analysis uses logistic regression to estimate the probability that at least one residential solar installation exists in a census tract, controlling for the variables in Table 2. I model the first phase using a general logistic regression function:

$$\hat{Y}_i = \frac{1}{1 + e^{-(\hat{\beta}_0 + \widehat{\beta_1} X_{1i} + \widehat{\beta_2} X_{2i} + \cdots + \widehat{\beta_k} X_{ki})}} \tag{2}$$

where $\widehat{\beta_0}$ is a constant, $\widehat{\beta_1} \dots \widehat{\beta_k}$ are the estimated coefficients and $X_{1i}, X_{2i}, \dots, X_{ki}$ represent the value of the independent variables for each observation i included in the DeepSolar or Project Sunroof datasets. Similarly, for the second phase, I run an OLS model, generalized as:

$$\hat{Y}_i = \hat{\beta}_0 + \widehat{\beta_1} X_{1i} + \widehat{\beta_2} X_{2i} + \cdots + \widehat{\beta_k} X_{ki} \tag{2}$$

where $\hat{Y}_i$ is the log-transformed dependent variable, measuring the estimated total number of observed installations Y observed in census tract i, $\hat{\beta}_0$ is a constant, $\widehat{\beta_1} \dots \widehat{\beta_k}$ are coefficient estimates for each regressor in the model, and $X_{1i}, X_{2i}, \dots, X_{ki}$ denote the values of the independent variables for each observation i. The results are detailed in the next section.

Results

Descriptive Analysis

Summary Statistics

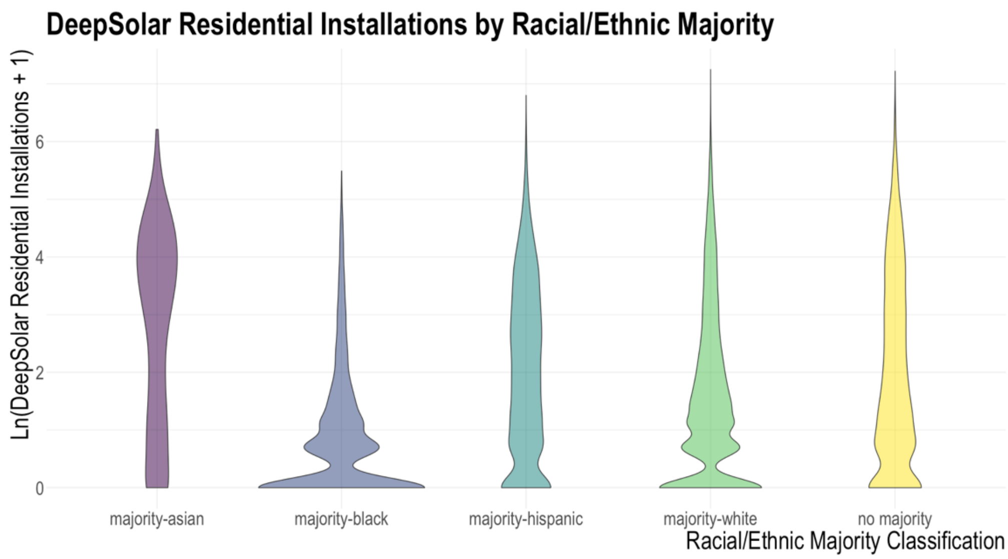


Figure 1. Mirrored Density Plot of the Distribution of Residential Solar, by Race/Ethnicity.

Table 3. Summary Statistics for DeepSolar Installations, by Race/Ethnic Majority Classification.

	Total DeepSolar Installations	Total DeepSolar Tracts	DeepSolar Tracts with 0 Installations	DeepSolar Tracts with >0 Installations	Mean DeepSolar Installations
Majority-Asian	22,412	510	67	443	43.9
Majority-Black	29,368	6,092	2,743	3,349	4.8
Majority-Hispanic	137,460	6,639	1,244	5,395	20.7
Majority-White	853,294	50,177	12,729	37,448	17.0
No Majority	234,602	8,522	1,762	6,760	27.5
Total	**1,277,136**	**71,940**	**18,545**	**53,395**	**17.8**

First, I analyze how the total residential solar installations varies by race and ethnicity for the DeepSolar data (Project Sunroof figures are in the Appendix). Figure 1 plots the density of observed installations, broken out by racial and ethnic majority classification to highlight differences in the frequency and distribution of the total number of residential solar installations across groups. The y-axis values are log-transformed, according to Equation 1.

For each group, with the exception of majority-Asian tracts, I observe heightened clustering around tracts with zero solar installations. These groups follow a general trajectory of having a mode of zero near zero, with several lesser "peaks" around logged-values of one, with a significant remainder being outlier values. For majority-Asian tracts, however, the highest density is clustered around y = ~4, roughly corresponding to the mean value of 43.9 solar installations (see Table 3). This is in stark contrast to majority-Black tracts, for which I observe a higher density of zero values, as compared to the other groups, suggesting potential negative bias in the likelihood of having at least one residential solar PV installation.

The mean number of installations, defined as the total number of residential installations divided by the total number of tracts, reflects this observation. For the entire dataset, that value is 17.8; however, majority-Asian tracts have a mean of 43.9, majority-Black tracts have a mean of 4.8 installations, and majority-Hispanic tracts have a mean of 20.7 installations. No majority tracts appear to outperform other groups on this metric, with a mean of 27.5 installations.

From the accompanying summary statistics in Table 3, I estimate that approximately 25% of all census tracts included in the DeepSolar dataset have zero residential solar installations. However, there are significant differences in how that value appears for different races and ethnicities. For example, 13.1% of majority-Asian tracts, 18.7% of majority-Hispanic tracts, and 20.7% of no majority tracts are categorized as having zero installations. On the other hand, 45% of majority-Black tracts do not have any residential solar installations, nearly twice the average for the entire dataset. Additionally, I observe that while majority-Black tracts make up approximately 8.5% of total tracts in the DeepSolar sample, installations in majority-Black communities comprise 2.3% of total installations. This suggests that majority-Black tracts might be overrepresented in the composition of tracts with zero residential installations, and underrepresented in tracts with at least one residential installation.

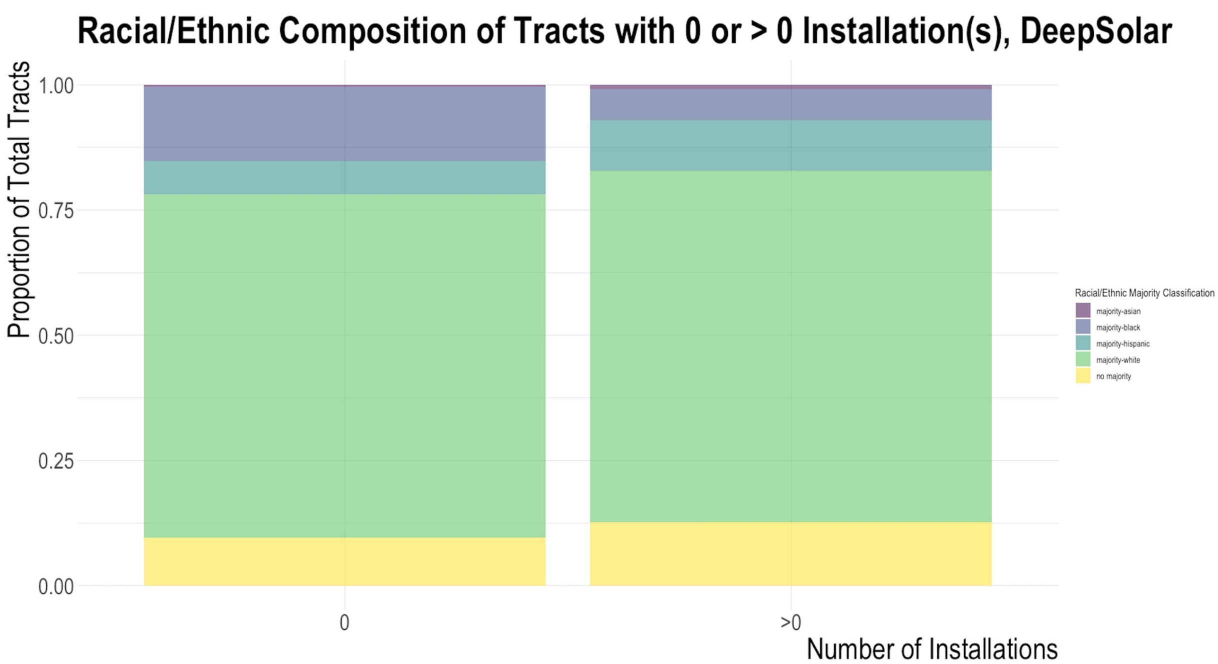


Figure 2. Proportion of Tracts with Zero or at Least 1 Installation (DeepSolar), by Race/Ethnicity.

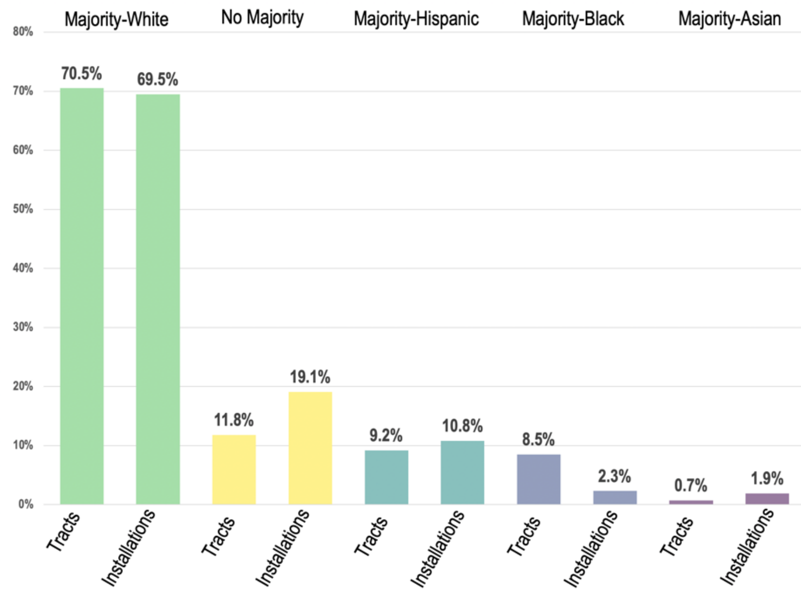


Figure 3. Proportion of Total Tracts and Installations (DeepSolar), by Race/Ethnicity.

Figure 2 visualizes proportions derived from Table 3, highlighting the relative contributions of each racial/ethnic group to the total number of tracts with either zero or at least one residential solar installation. Figure 3 illustrates how the proportion of installations across the racial/ethnic groups included in the study, compares to their overall representation in the dataset. I observe that total installations in majority-Asian, majority-Hispanic, and no majority tracts trend in the direction of overrepresentation, at first glance.

Geographies of Race, Ethnicity, and Residential Solar PV

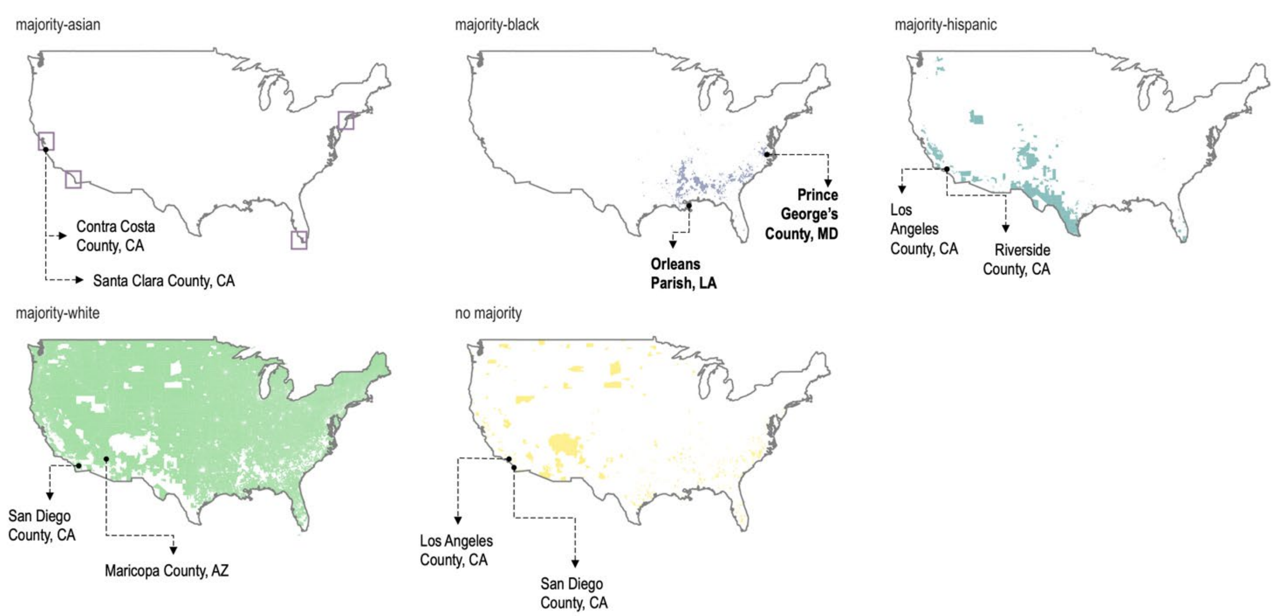


Figure 4. Spatial Distribution of Race/Ethnic Majorities and Counties with Highest Installations, by Race/Ethnicity (DeepSolar).
NOTE: Because there are different racial and ethnic majority classified tracts in certain counties, some places have the highest installation counts across several groups (e.g. Los Angeles, above).

Table 4. Top Counties with the Highest Number of Solar Installations, by Race/Ethnicity.

NOTE: Because there are different racial and ethnic majority classified tracts in certain counties, some places have the highest installation counts across several groups.

	County Name	Number of Tracts in the County	% of Total Tracts in the County	Total DeepSolar Installations	Racial/Ethnic Majority Installations as % of Total Installations in the County	Racial/Ethnic Majority Installations as % of Total Installations Nationally
Majority-Asian	Santa Clara, County, CA	81	0.3%	6,993	21.2%	31.2%
	Contra Costa, County, CA	120	5.2%	5,152	5.6%	23.0%
Majority-Black	Prince George's County, MD	157	72.0%	6,065	81.5%	20.7%
	Orleans Parish, LA	107	61.5%	4,958	76.7%	16.9%
Majority-Hispanic	Los Angeles County, CA	1081	46.5%	24,622	26.7%	17.9%
	Riverside County, CA	183	40.5%	12,064	21.9%	8.8%
Majority-White	San Diego County, CA	335	53.5%	66,459	68.6%	7.8%
	Maricopa County, AZ	620	67.9%	48,723	84.8%	5.7%
No Majority	Los Angeles County, CA	501	21.5%	23,167	25.0%	9.9%
	San Diego County, CA	134	21.4%	20,499	21.2%	2.4%

Figure 4 and Table 4 describe the geography of where each racial/ethnic-majority classification is present at the tract-level; For many groups the areas with the highest number of installations coincide with higher average daily solar radiation with and regulatory environments that are favorable to residential solar PV adoption (e.g., California). However, majority-Black tracts exhibit a markedly different geographic distribution in residential, with the highest concentrations of solar installations for those communities located in the Southeast.

Table 4 sheds light into some of the nuances regarding representation across groups within particular geographies. For example, the top two counties with the highest number of installations in majority-Asian tracts contain 54.2% of all installations for this group. Similarly, 37.6% of all installations in majority-Black tracts can be found in the DC suburb of Prince George's County, Maryland and New Orleans, Louisiana. This suggests that installations in majority-Black and majority-Asian communities are concentrated in fewer areas as compared to majority-Hispanic, majority-White, and no majority tracts.

Statistical Analysis

Overview of Regression Models

Results from the logistic and OLS regression models are presented in the following subsections. Identical variable mixes are selected for each set of regressions, according to Table 5 below.

Table 5. Specified Logit and OLS Models.

	General Model Specification				
	Dependent variable: ln(installations + 1) -*OR*- logit(installations)				
	(1)	(2)	(3)	(4)	(5)
Explanatory	Majority-Black Majority-Asian Majority-Hispanic No Majority	Majority-Black Majority-Asian Majority-Hispanic No Majority	Majority-Black Majority-Asian Majority-Hispanic No Majority	Majority-Black Majority-Asian Majority-Hispanic No Majority	Majority-Black Majority-Asian Majority-Hispanic No Majority
Market/Environmental	Total Number of Units*	Total Number of Units* Avg Daily Solar Radiation Avg Residential Electricity Price	Total Number of Units* Avg Daily Solar Radiation Avg Residential Electricity Price	Total Number of Units* Avg Daily Solar Radiation Avg Residential Electricity Price	Total Number of Units* Avg Daily Solar Radiation Avg Residential Electricity Price
Demographic	-	-	Age Education Detached, single-family homes Limited English Proficiency Population	Age Income* Detached, single-family homes Limited English Proficiency Population	Age Income* Education Detached, single-family homes Limited English Proficiency Population

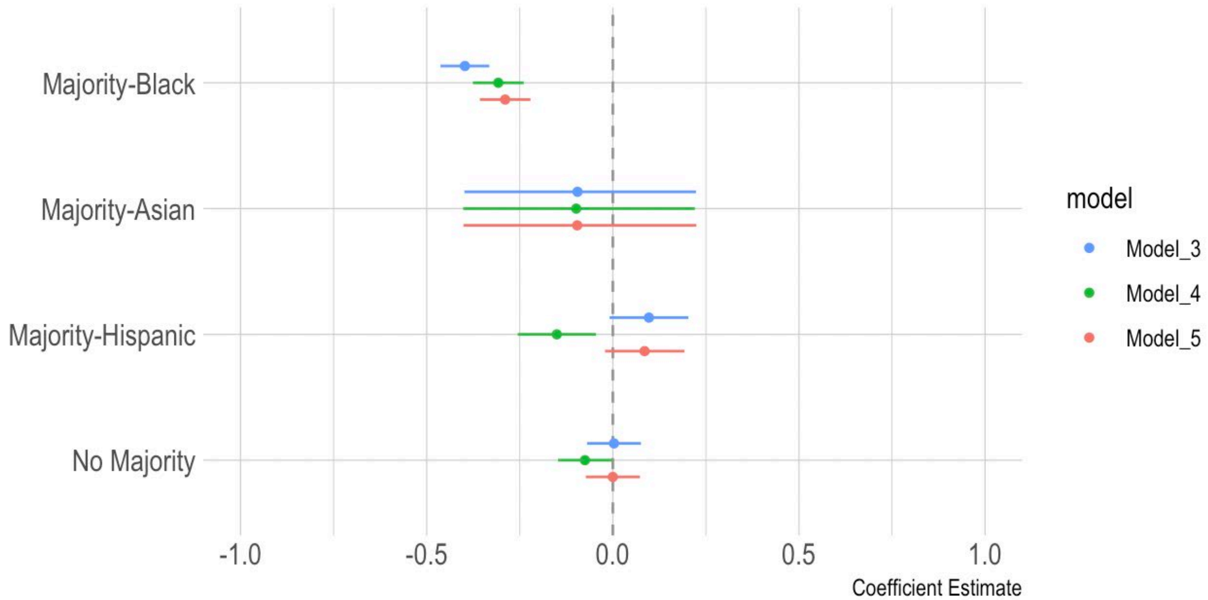
*For consistency, these values are also log-transformed according to equation (1). The full table of estimates is found in the Appendix.

Model 1 includes the race and ethnicity variables with the only control being the total number of units in the tract. Model 2 adds solar radiation and electricity price. Models 3 – 5 introduce the demographic variables. Model 3 includes educational attainment but excludes the log-transformed median income, to minimize bias related to collinearity between those two, closely correlated variables. Model 4 excludes educational attainment in favor of the log-transformed median income, while Model 5 includes both variables as a sensitivity check on the model specifications.

Because both the logistic and OLS models are specified with log-transformed dependent variables, results are presented in terms of the estimated coefficient and on occasion, the corresponding percentage change in the dependent variable.

Logistic Regression

DeepSolar



Project Sunroof

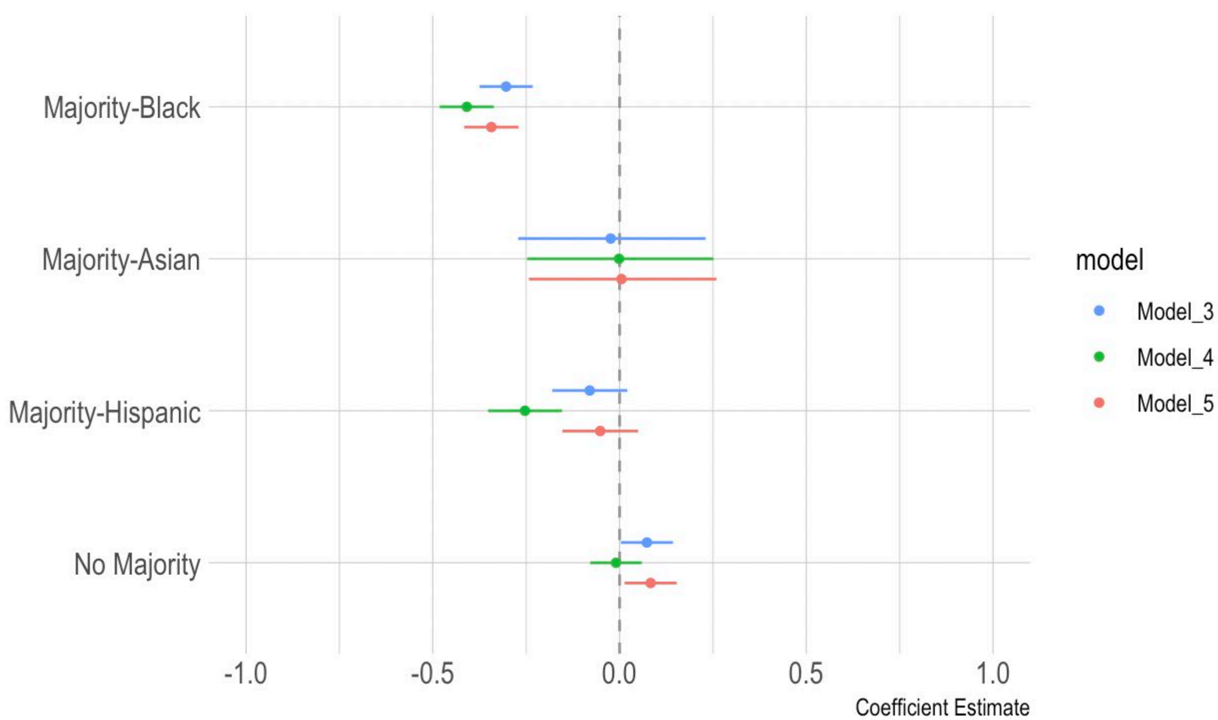


Figure 5. Estimated Logistic Regression Coefficients for Models 3-5, with 95% Confidence Intervals.

Results from the logistic regression models indicate that majority-Black census tracts are associated with a statistically significant decrease in the log-odds of there being a solar installation, ranging from -129.3% to -33.6% (see Table 6 for the full range of values, and Figure 5 for visualizations of the coefficient estimates for Models 3-5). This result holds for each of the model specifications and across both datasets. However, it did not always hold for majority-Asian, majority-Hispanic, and no majority tracts, which varied in both magnitude and statistical significance, depending on the model specification and input data.

DeepSolar

In Model 1, the estimated coefficients for the race variables are: -0.76 for majority-Black tracts, 0.90 for majority-Asian tracts, 0.48 for majority-Hispanic tracts, and 0.34 for no majority tracts. These estimates correspond to a changes in the log-odds of residential solar in these communities by -113.8%, 146.0%, 61.6%, and 40.5% respectively, all of which are statistically significant at the 0.1% level.

For majority-Black tracts in Model 2, the estimated coefficient for majority-Black tracts is identical in magnitude, direction, and statistical significance to that of Model 1. The coefficient on majority-Asian, majority-Hispanic and no majority all change direction to -0.28, -0.38, and -10, though the estimate for majority-Asian is not statistically significant and the coefficient for no majority is significant at the 1% level.

In Model 3, the coefficient on majority-Black tracts remains negative and statistically significant at the 0.1% level, however its magnitude exhibits a relatively large decrease from -0.76 to -0.40, suggesting that differences in socioeconomic factors absorb some of the effects of race on the log-odds of the presence of residential solar PV installations, for this group. For the remaining groups, however, all of these effects are not statistically significant, diminishing the effect of race on the likelihood of residential solar PV installations in a census tract. This also raises a point central to the question of measuring systemic disadvantage using these methods: inequities tied to race and ethnicity are closely correlated to many of the socioeconomic variables in this analysis. This may partially explain the coefficient decrease observed once I control for them in the models.

Model 4 yields several interesting results, of relevance to this set of regressions as well as the OLS regressions discussed in the next subsection. Controlling for median income, rather than educational attainment, results in a 0.9 increase in the estimated coefficient for majority-Black tracts (from -0.40 to -0.31), while the majority-Hispanic and no majority coefficients (-0.15 and -0.07) exhibit increases in magnitude and changes in their direction. The coefficients on the latter groups are also significant at the 1% and 5% levels, respectively. This suggests that effect of median income may not be uniform across different racial and ethnic groups. Finally, model 5 results in an increase in the coefficient on majority-Black from -0.31 to -0.29, maintaining significance at the 0.1% level. The estimates for the rest of the groups are not statistically significant.

From the output of each of these models using the DeepSolar dataset, I find evidence of a strong, negative correlation between majority-Black census tracts and the log-odds of a tract having at least one solar installation, even when controlling for differences in income, education, home ownership, and English proficiency. There also appears to be distinct relationships between income and different racial and ethnic groups.

Project Sunroof

Next, I replicate the analysis on the Project Sunroof data. For Model 1, the estimated coefficient on majority-Black is -0.83, which is larger in magnitude than its DeepSolar counterpart. Majority-Asian and no majority tracts are associated with a statistically significant increase in the log-odds of having at least one installation (0.47 and 0.06). The estimated coefficient for the majority-Hispanic classification is not statistically significant. As highlighted in the descriptive analysis, differences in the represented racial composition of both datasets may account for variations observed in the outputs for each of them.

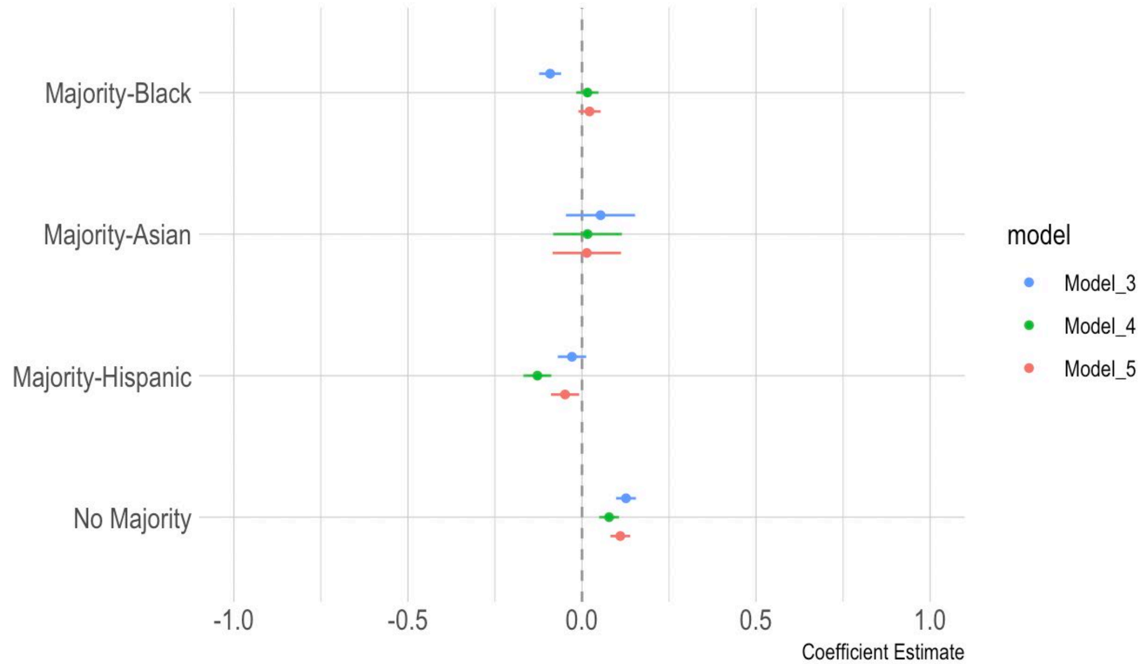
The coefficient for majority-Black tracts increases to -0.74 in in Model 2, maintaining significance at the 0.1% level. For the majority-Asian, majority-Hispanic, and no majority classifications, the sign of the coefficient flips from Model 1 to Model 2, such that the estimates are -0.56, -0.83, and -0.33, respectively; they are all statistically significant. Model 3 sees the coefficient on majority-Black increase from -0.74 to -0.30 and remains statistically significant at the 0.1% level. The coefficient for no majority tracts, estimated to be 0.07, decreases in significance to the 5% level. For the remaining groups, the estimated coefficients are not statistically significant. From this, I conclude that the inclusion of key socioeconomic variables decreases the previously observed negative effect of race and ethnicity on the likelihood of a residential solar installation, indicating that the model may be picking up on systemic inequity effects within the control variables.

Controlling for median income in Model 4 results in large changes in the estimated coefficients for majority-Black and majority-Hispanic; with the former, the coefficient decreases to -0.41, while the latter changes direction to -0.25. Both are significant at the 0.1% level. Finally, the majority-Black (-0.34) coefficient estimate in Model 5 maintains its significance with the estimate for no majority tracts changing direction from -0.01 to 0.08 and gaining significance at the 5% level.

Analysis of both datasets provides empirical support for the existence of racial disparities in the likelihood of there being at least one solar installation in a given tract for majority-Black communities, even after controlling for important socio-economic factors. Across each model specification, majority-Black census tracts are associated with large, statistically significant decreases in the log-odds of a having at least one solar installation. On the other hand, these data do not provide definitive evidence of that disparity holding for majority-Asian, majority-Hispanic, and no majority census tracts. Next, I examine whether there is a correlation between race and ethnicity and the total number of residential solar PV installations in a given tract, using OLS regression.

Ordinary Least Squares (OLS) Regression

DeepSolar



Project Sunroof

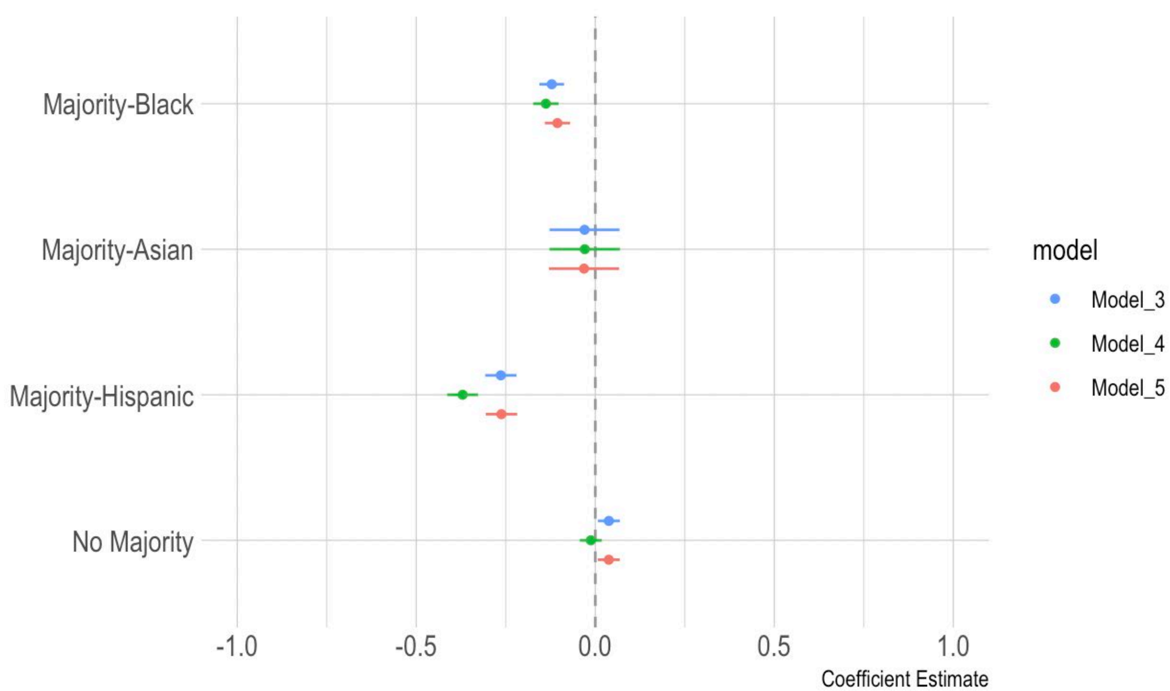


Figure 6. Estimated OLS Coefficients for Models 3-5, with 95% Confidence Intervals.

Tables 7 and 8 display unstandardized and standardized coefficient estimates for the race and ethnicity explanatory variables from the OLS regressions, respectively. Table 8 serves primarily to enable comparison of the estimated coefficients across the control variables; because the explanatory variables are binary, standardization by z-scoring complicates direct interpretation of those results. Direct interpretation of the coefficients on race and ethnicity should therefore be drawn from Table 7. Both tables follow identical variable mixes as those outlined in the preceding section, however, in these models, the dependent variable is transformed according to Equation 1. Figure 6 visualizes the estimated unstandardized coefficients from Models 3-5.

DeepSolar

The results of Model 1 indicate a disparity for majority-Black tracts, with an estimated coefficient on majority-Black of -0.62, meaning that majority Black tracts have a 46.2% decrease in residential solar installations. The coefficients for majority-Asian, majority-Hispanic, and no majority tracts are all positive at 1.26, 0.49, and 0.43 respectively. All coefficients are statistically significant at the 0.1% level, under this model specification.

I observe a change in direction for these three coefficients in Model 2. The coefficients on majority-Asian, majority-Hispanic and no majority tracts are -0.29, -0.64, and -0.19 respectively and maintain the same level of statistical significance. This suggests that some of the apparent positive effects related to those groups may exist due to increased presence of those communities in areas with increased average daily solar radiation, more state-level, residential solar incentives, and higher average state-level residential electricity prices. In this specification, the coefficient on majority-Black increases to -0.50, but also retains significance at the 0.1% level.

Introducing socioeconomic control variables has different effects on the estimated coefficients for each group, depending on the model specification. For no majority tracts, the estimates for Models 3-5 are consistently significant at the 0.1% level, ranging from 0.08 to 0.13, corresponding to an 8.3 – 13.9% increase in installations for tracts with this classification. This provides strong evidence of a positive correlation between tracts without a racial or ethnic majority and residential solar PV installations.

The results of Model 3 show a sizeable decrease in the coefficient on majority-Black, from -0.50 to -0.09; conditioning on the variables in column 4 in Table 5 (notably, educational attainment). The coefficients on majority-Asian and majority-Hispanic are no longer significant, suggesting that demographic characteristics across all three groups contribute to the initial observed racial disparities associated with the estimates in Model 2.

Conditioning on median income in Model 4 results in diminished statistical significance for the majority-Black variable. This also holds true in Model 5, and in additional models that use the "percent of population living in owner-occupied units" variable in lieu of the "percent of detached, single-family homes" variable, in a given tract (see Appendix). For majority-Hispanic communities, I observe the opposite effect; the coefficient on ethnicity is only statistically significant at the 0.1% level in Model 4 once I control for income. In Model 5, when educational attainment is reintroduced, the coefficient on majority-Hispanic decreases in significance to the 5% level. Estimated coefficients for all other groups are no longer statistically significant, except for no majority tracts.

Project Sunroof

In Model 1, the coefficient on majority-Black is -0.76 and statistically significant at the 0.1% level; this corresponds to a -53.2% decrease in the log-odds of the presence of at least one residential solar PV installation. Majority-Asian and no majority tracts have estimated coefficients of 0.73 and 0.10, corresponding with increases of 107.5% and 10.5% respectively, both of which are significant at the 0.1% level. The estimated coefficient on majority-Hispanic tracts in -0.04 (-4.1%), with a 5% significance level.

Controlling for market/environmental factors in Model 2, yields a decrease in the coefficient on majority-Black to -0.55 (or a -42.3% decrease in the number of installations). Similarly, every estimated coefficient for the remaining racial and ethnic groups are both negative and statistically significant at the 0.1% level. Like the aforementioned regressions, this indicates that after controlling for variables that address solar potential and policy environments favorable to residential solar adoption, race and ethnicity may have a negative correlation with the total number of installations in a community.

The outputs from Models 3-5 follow a similar trend observed in the prior regression models, however Project Sunroof differs from DeepSolar in one key way: there is a consistent, statistically significant negative correlation between tracts classified as majority-Black and the total number of residential solar installations. Under these three fully specified models, the range of percentage change in residential solar installations for the effect of race/ethnicity is -13.1% to -10.4% for majority-Black tracts and -30.9% to -22.9% for majority-Hispanic tracts.

The introduction of socioeconomic variables in Model 3, leads to an increase in the coefficient on majority-Black from -0.55 to -0.12. In this specification, the coefficient on majority-Asian loses significance, while the coefficients on both majority-Hispanic and no majority tracts are significant at the 0.1% and 5% levels, respectively. Controlling for income, rather than educational attainment, in Model 4 leads to an decrease in the estimated coefficients on both the majority-Black and majority-Hispanic regressors, indicating the effect of race and ethnicity is more negative than in Model 3. When controlling for both income and education, the negative coefficients on majority-Black and majority-Hispanic remain statistically significant at the 0.1% level. For majority-Asian tracts, the effect is not statistically significant after factoring in those variables.

Results from both sets of OLS models suggest that there is evidence that race and ethnicity are negatively correlated with under many of the model specifications, but the effect of income changes according to different group classifications. Further discussion of these findings follows in the next section.

Table 6. Logistic Regression Results for Explanatory Variables.

	Dependent Variable: logit(Residential Solar Installations)									
	Maximum Likelihood Estimation (MLE)									
	(1)		(2)		(3)		(4)		(5)	
	Deep Solar	Project Sunroof	Deep Solar	Project Sunroof	Deep Solar	Project Sunroof	Deep Solar	Project Sunroof	Deep Solar	Project Sunroof
Majority Black	-0.76*** (0.03)	-0.83*** (0.03)	-0.76*** (0.03)	-0.74*** (0.03)	-0.40*** (0.03)	-0.30*** (0.04)	-0.31*** (0.03)	-0.41*** (0.04)	-0.29*** (0.03)	-0.34*** (0.04)
Majority Asian	0.90*** (0.13)	0.47*** (0.11)	-0.28 (0.14)	-0.56*** (0.11)	-0.09 (0.16)	-0.02 (0.13)	-0.10 (0.16)	-0.001 (0.13)	-0.10 (0.16)	0.01 (0.13)
Majority Hispanic	0.48*** (0.03)	0.01 (0.03)	-0.38*** (0.04)	-0.83*** (0.04)	0.10 (0.05)	-0.08 (0.05)	-0.15** (0.05)	-0.25*** (0.05)	0.09 (0.05)	-0.05 (0.05)
No Majority	0.34*** (0.03)	0.06* (0.03)	-0.10** (0.03)	-0.33*** (0.03)	0.003 (0.04)	0.07* (0.04)	-0.07* (0.04)	-0.01 (0.04)	0.0001 (0.04)	0.08* (0.04)
Observations	71,940	51,646	66,357	47,853	66,166	47,715	66,019	47,608	66,019	47,608
Log Likelihood	-39,755.20	-32,252.91	-34,112.90	-27,275.16	-32,192.15	-26,470.71	-32,378.28	-26,583.64	-31,971.45	-26,390.22
Akaike Inf. Crit.	79,522.40	64,517.83	68,243.81	54,568.31	64,410.29	52,967.42	64,782.56	53,193.27	63,970.90	52,808.45

* p < 0.05; ** p < 0.01; *** p < 0.001

Table 7. Unstandardized OLS Regression Results for Explanatory Variables.

	Dependent Variable: Ln(Residential Solar Installations + 1)									
	Ordinary Least Squares Estimation (OLS)									
	(1)		(2)		(3)		(4)		(5)	
	Deep Solar	Project Sunroof	Deep Solar	Project Sunroof	Deep Solar	Project Sunroof	Deep Solar	Project Sunroof	Deep Solar	Project Sunroof
Majority Black	-0.62*** (0.02)	-0.76*** (0.02)	-0.50*** (0.02)	-0.55*** (0.02)	-0.09*** (0.02)	-0.12*** (0.02)	0.02 (0.02)	-0.14*** (0.02)	0.02 (0.02)	-0.11*** (0.02)
Majority Asian	1.26*** (0.06)	0.73*** (0.06)	-0.29*** (0.05)	-0.45*** (0.05)	0.05 (0.05)	-0.03 (0.05)	0.02 (0.05)	-0.03 (0.05)	0.01 (0.05)	-0.03 (0.05)
Majority Hispanic	0.49*** (0.02)	-0.04* (0.02)	-0.64*** (0.02)	-0.98*** (0.02)	-0.03 (0.02)	-0.26*** (0.02)	-0.13*** (0.02)	-0.37*** (0.02)	-0.05* (0.02)	-0.26*** (0.02)
No Majority	0.43*** (0.02)	0.10*** (0.02)	-0.19*** (0.01)	-0.37*** (0.01)	0.13*** (0.01)	0.04* (0.02)	0.08*** (0.01)	-0.01 (0.02)	0.11*** (0.01)	0.04* (0.02)
Observations	71,940	51,646	66,357	47,853	66,166	47,715	66,019	47,608	66,019	47,608
Adjusted R^2	0.07	0.06	0.43	0.40	0.50	0.47	0.50	0.46	0.51	0.47
F-Statistic	1,029.12***	617.44***	6,182.15***	4,030.16***	5,477.46**	3,528.95***	5,605.54***	3,443.85***	5,250.07***	3,257.69***

* p < 0.05; ** p < 0.01; *** p < 0.001

Table 8. Standardized OLS Regression Results, including control variables. **NOTE:** Standardizing coefficients for these binary variables is primarily to compare effect sizes, not for direct interpretation. Coefficients presented in units of standard deviation.

	Dependent Variable: Ln(Residential Solar Installations + 1)									
	Ordinary Least Squares (OLS)									
	(1)		(2)		(3)		(4)		(5)	
	Deep Solar	Project Sunroof	Deep Solar	Project Sunroof	Deep Solar	Project Sunroof	Deep Solar	Project Sunroof	Deep Solar	Project Sunroof
Majority Black	-0.12*** (0.02)	-0.16*** (0.02)	-0.09*** (0.02)	-0.12*** (0.02)	-0.02*** (0.02)	-0.03*** (0.02)	0.003 (0.02)	-0.03*** (0.02)	0.004 (0.02)	-0.02*** (0.02)
Majority Asian	0.07*** (0.06)	0.05*** (0.06)	-0.02*** (0.05)	-0.03*** (0.05)	0.003 (0.05)	-0.002 (0.05)	0.001 (0.05)	-0.002 (0.05)	0.001 (0.05)	-0.002 (0.05)
Majority Hispanic	0.10*** (0.02)	-0.01* (0.02)	-0.13*** (0.02)	-0.22*** (0.02)	-0.01 (0.02)	-0.06*** (0.02)	-0.03*** (0.02)	-0.08*** (0.02)	-0.01* (0.02)	-0.06*** (0.02)
No Majority	0.09*** (0.02)	0.03*** (0.02)	-0.04*** (0.01)	-0.09*** (0.01)	0.03*** (0.01)	0.01* (0.02)	0.02*** (0.01)	-0.003 (0.02)	0.02*** (0.01)	0.01* (0.02)
Total Number of Housing Units	0.16*** (0.01)	0.14*** (0.01)	0.17*** (0.01)	0.14*** (0.01)	0.18*** (0.01)	0.15*** (0.01)	0.18*** (0.01)	0.15*** (0.01)	0.18*** (0.01)	0.15*** (0.01)
Average Daily Solar Radiation	-	-	0.48*** (0.01)	0.51*** (0.01)	0.46*** (0.01)	0.47*** (0.01)	0.46*** (0.01)	0.47*** (0.01)	0.46*** (0.01)	0.47*** (0.01)
Average Residential Electricity Price	-	-	0.06*** (0.002)	-0.06*** (0.003)	0.07*** (0.002)	-0.05*** (0.003)	0.06*** (0.002)	-0.06*** (0.003)	0.06*** (0.002)	-0.05*** (0.003)
Total State-Level Incentives	-	-	0.35*** (0.001)	0.36*** (0.002)	0.35*** (0.001)	0.39*** (0.002)	0.32*** (0.001)	0.38*** (0.002)	0.33*** (0.001)	0.38*** (0.002)
Median Age	-	-	-	-	-0.05*** (0.001)	0.04*** (0.001)	-0.06*** (0.001)	0.03*** (0.001)	-0.06*** (0.001)	0.03*** (0.001)
% with a Bachelor's or Higher	-	-	-	-	0.19*** (0.02)	0.14*** (0.03)	-	-	0.10*** (0.04)	0.13*** (0.04)
Median Income	-	-	-	-	-	-	0.23*** (0.01)	0.12*** (0.01)	0.15*** (0.02)	0.01* (0.02)
% of Detached, Single-Family Homes	-	-	-	-	0.21*** (0.02)	0.21*** (0.02)	0.11*** (0.02)	0.16*** (0.02)	0.15*** (0.02)	0.21*** (0.02)
% of LEP Population	-	-	-	-	-0.05*** (0.08)	-0.07*** (0.08)	-0.05*** (0.08)	-0.08*** (0.08)	-0.04*** (0.08)	-0.07*** (0.08)
Observations	71,940	51,646	66,357	47,853	66,166	47,715	66,019	47,608	66,019	47,608
Adjusted R2	0.07	0.06	0.43	0.40	0.50	0.47	0.50	0.46	0.51	0.47
F-Statistic	1,029.12***	617.44***	6,182.15***	4,030.16***	5,477.46**	3,528.95***	5,605.54***	3,443.85***	5,250.07***	3,257.69***

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.00$

Discussion

Key Findings

Overall, the findings demonstrate strong evidence that majority-Black census tracts are associated with decreased probability of having any solar installations at all (in 2015) and fewer installations, in most of the specified models. Researchers have grappled with the often confounding interaction between income and race in prior work; several hypotheses have been set forth as explanations, ranging from inequities in the solar workforce (Sunter, Castellanos, and Kammen 2019) to the efficacy of installers across communities (Darghouth et al. 2022). I observe a similar phenomenon in my data. I hypothesize that this counterintuitive finding can be attributed to the systemic disadvantage observed in the control variables for majority-Black tracts in the analysis. For example, majority-Black tracts have an average value of 16.3% for the percent of population with a bachelor's degree or higher, an average value of 45.6% for the percent of the population living in owner-occupied units, and an average median income of $34,537 For majority-Hispanic tracts, those values are 13.4%, 46.3%, and $41,369, respectively; these trends may help explain why the coefficient estimates shift for both groups in Models 3-5. Both can be considered relative to the national averages of 28.6%, 62.7% and $57,752 for those variables.

Table 9. Comparison of Tracts and Installations in Tracts Below the Federal Poverty Line for a Family of Four in 2015 ($24,250) by Race/Ethnicity.

	Percent of Tracts Below the FPL (2015)	**Percent of Installations in Tracts Below the FPL (2015)**
Majority-Asian	3.1%	0.1%
Majority-Black	29.6%	13.0%
Majority-Hispanic	9.0%	2.2%
Majority-White	1.9%	0.3%
No Majority	6.6%	0.7%
All Tracts in DeepSolar	**5.4%**	**0.9%**

This follows for observed patterns in residential solar installations. Table 9 highlights the proportion of tracts and installations with median incomes below the poverty line for a family of four in 2015 ($24,250). Not only do majority-Black tracts have a significantly larger proportion of tracts below that threshold, the percentage of installations in tracts below is also the highest of any group in the analysis. The combination of systemic disadvantage for majority-Black communities detected in the control variables and the solar installation outliers overlapping with tracts at lower income, educational attainment, and homeownership rate ranges. Controlling for these socioeconomic variables—particularly median income—in the regression models might explain the decrease in statistical significance for the coefficient on majority-Black in Models 4 and 5. The statistical significance is therefore not indicative of a lack of the effect of race and ethnicity on solar installations; rather, the model is picking up on the fact that these communities have comparatively worse outcomes across the control variables. Improving racial equity outcomes in solar deployment for this group should therefore be addressed under the backdrop of structural racism and discrimination underpinning these group dynamics.

Placing the logistic regression results into the broader literature on residential solar PV technology diffusion yields several insights. Prior work to model the diffusion of residential solar installations within communities has found that the diffusion exhibits positive spatial autocorrelation, meaning that areas in closer proximity tend to have similar outcomes (Graziano and Gillingham 2015; Richter 2013; Mundaca and Samahita 2020; Rode and Weber 2016; Bollinger and Gillingham 2012). Similarly, earlier research has found that certain areas are slower to "seed" (e.g. have an initial instance of solar adoption) and tend to saturate more quickly (Holt and Sunter 2021; Castellanos, Sunter, and Kammen 2021; Wang et al. 2022). My results indicate that there may be significant barriers to "seeding" in majority-Black census tracts, even after controlling for many of the barriers set forth earlier (e.g. income, access to subsidies, etc.). These barriers potentially arise as a result of systemic inequities beyond the socio-demographic controls included in the regressions. Such inequities could be the result of lack of access to capital or low-cost financing for solar installations, higher proportions of "underbanked" individuals within particular racial or ethnic groups, or potentially discriminatory practices on the part of installers, leading to exclusion of certain populations from the solar market altogether.

While the significance of the effects of race and ethnicity diminish as more demographic variables are included in the models, the variable on limited English proficiency (LEP) proportion of the population stays consistently negative and statistically significant. This suggests that fraction of limited English speakers, may have a greater influence on solar installation outcomes than race or ethnicity alone, even when taking educational attainment and median income into account. This is particularly important for Asian and Hispanic populations, which exhibit higher proportions of LEP populations (Zong 2016). This raises questions about marketing efforts of installers, as it relates to limited-English proficient markets. Further research on the motivations of individual installer behaviors, including determining which market segments to engage with, could provide insight into potential sources of systemic inequities in installation patterns in addition to identifying opportunities to engage with LEP populations, with the goal of increasing their participation in the market for solar PVs (Sinitskaya et al. 2020).

Finally, despite the findings providing partial evidence that race and ethnicity are negatively correlated with residential solar installations, that the comparative effect is smaller when evaluated against other variables in the specified models. Reviewing the standardized coefficient estimates for the OLS models in Table 8 gives us a sense of the relative effect size of each regressor included in this analysis. In line with prior work across disciplines, my results indicate that the number of housing units, average solar radiation, and subsidies for residential solar PV uptake have the largest relative correlations to the total number of installations (Yu et al. 2018; Kwan 2012; Mundaca and Samahita 2020; Wang et al. 2022). Therefore while I observe correlations between race, ethnicity, and residential solar installations, the largest determinants in terms of their effect sizes, relate to market and environmental characteristics.

The Spatial Politics of Residential Solar PV Adoption

The descriptive analysis outlined in preceding section helps to facilitate the selection of case studies centered around the adoption of residential solar PV in areas the statistical models might categorized as “disadvantaged”. These areas correspond to census tracts with higher solar adoption than expected given the regression results. The goals of these cases are 1) to identify areas that “overperform” under the models specified, 2) to place the results into a real-word context, and 3) to discuss high-level policy recommendations considerations for current and future interventions in this area.

Recall Table 4, which lists the top five counties in terms of the total number of installations for each racial and ethnic majority group. Notably, installations in majority-Black tracts are clustered around the Southeastern and Mid-Atlantic regions. This might be partially attributed to legacies of racial and ethnic discrimination and its effects on settlement patterns of different racial/ethnic groups in the U.S (Frazier, Margai, and Tettey-Fio 2003). I select Orleans Parish, LA (or New Orleans) as a case study, as it represents an “outlier” majority-Black community with higher-than expected solar installation, while also having lower educational attainment and median income. Generally speaking, majority-Black census tracts in this area have high residual values from the outputs of Model 5 in both the logit and OLS regressions, indicating overperformance.

Case Study

On the surface, New Orleans appears to be an unlikely region for high solar penetration, due to its demographic profile and more conservative political climate at the state-level. While my analysis identifies New Orleans as an outlier in terms of the number of residential solar installations it has, the city has been informally recognized as such prior to this work (Environment America 2017; Hanley 2017). Several aspects of the trajectory of New Orleans’ solar industry warrant further examination, given the context of the results. I explore two elements for the purpose of this analysis—1) the broader backdrop of Hurricane Katrina and the area’s rebuilding efforts in the decade following that disaster and 2) incentives for residential solar provided by the State of Louisiana.

To this day, Hurricane Katrina, which landed in New Orleans in August of 2005, remains one of the costliest and most fatal storms in United States history (National Weather Service 2022). In its wake, local government officials, the State of Louisiana, and the federal government worked in tandem to disburse tens of billions of dollars in public funding to aid in relief and long-term recovery efforts (Richardson 2021). These efforts included significant investments in energy efficiency, renewable energy technologies, and the electric grid in an attempt to build local regional resilience against future disasters (Department of Energy 2011). The combination of significant direct financial assistance via relief funding and an overhaul of the regulatory barriers to adoption placed New Orleans at the center of what would be a defining era for the development of its burgeoning solar industry.

These actions overlapped with parallel, state-level efforts to enact historic incentives in 2007, resulting in the state’s adoption of net-metering and disbursing what would still be some of the most generous tax subsidies for solar adoption, nationally. The now-expired tax credit included funding for household installations, up to the lesser of $25,000 or 50% of the total installation. Combined with the federal tax credit of 30%, residents of Louisiana could have up to 80% of total installation costs subsidized via tax credits. This led to great success in deploying solar within the state (Upton 2019). From 2008 to 2019, installed capacity increased from roughly 0 to over 140 MW (Upton 2019). Despite their apparent success, these incentives were short-lived; as of 2017, the incentives were discontinued due in part to oversubscription and lack of long-term funding to sustain them (Upton 2019). The combination of an influx of federal disaster recovery funding, coupled with the passing of unusually generous solar subsidies at the state level might explain how the region became an outlier in the datasets included in my analysis.

From this preliminary assessment, future researchers can leverage national-level model outputs to identify relative over- and underperformers at the local level. As demonstrated above, this may serve as a starting point for digging into more substantive questions of policy and incentive structure for equitable residential solar PV adoption at the local level. While this study has several limitations, there is ample opportunity for future work to build on these findings.

Limitations + Future Research

Study Limitations

There are several limitations of this study with implications for future work in this area. First, due to limitations in the DeepSolar and Project Sunroof datasets, the analysis relies on data aggregated at the census tract level, rather than household-level data. This limits the extent to which I can infer causality between race and residential solar PV deployment. Consequently, the observational nature of the research design requires that the findings from the statistical outputs should be interpreted as correlational, rather than causal. Because of this limitation, I cannot identify race and ethnicity alone as the direct causal mechanism driving the disparities observed in the data.

Furthermore, aggregation at the census tract level may obscure intracommunity dynamics that. For example, in higher cost urban areas, there could in theory be increased solar deployment in neighborhoods with higher minority populations and lower median incomes, on average, as a result of gentrification pressures. In these scenarios, higher income households with greater educational attainment may be driving solar adoption in census tracts that would otherwise be classified as less likely to have any solar installations. Aggregating to larger geographies may therefore introduce potential biases in the coefficient estimates, leading to higher observed installations in tracts where models predict lower levels of solar penetration. Future research could therefore benefit from data at a higher spatial resolution, to mitigate against any potential obscuring of household-level dynamics.

Next, both the DeepSolar and Project Sunroof are subject to limitations in their geographic representation. As previously mentioned, the DeepSolar dataset contains installation data on the contiguous United States, so the models specified on that dataset do not include solar or demographic data for Alaska, Hawaii, or U.S. territories, all of which have higher minority populations than the national average. On the other hand, the Project Sunroof dataset excludes large swaths of the country's rural population, resulting in a sample that is less representative of the nation. I also hypothesize this as one potential reason for some of the differences observed in the model outputs across the DeepSolar and Project Sunroof datasets. Because Project Sunroof excludes a number of rural, majority-white census tracts with lower incomes and educational attainment, disparities across race and ethnicity may be more exaggerated in their absence. Regardless, both datasets do exclude portions of the population that may result in biased coefficient estimates.

Another limitation is found in the static nature of this analysis. As mentioned, the datasets were compiled in 2016. With annual residential solar PV installations reaching levels that exceed several hundreds of thousands in the years following 2016, the number of residential solar PV installations has increased rapidly since then (Galen Barbose et al. 2022). Constraining this study to one time period obscures temporal dynamics.

This research also focuses narrowly on a subset of solar technology diffusion—solar panel installations residential structures. Recent policy trends centering on equity in solar PV adoption have emerged with a particular focus on incentivizing participation in leasing and community solar programs (Chan et al. 2017). In this analysis, it is difficult to distinguish between the financing mechanisms that are tied to specific installations in the data. Consequently community solar programs and are not explicitly considered as they are not delineated the DeepSolar and Project Sunroof datasets. These programs have shown promise as a means of diversifying the end users of solar power, and therefore warrant more rigorous evaluation on their performance through the lens of racial equity.

Next Steps

In terms of building on the data and methodologies used in this project, there are several possible pathways forward to improve upon them. First, the research group at Stanford University that published the DeepSolar dataset is set to release a new spatiotemporal dataset later in 2023, which would allow for analysis of annual installations spanning the years 2005 to 2021. As of writing, the full dataset has not yet been published. Replicating this analysis on this larger, panel dataset could yield more nuanced results, regarding how solar PV technologies have spread across both time and space. This would enable the assessment of several preliminary hypotheses offered in this work. For example, researchers could leverage this dataset to assess the rate at which residential solar PV installations increased before and after Hurricane Katrina, taking into considerations data on federal, state, and local spending on renewable energy upgrades as part of longer-term rebuilding efforts.

Next, to address the issues arising due to the resolution of the data (e.g. census tract as opposed to household-level data), future work could leverage datasets with higher spatial resolutions. In other contexts, IRS data, when available, has been previously leveraged to provide empirical evidence of disparities in earnings, among different groups over longer lengths of time (Chetty et al. 2014). Accessing more granular data on household dynamics would enable researchers to move beyond quasi-experimental and correlational studies (such as this one) into causal inference. This is particularly relevant, as the recently passed Inflation Reduction Act (IRA) includes several tax provisions related to solar PV deployment (Barbanell 2022). Applying econometric methods to the study of solar deployment using “big data” sources, could yield additional insight into how adoption patterns have changed over time, as incomes and migration patterns change.

Finally, drawing on the descriptive analysis, future work could critically evaluate elements of existing program design that have led to more or less equitable outcomes, from both quantitative and qualitative perspectives. The brief case study of New Orleans provides a starting point for prioritizing jurisdictions for a more rigorous assessment of the aspects of residential solar PV incentive design and implementation that have led to increased better outcomes in more disadvantaged communities. This research underscore the need to consider residential solar deployment as part of a broader discussion of energy justice, and perhaps more importantly issues of historic and systematic discrimination that led to the outcomes observed in this research.

Conclusion

From this research, I quantify an observed systematic disadvantage for majority-Black communities in the likelihood and extent of solar installations, nationwide. While the logistic regression results provide robust evidence of that trend, the OLS regressions underscore the difficulties faced when attempting to quantify effects of race and ethnicity, both in general and for this particular group, due to the associations between race, ethnicity, and socioeconomic disparities. Placed within the broader context of the clean energy transition in the United States, several themes emerge: 1) residential solar PV adoption has not been equitable among racial and ethnic minority groups, particularly for majority-Black communities, 2) the geographic distribution of residential solar PV installations is not uniform across racial and ethnic groups, with some groups outperforming majority-White and no majority communities, and 3) solar PV diffusion may be constrained for some groups as a result of systemic inequities, as measured by the socioeconomic variables used in this research.

As a result, climate and clean energy policy efforts cannot be considered separate from the broader socioeconomic contexts into which they are introduced. The results underscore this notion by demonstrating how the diffusion of clean energy technologies is not inherently equitable, despite the drastic cost declines for residential solar PVs. They also provide a framework through which clean energy technology adoption and diffusion can be considered through the lens of racial equity. Failing to address underlying systemic disadvantage within and between groups poses a critical challenge to equitably addressing climate change in the United States. Further research should be undertaken to uncover causal mechanisms driving the disparities for majority-Black and majority-Hispanic communities observed in the results. Likewise, policy efforts, from the energy and climate field and beyond, will need to incorporate measures to correct for identified sources of disparities and ensure that clean technology deployment explicitly considers these disparities moving forward. The example of residential solar PV technologies provide a useful case for meaningfully assessing deployment disparities across groups, helping to embed racial equity into a just clean energy transition in the coming decades.

References

Åhman, Max, Lars J. Nilsson, and Bengt Johansson. 2017. "Global Climate Policy and Deep Decarbonization of Energy-Intensive Industries." *Climate Policy* 17 (5): 634–49. https://doi.org/10.1080/14693062.2016.1167009.

Aihounton, Ghislain B D, and Arne Henningsen. 2021. "Units of Measurement and the Inverse Hyperbolic Sine Transformation." *The Econometrics Journal* 24 (2): 334–51. https://doi.org/10.1093/ectj/utaa032.

Barbanell, Melissa. 2022. "A Brief Summary of the Climate and Energy Provisions of the Inflation Reduction Act of 2022," October. https://www.wri.org/update/brief-summary-climate-and-energy-provisions-inflation-reduction-act-2022.

Bollinger, Bryan, and Kenneth Gillingham. 2012. "Peer Effects in the Diffusion of Solar Photovoltaic Panels." *Marketing Science* 31 (6): 900–912. https://doi.org/10.1287/mksc.1120.0727.

"Bringing the Benefits of Solar Energy to Low-Income Consumers." n.d. *Clean Energy States Alliance* (blog). Accessed September 22, 2022. https://www.cesa.org/resource-library/resource/bringing-the-benefits-of-solar-energy-to-low-income-consumers/.

Brockway, Anna M., Jennifer Conde, and Duncan Callaway. 2021. "Inequitable Access to Distributed Energy Resources Due to Grid Infrastructure Limits in California." *Nature Energy* 6 (9): 892–903. https://doi.org/10.1038/s41560-021-00887-6.

Bumpus, A., and S. Comello. 2017. "Emerging Clean Energy Technology Investment Trends." *Nature Climate Change* 7 (6): 382–85. https://doi.org/10.1038/nclimate3306.

Carley, Sanya, and David M. Konisky. 2020. "The Justice and Equity Implications of the Clean Energy Transition." *Nature Energy* 5 (8): 569–77. https://doi.org/10.1038/s41560-020-0641-6.

Castellanos, Sergio, Deborah A. Sunter, and Daniel M. Kammen. 2021. "CHAPTER 6 - Exploring Rooftop Solar Photovoltaics Deployment and Energy Injustice in the US through a Data-Driven Approach." In *Data Science Applied to Sustainability Analysis*, edited by Jennifer Dunn and Prasanna Balaprakash, 109–28. Elsevier. https://doi.org/10.1016/B978-0-12-817976-5.00007-3.

Chan, Gabriel, Isaac Evans, Matthew Grimley, Ben Ihde, and Poulomi Mazumder. 2017. "Design Choices and Equity Implications of Community Shared Solar." *The Electricity Journal*, Energy Policy Institute's Seventh Annual Energy Policy Research Conference, 30 (9): 37–41. https://doi.org/10.1016/j.tej.2017.10.006.

Chandler, William S., Charles H. Whitlock, and Stackhouse Paul W. , Jr. 2004. "NASA Climatological Data for Renewable Energy Assessment." *Journal of Solar Energy Engineering* 126 (3): 945–49. https://doi.org/10.1115/1.1748466.

Chetty, Raj, Nathaniel Hendren, Patrick Kline, and Emmanuel Saez. 2014. "Where Is the Land of Opportunity? The Geography of Intergenerational Mobility in the United States *." *The Quarterly Journal of Economics* 129 (4): 1553–1623. https://doi.org/10.1093/qje/qju022.

Comello, Stephen, Stefan Reichelstein, and Anshuman Sahoo. 2018. "The Road Ahead for Solar PV Power." *Renewable and Sustainable Energy Reviews* 92 (September): 744–56. https://doi.org/10.1016/j.rser.2018.04.098.

Corrado, Casey, Emily Holt, and Lauren Schambach. 2022. "Barriers to Solar Photovoltaic (PV) Adoption on a National Scale in the United States." In *2022 IEEE 49th Photovoltaics Specialists Conference (PVSC)*, 1110–17. https://doi.org/10.1109/PVSC48317.2022.9938533.

Crago, Christine L., Emma Grazier, and Dwayne Breger. 2023. "Income and Racial Disparities in Financial Returns from Solar PV Deployment." *Energy Economics* 117 (January): 106409. https://doi.org/10.1016/j.eneco.2022.106409.

Darghouth, Naïm R., Eric O'Shaughnessy, Sydney Forrester, and Galen Barbose. 2022. "Characterizing Local Rooftop Solar Adoption Inequity in the US." *Environmental Research Letters* 17 (3): 034028. https://doi.org/10.1088/1748-9326/ac4fdc.

"Database of State Incentives for Renewables & Efficiency®." n.d. DSIRE. Accessed April 9, 2023. https://www.dsireusa.org/.

Department of Energy. 2011. "New Orleans, Louisiana: Solar in Action."

EIA. 2015. "State Energy Profiles and Estimates (SEDS) Report Archives." 2015. https://www.eia.gov/state/seds/archive/#2015.

Environment America. 2017. "New Orleans Ranks among the Nation's Leading Cities for Solar Power." Environment America Research & Policy Center. April 4, 2017. https://environmentamerica.org/center/media-center/new-orleans-ranks-among-the-nations-leading-cities-for-solar-power/.

Frazier, John W., Florence M. Margai, and Eugene Tettey-Fio. 2003. *Race and Place: Equity Issues in Urban America*. Avalon Publishing.

Galen Barbose, Naim Darghouth, Eric O'Shaughnessy, and Sydney Forrester. 2022. "Tracking the Sun: Pricing and Design Trends for Distributed Photovoltaic Systems in the United States (2022 Edition)." September 2022. https://emp.lbl.gov/tracking-the-sun.

Gao, Xue, and Shan Zhou. 2022. "Solar Adoption Inequality in the U.S.: Trend, Magnitude, and Solar Justice Policies." *Energy Policy* 169 (October): 113163. https://doi.org/10.1016/j.enpol.2022.113163.

Geels, Frank W., Benjamin K. Sovacool, Tim Schwanen, and Steve Sorrell. 2017. "Sociotechnical Transitions for Deep Decarbonization." *Science* 357 (6357): 1242–44. https://doi.org/10.1126/science.aao3760.

Goldstein, Benjamin, Tony G. Reames, and Joshua P. Newell. 2022. "Racial Inequity in Household Energy Efficiency and Carbon Emissions in the United States: An Emissions Paradox." *Energy Research & Social Science* 84 (February): 102365. https://doi.org/10.1016/j.erss.2021.102365.

Graziano, Marcello, and Kenneth Gillingham. 2015. "Spatial Patterns of Solar Photovoltaic System Adoption: The Influence of Neighbors and the Built Environment ‡." *Journal of Economic Geography* 15 (4): 815–39. https://doi.org/10.1093/jeg/lbu036.

Hanke, Florian, Rachel Guyet, and Marielle Feenstra. 2021. “Do Renewable Energy Communities Deliver Energy Justice? Exploring Insights from 71 European Cases.” *Energy Research & Social Science* 80 (October): 102244. https://doi.org/10.1016/j.erss.2021.102244.

Hanley, Steve. 2017. “New Report Says New Orleans Is Among Leading US Cities For Solar Power.” CleanTechnica. April 10, 2017. https://cleantechnica.com/2017/04/10/new-report-says-new-orleans-among-leading-us-cities-solar-power/.

Hanna, Ryan, and David G. Victor. 2021. “Marking the Decarbonization Revolutions.” *Nature Energy* 6 (6): 568–71. https://doi.org/10.1038/s41560-021-00854-1.

Holmes, K. J., E. Zeitler, M. Kerxhalli-Kleinfield, and R. DeBoer. 2021. “Scaling Deep Decarbonization Technologies.” *Earth’s Future* 9 (11): e2021EF002399. https://doi.org/10.1029/2021EF002399.

Holt, Emily, and Deborah A. Sunter. 2021. “Historical Patterns for Rooftop Solar Adoption Growth Rates in Connecticut.” In *2021 IEEE 48th Photovoltaic Specialists Conference (PVSC)*, 1610–13. https://doi.org/10.1109/PVSC43889.2021.9518878.

Kwan, Calvin Lee. 2012. “Influence of Local Environmental, Social, Economic and Political Variables on the Spatial Distribution of Residential Solar PV Arrays across the United States.” *Energy Policy* 47 (August): 332–44. https://doi.org/10.1016/j.enpol.2012.04.074.

Lukanov, Boris R., and Elena M. Krieger. 2019. “Distributed Solar and Environmental Justice: Exploring the Demographic and Socio-Economic Trends of Residential PV Adoption in California.” *Energy Policy* 134 (November): 110935. https://doi.org/10.1016/j.enpol.2019.110935.

Margolis, R., and J. Zuboy. 2006. “Nontechnical Barriers to Solar Energy Use: Review of Recent Literature.” NREL/TP-520-40116. National Renewable Energy Lab. (NREL), Golden, CO (United States). https://doi.org/10.2172/893639.

Meckling, Jonas, Thomas Sterner, and Gernot Wagner. 2017. “Policy Sequencing toward Decarbonization.” *Nature Energy* 2 (12): 918–22. https://doi.org/10.1038/s41560-017-0025-8.

Mundaca, Luis, and Margaret Samahita. 2020. “What Drives Home Solar PV Uptake? Subsidies, Peer Effects and Visibility in Sweden.” *Energy Research & Social Science* 60 (February): 101319. https://doi.org/10.1016/j.erss.2019.101319.

National Weather Service. 2022. “Extremely Powerful Hurricane Katrina Leaves a Historic Mark on the Northern Gulf Coast.” Hurricane Katrina - August 2005. September 2022. https://www.weather.gov/mob/katrina.

O’Shaughnessy, Eric. 2022. “Rooftop Solar Incentives Remain Effective for Low- and Moderate-Income Adoption.” *Energy Policy* 163 (April): 112881. https://doi.org/10.1016/j.enpol.2022.112881.

O’Shaughnessy, Eric, Galen Barbose, Ryan Wiser, and Sydney Forrester. 2021. “Income-Targeted Marketing as a Supply-Side Barrier to Low-Income Solar Adoption.” *IScience* 24 (10): 103137. https://doi.org/10.1016/j.isci.2021.103137.

O’Shaughnessy, Eric, Galen Barbose, Ryan Wiser, Sydney Forrester, and Naïm Darghouth. 2021. “The Impact of Policies and Business Models on Income Equity in Rooftop Solar Adoption.” *Nature Energy* 6 (1): 84–91. https://doi.org/10.1038/s41560-020-00724-2.

Palm, Jenny. 2018. "Household Installation of Solar Panels – Motives and Barriers in a 10-Year Perspective." *Energy Policy* 113 (February): 1–8. https://doi.org/10.1016/j.enpol.2017.10.047.

Paulos, Bentham, Sydney Forrester, Eric O'Shaughnessy, Christopher Dyson, Galen L. Barbose, and Ryan H. Wiser. 2021. "An Assessment of Evaluation Practices of Low- And Moderate-Income Solar Programs." Lawrence Berkeley National Lab. (LBNL), Berkeley, CA (United States). https://doi.org/10.2172/1780757.

Ramasamy, Vignesh. 2022. "Q1-2022 U.S. Solar Photovoltaic System and Energy Storage Cost Benchmarks With Minimum Sustainable Price Analysis Data File." 38269. National Renewable Energy Laboratory - Data (NREL-DATA), Golden, CO (United States); National Renewable Energy Lab. (NREL), Golden, CO (United States). https://doi.org/10.7799/1897209.

Reames, Tony G. 2020. "Distributional Disparities in Residential Rooftop Solar Potential and Penetration in Four Cities in the United States." *Energy Research & Social Science* 69 (November): 101612. https://doi.org/10.1016/j.erss.2020.101612.

Richardson, Tom. 2021. "A Look Back at Hurricane Katrina | HUD USER." September 21, 2021. https://www.huduser.gov/portal/pdredge/pdr-edge-frm-asst-sec-092121.html.

Richter, L.-L. 2013. "Social Effects in the Diffusion of Solar Photovoltaic Technology in the UK," July. https://www.repository.cam.ac.uk/handle/1810/255233.

Rode, Johannes, and Alexander Weber. 2016. "Does Localized Imitation Drive Technology Adoption? A Case Study on Rooftop Photovoltaic Systems in Germany." *Journal of Environmental Economics and Management* 78 (July): 38–48. https://doi.org/10.1016/j.jeem.2016.02.001.

Scheller, Fabian, Isabel Doser, Emily Schulte, Simon Johanning, Russell McKenna, and Thomas Bruckner. 2021. "Stakeholder Dynamics in Residential Solar Energy Adoption: Findings from Focus Group Discussions in Germany." *Energy Research & Social Science* 76 (June): 102065. https://doi.org/10.1016/j.erss.2021.102065.

Schulte, Emily, Fabian Scheller, Daniel Sloot, and Thomas Bruckner. 2022. "A Meta-Analysis of Residential PV Adoption: The Important Role of Perceived Benefits, Intentions and Antecedents in Solar Energy Acceptance." *Energy Research & Social Science* 84 (February): 102339. https://doi.org/10.1016/j.erss.2021.102339.

Si, Yutong, and Jennie C. Stephens. 2021. "Energy Justice Through Solar: Constructing and Engaging Low-Income Households." *Frontiers in Sustainable Cities* 3. https://www.frontiersin.org/articles/10.3389/frsc.2021.632020.

Sinitskaya, Ekaterina, Kelley J. Gomez, Qifang Bao, Maria C. Yang, and Erin F. MacDonald. 2020. "Designing Linked Journey Maps to Understand the Complexities of the Residential Solar Energy Market." *Renewable Energy* 145 (January): 1910–22. https://doi.org/10.1016/j.renene.2019.06.018.

Sovacool, Benjamin K., Max Lacey Barnacle, Adrian Smith, and Marie Claire Brisbois. 2022. "Towards Improved Solar Energy Justice: Exploring the Complex Inequities of Household Adoption of Photovoltaic Panels." *Energy Policy* 164 (May): 112868. https://doi.org/10.1016/j.enpol.2022.112868.

Sovacool, Benjamin K., Peter Newell, Sanya Carley, and Jessica Fanzo. 2022. "Equity, Technological Innovation and Sustainable Behaviour in a Low-Carbon Future." *Nature Human Behaviour* 6 (3): 326–37. https://doi.org/10.1038/s41562-021-01257-8.

Sunter, Deborah A., Sergio Castellanos, and Daniel M. Kammen. 2019. "Disparities in Rooftop Photovoltaics Deployment in the United States by Race and Ethnicity." *Nature Sustainability* 2 (1): 71–76. https://doi.org/10.1038/s41893-018-0204-z.

"The Comprehensive R Archive Network." n.d. Accessed April 30, 2023. https://cran.r-project.org/.

Upton, Gregory. 2019. "The Future of Solar in Lousiana." February 2019. https://www.lsu.edu/ces/research/solarreport.php.

Walker, Kyle, Matt Herman, and Kris Eberwein. 2023. "Tidycensus: Load US Census Boundary and Attribute Data as 'tidyverse' and 'Sf'-Ready Data Frames." https://cran.r-project.org/web/packages/tidycensus/index.html.

Wang, Zhecheng, Marie-Louise Arlt, Chad Zanocco, Arun Majumdar, and Ram Rajagopal. 2022. "DeepSolar++: Understanding Residential Solar Adoption Trajectories with Computer Vision and Technology Diffusion Models." *Joule* 6 (11): 2611–25. https://doi.org/10.1016/j.joule.2022.09.011.

Wolske, Kimberly S. 2020. "More Alike than Different: Profiles of High-Income and Low-Income Rooftop Solar Adopters in the United States." *Energy Research & Social Science* 63 (May): 101399. https://doi.org/10.1016/j.erss.2019.101399.

Wolske, Kimberly S., Paul C. Stern, and Thomas Dietz. 2017. "Explaining Interest in Adopting Residential Solar Photovoltaic Systems in the United States: Toward an Integration of Behavioral Theories." *Energy Research & Social Science* 25 (March): 134–51. https://doi.org/10.1016/j.erss.2016.12.023.

Yu, Jiafan, Zhecheng Wang, Arun Majumdar, and Ram Rajagopal. 2018. "DeepSolar: A Machine Learning Framework to Efficiently Construct a Solar Deployment Database in the United States." *Joule* 2 (12): 2605–17. https://doi.org/10.1016/j.joule.2018.11.021.

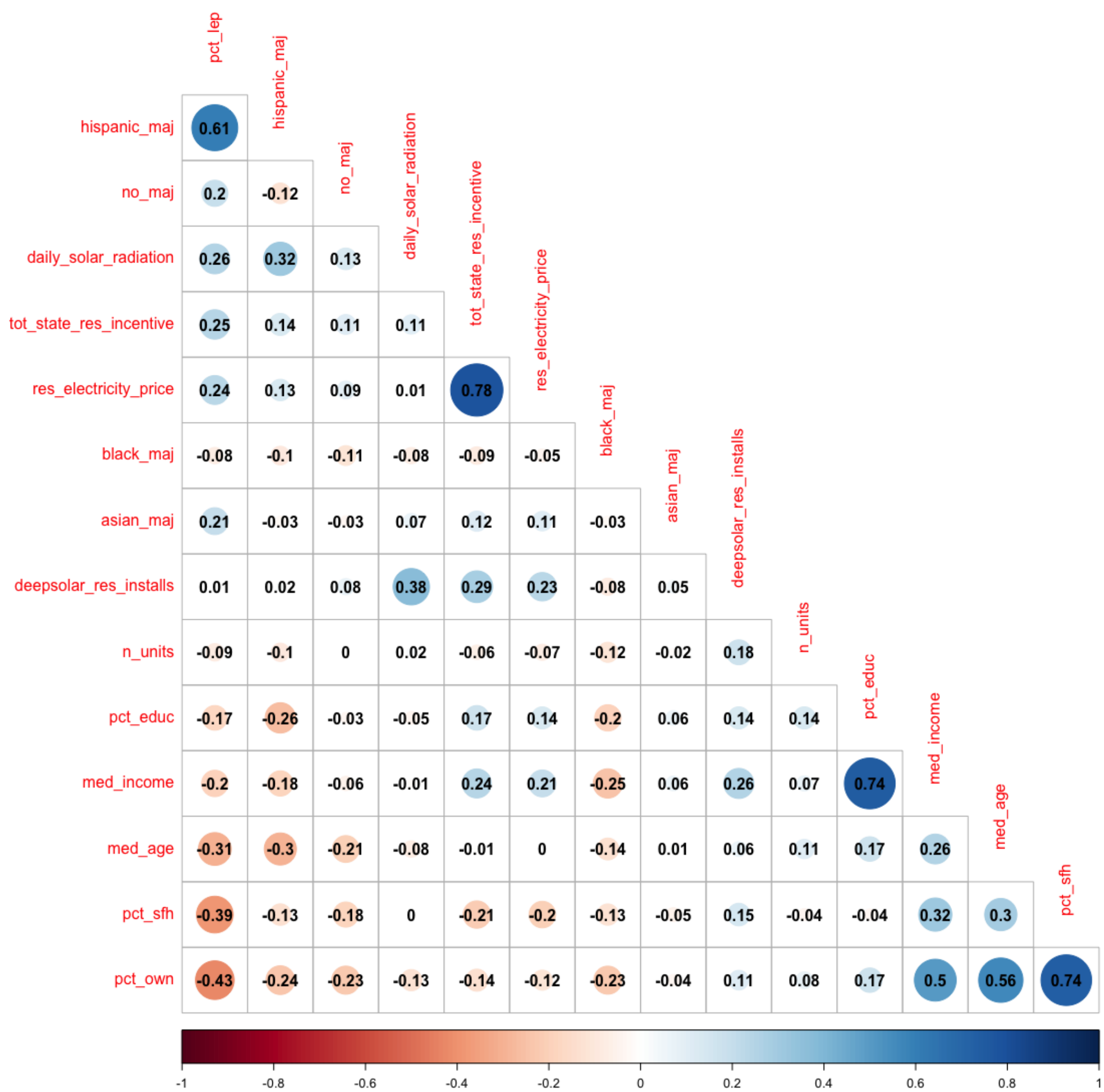
Zong, Jeanne Batalova, Jie Zong Jeanne Batalova and Jie. 2016. "Language Diversity and English Proficiency in the United States." Migrationpolicy.Org. November 10, 2016. https://www.migrationpolicy.org/article/language-diversity-and-english-proficiency-united-states.

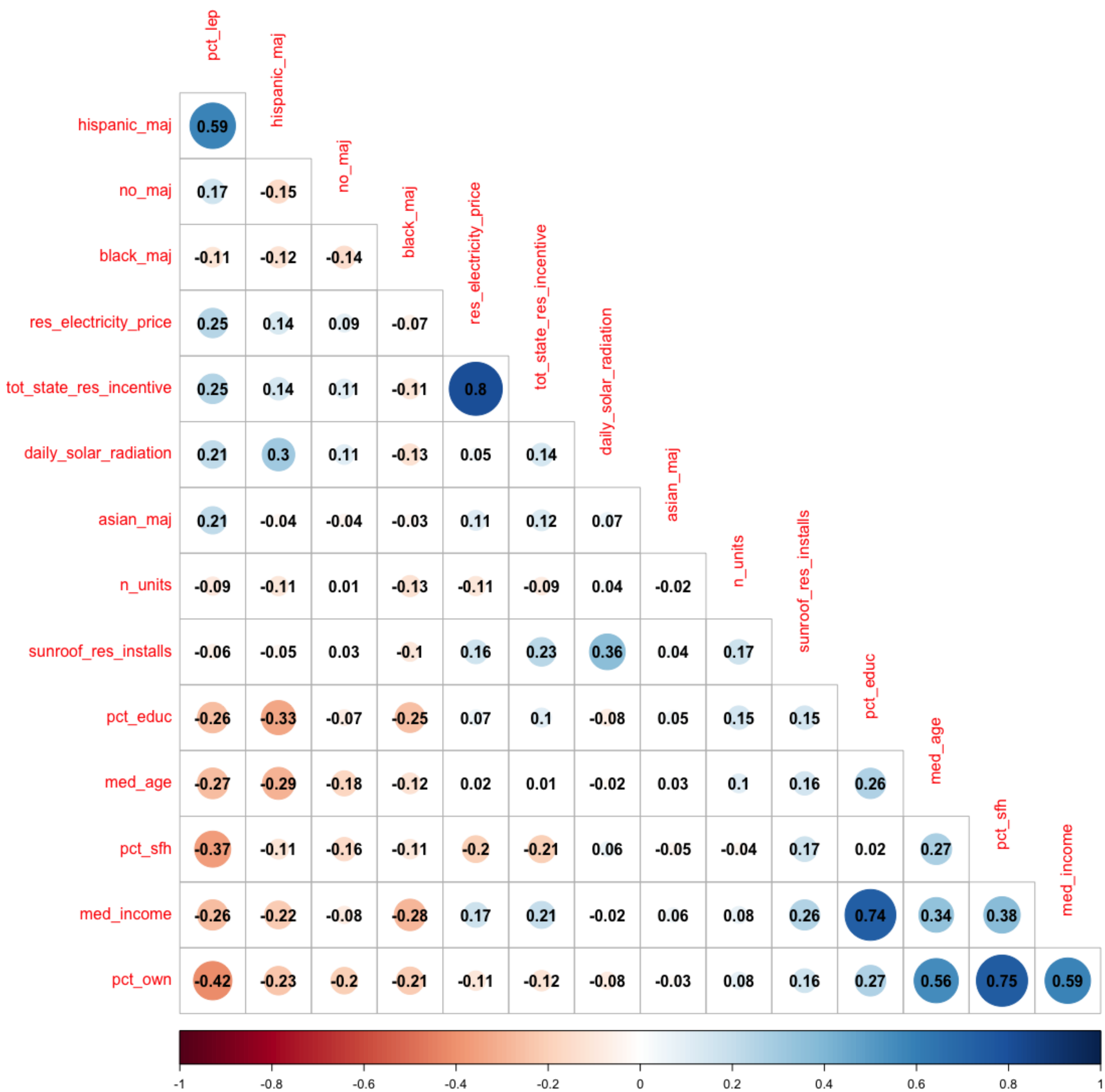
Appendix

All data and code used to undertake this analysis can be found at [this link](). This section includes the full model specifications and output for each dataset, correlation matrices for the variables in each model, and graphics for the Project Sunroof Data not included in the main work.

Correlation Matrices

DeepSolar




pct_lep
hispanic_maj
no_maj
black_maj
res_electricity_price
tot_state_res_incentive
daily_solar_radiation
asian_maj
n_units
sunroof_res_installs
pct_educ
med_age
pct_sfh
med_income
hispanic_maj 0.59
no_maj 0.17 -0.15
black_maj -0.11 -0.12 -0.14
res_electricity_price 0.25 0.14 0.09 -0.07
tot_state_res_incentive 0.25 0.14 0.11 -0.11 0.8
daily_solar_radiation 0.21 0.3 0.11 -0.13 0.05 0.14
asian_maj 0.21 -0.04 -0.04 -0.03 0.11 0.12 0.07
n_units -0.09 -0.11 0.01 -0.13 -0.11 -0.09 0.04 -0.02
sunroof_res_installs -0.06 -0.05 0.03 -0.1 0.16 0.23 0.36 0.04 0.17
pct_educ -0.26 -0.33 -0.07 -0.25 0.07 0.1 -0.08 0.05 0.15 0.15
med_age -0.27 -0.29 -0.18 -0.12 0.02 0.01 -0.02 0.03 0.1 0.16 0.26
pct_sfh -0.37 -0.11 -0.16 -0.11 -0.2 -0.21 0.06 -0.05 -0.04 0.17 0.02 0.27
med_income -0.26 -0.22 -0.08 -0.28 0.17 0.21 -0.02 0.06 0.08 0.26 0.74 0.34 0.38
pct_own -0.42 -0.23 -0.2 -0.21 -0.11 -0.12 -0.08 -0.03 0.08 0.16 0.27 0.56 0.75 0.59
-1 -0.8 -0.6 -0.4 -0.2 0 0.2 0.4 0.6 0.8 1

Variance Inflation Factor Results

Calculating a Variance Inflation Factor (VIF) is one method of measuring multicollinearity in regression models. As part of my model selection process, I calculated VIFs for each independent variable in the dataset. Because of the results below, models were specified to minimize the effects of multicollinearity; this involved running different sets of regressions for the percent of the population in owner-occupied units vs the percent of detached, single-family units at the tract level, as well as alternating between the median income and educational attainment variables. These variables were selected to their relatively high VIF values (bolded below). All regression tables are at the end of this Appendix.

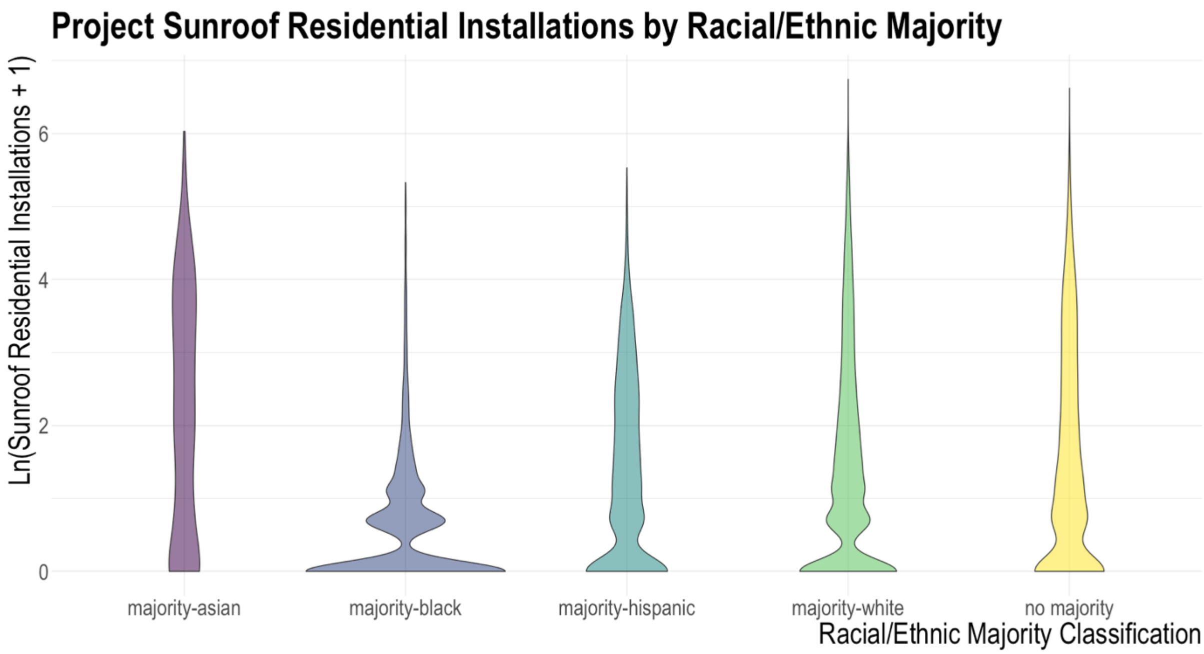
DeepSolar

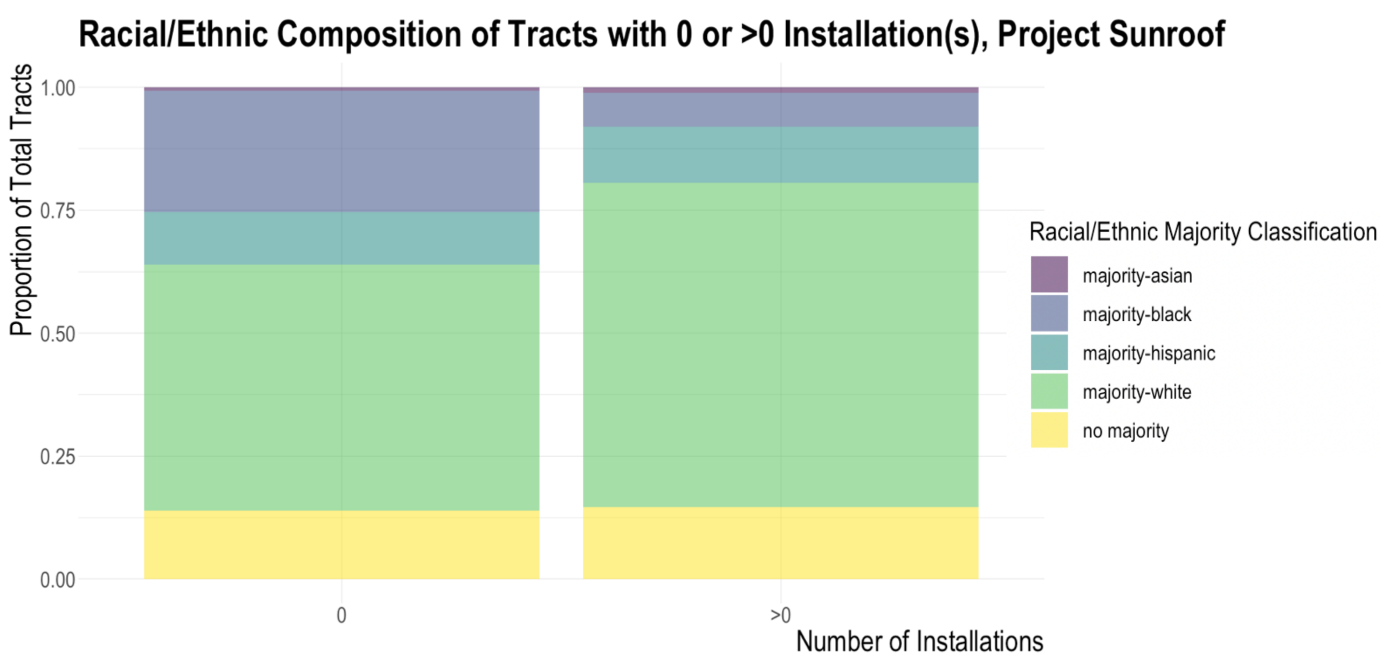
Variable	VIF	Variable	VIF	Variable	VIF
n_units	1.072258	daily_solar_radiation	1.239860	**med_income**	**4.063987**
black_maj	1.217422	res_electricity_price	2.691193	**pct_own**	**4.130169**
asian_maj	1.131770	tot_state_res_incentive	2.823214	pct_sfh	2.730783
hispanic_maj	2.254223	med_age	1.714393	pct_lep	2.309355
no_maj	1.342333	**pct_educ**	**3.164690**		

Project Sunroof

Variable	VIF	Variable	VIF	Variable	VIF
n_units	1.088379	daily_solar_radiation	1.264686	**med_income**	**4.285642**
black_maj	1.304304	res_electricity_price	2.925605	**pct_own**	**4.572537**
asian_maj	1.147400	tot_state_res_incentive	3.060610	pct_sfh	3.036088
hispanic_maj	2.317602	med_age	1.724006	pct_lep	2.253375
no_maj	1.366696	**pct_educ**	**3.253101**		

Descriptive Graphics and Tables for Project Sunroof Data





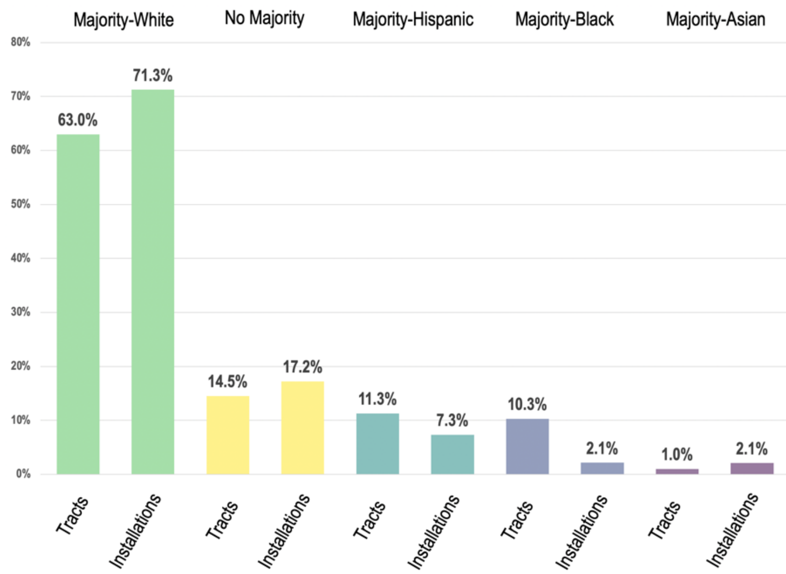


Table 10. Summary Statistics for Project Sunroof Installations, by Race/Ethnic Majority Classification.

	Total Sunroof Installations	Total Sunroof Tracts	Sunroof Tracts with 0 Installations	Sunroof Tracts with >0 Installations	Mean Sunroof Installations
Majority-Asian	13,418	509	119	390	26.4
Majority-Black	13,937	5,303	2,838	2,465	2.6
Majority-Hispanic	47,501	5,820	1,905	3,915	8.2
Majority-White	463,494	32,520	10,269	22,251	14.3
No Majority	112,011	7,494	2,327	5,167	14.9
Total	**650,361**	**51,646**	**17,458**	**34,188**	**12.5**

*__NOTE__: the total number of installations is slightly less than what is listed in the Data and Methods Section, as the numbers in this table reflect the total installations for which I was able to calculate racial/ethnic majority classification variables.

Table 11. T-test Results for DeepSolar and Project Sunroof (Compared to ACS National Averages).

	DeepSolar		**Project Sunroof**	
	t-statistic	**p-value**	**t-statistic**	**p-value**
% White	1.0789	0.2806	-34.058	< 2.2e-16
% Black	0.64902	0.5163	17.131	< 2.2e-16
% Asian	-3.1186	0.001817	22.117	< 2.2e-16
% Hispanic	0.46084	0.6449	21.564	< 2.2e-16
% LEP	-0.060812	0.9515	22.946	< 2.2e-16
Avg Median Income	-0.63407	0.526	13.98	< 2.2e-16
Avg Median Age	0.09494	0.9244	-22.309	< 2.2e-16
% with At Least a Bachelor's Degree	-0.087516	0.9303	26.005	< 2.2e-16

Model Outputs

NOTE: To derive percentage changes from the estimated coefficients, the coefficients should be exponentiated (e.g. (exp(coefficient * X) – 1) * 100) = percentage change).

DeepSolar – Logit – Single-Family Home

	Dependent variable:					
	DeepSolar Residential Installations					
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Total Number of Units + 1)	0.41***	0.48***	0.50***	0.71***	0.77***	0.78***
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Majority-Black		-0.76***	-0.76***	-0.40***	-0.31***	-0.29***
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Majority-Asian		0.90***	-0.28	-0.09	-0.10	-0.10
		(0.13)	(0.14)	(0.16)	(0.16)	(0.16)
Majority-Hispanic		0.48***	-0.38***	0.10	-0.15**	0.09
		(0.03)	(0.04)	(0.05)	(0.05)	(0.05)
No Majority		0.34***	-0.10**	0.003	-0.07*	0.0001
		(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
Average Daily Solar Radiation			1.13***	1.12***	1.15***	1.13***
			(0.02)	(0.02)	(0.02)	(0.02)
Average Residential Electricity Price			0.002	0.01	-0.001	0.002
			(0.01)	(0.01)	(0.01)	(0.01)
Total Number of State-Level Residential Solar Incentives			0.10***	0.09***	0.08***	0.08***
			(0.003)	(0.003)	(0.003)	(0.003)
Median Age				-0.04***	-0.04***	-0.04***
				(0.001)	(0.001)	(0.001)
% with Bachelor's or Higher				3.21***		2.51***
				(0.07)		(0.09)
ln(Median Income + 1)					1.13***	0.42***
					(0.03)	(0.04)
% Detached Single Family Homes				0.74***	-0.08	0.49***
				(0.04)	(0.05)	(0.05)
% of Limited English Proficient Population				-0.56**	-0.54**	-0.48*
				(0.19)	(0.19)	(0.19)
Constant	-1.93***	-2.48***	-8.00***	-9.38***	-20.49***	-13.98***
	(0.08)	(0.11)	(0.17)	(0.20)	(0.33)	(0.41)
Observations	72,537	71,940	66,357	66,166	66,019	66,019
Log Likelihood	-40,758.47	-39,755.20	-34,112.90	-32,192.15	-32,378.28	-31,971.45
Akaike Inf. Crit.	81,520.94	79,522.40	68,243.81	64,410.29	64,782.56	63,970.90
Note:						*p<0.05; **p<0.01; ***p<0.001

Sunroof – Logit – Single-Family Home

	Dependent variable:					
	Sunroof Residential Installations					
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Total Number of Units + 1)	0.37***	0.37***	0.38***	0.49***	0.50***	0.52***
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Majority-Black		-0.83***	-0.74***	-0.30***	-0.41***	-0.34***
		(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
Majority-Asian		0.47***	-0.56***	-0.02	-0.001	0.01
		(0.11)	(0.11)	(0.13)	(0.13)	(0.13)
Majority-Hispanic		0.01	-0.83***	-0.08	-0.25***	-0.05
		(0.03)	(0.04)	(0.05)	(0.05)	(0.05)
No Majority		0.06*	-0.33***	0.07*	-0.01	0.08*
		(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
Average Daily Solar Radiation			1.19***	1.12***	1.13***	1.12***
			(0.02)	(0.02)	(0.02)	(0.02)
Average Residential Electricity Price			-0.07***	-0.06***	-0.06***	-0.06***
			(0.01)	(0.01)	(0.01)	(0.01)
Total Number of State-Level Residential Solar Incentives			0.11***	0.12***	0.12***	0.12***
			(0.003)	(0.004)	(0.004)	(0.004)
Median Age				-0.01***	-0.01***	-0.004*
				(0.002)	(0.002)	(0.002)
% with Bachelor's or Higher				1.36***		1.72***
				(0.06)		(0.09)
ln(Median Income + 1)					0.30***	-0.23***
					(0.03)	(0.04)
% Detached Single Family Homes				1.10***	0.82***	1.26***
				(0.04)	(0.05)	(0.05)
% of Limited English Proficient Population				-1.44***	-1.68***	-1.53***
				(0.18)	(0.18)	(0.18)
Constant	-2.02***	-1.98***	-6.91***	-8.54***	-11.25***	-6.56***
	(0.10)	(0.12)	(0.18)	(0.21)	(0.33)	(0.41)
Observations	51,868	51,646	47,853	47,715	47,608	47,608
Log Likelihood	-32,808.87	-32,252.91	-27,275.16	-26,470.71	-26,583.64	-26,390.22
Akaike Inf. Crit.	65,621.73	64,517.83	54,568.31	52,967.42	53,193.27	52,808.45
Note:						*p<0.05; **p<0.01; ***p<0.001

DeepSolar – OLS – Single-Family Home

	Dependent variable:					
	DeepSolar Residential Installations					
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Total Number of Units + 1)	0.27^{***}	0.38^{***}	0.39^{***}	0.53^{***}	0.57^{***}	0.57^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Majority-Black		-0.62^{***}	-0.50^{***}	-0.09^{***}	0.02	0.02
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Majority-Asian		1.26^{***}	-0.29^{***}	0.05	0.02	0.01
		(0.06)	(0.05)	(0.05)	(0.05)	(0.05)
Majority-Hispanic		0.49^{***}	-0.64^{***}	-0.03	-0.13^{***}	-0.05^{*}
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
No Majority		0.43^{***}	-0.19^{***}	0.13^{***}	0.08^{***}	0.11^{***}
		(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Average Daily Solar Radiation			1.30^{***}	1.23^{***}	1.25^{***}	1.24^{***}
			(0.01)	(0.01)	(0.01)	(0.01)
Average Residential Electricity Price			0.03^{***}	0.04^{***}	0.03^{***}	0.03^{***}
			(0.002)	(0.002)	(0.002)	(0.002)
Total Number of State-Level Residential Solar Incentives			0.11^{***}	0.11^{***}	0.10^{***}	0.10^{***}
			(0.001)	(0.001)	(0.001)	(0.001)
Median Age				-0.01^{***}	-0.01^{***}	-0.01^{***}
				(0.001)	(0.001)	(0.001)
% with Bachelor's or Higher				1.55^{***}		0.77^{***}
				(0.02)		(0.04)
ln(Median Income + 1)					0.72^{***}	0.48^{***}
					(0.01)	(0.02)
% Detached Single Family Homes				1.15^{***}	0.64^{***}	0.84^{***}
				(0.02)	(0.02)	(0.02)
% of Limited English Proficient Population				-1.00^{***}	-0.89^{***}	-0.85^{***}
				(0.08)	(0.08)	(0.08)
Constant	-0.42^{***}	-1.28^{***}	-8.01^{***}	-9.63^{***}	-16.88^{***}	-14.56^{***}
	(0.04)	(0.06)	(0.07)	(0.08)	(0.13)	(0.17)
Observations	72,537	71,940	66,357	66,166	66,019	66,019
R^2	0.03	0.07	0.43	0.50	0.50	0.51
Adjusted R^2	0.03	0.07	0.43	0.50	0.50	0.51
Residual Std. Error	1.46 (df = 72535)	1.43 (df = 71934)	1.13 (df = 66348)	1.06 (df = 66153)	1.05 (df = 66006)	1.05 (df = 66005)
F Statistic	$2{,}167.05^{***}$ (df = 1; 72535)	$1{,}029.12^{***}$ (df = 5; 71934)	$6{,}182.15^{***}$ (df = 8; 66348)	$5{,}477.46^{***}$ (df = 12; 66153)	$5{,}605.54^{***}$ (df = 12; 66006)	$5{,}250.07^{***}$ (df = 13; 66005)
Note:						$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Sunroof – OLS – Single-Family Home

	Dependent variable:					
	Sunroof Residential Installations					
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Total Number of Units + 1)	0.28^{***}	0.31^{***}	0.31^{***}	0.41^{***}	0.43^{***}	0.43^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Majority-Black		-0.76^{***}	-0.55^{***}	-0.12^{***}	-0.14^{***}	-0.11^{***}
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Majority-Asian		0.73^{***}	-0.45^{***}	-0.03	-0.03	-0.03
		(0.06)	(0.05)	(0.05)	(0.05)	(0.05)
Majority-Hispanic		-0.04^{*}	-0.98^{***}	-0.26^{***}	-0.37^{***}	-0.26^{***}
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
No Majority		0.10^{***}	-0.37^{***}	0.04^{*}	-0.01	0.04^{*}
		(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
Average Daily Solar Radiation			1.24^{***}	1.14^{***}	1.15^{***}	1.14^{***}
			(0.01)	(0.01)	(0.01)	(0.01)
Average Residential Electricity Price			-0.03^{***}	-0.03^{***}	-0.03^{***}	-0.03^{***}
			(0.003)	(0.003)	(0.003)	(0.003)
Total Number of State-Level Residential Solar Incentives			0.10^{***}	0.11^{***}	0.11^{***}	0.11^{***}
			(0.002)	(0.002)	(0.002)	(0.002)
Median Age				0.01^{***}	0.01^{***}	0.01^{***}
				(0.001)	(0.001)	(0.001)
% with Bachelor's or Higher				0.99^{***}		0.93^{***}
				(0.03)		(0.04)
ln(Median Income + 1)					0.33^{***}	0.04^{*}
					(0.01)	(0.02)
% Detached Single Family Homes				1.04^{***}	0.78^{***}	1.02^{***}
				(0.02)	(0.02)	(0.02)
% of Limited English Proficient Population				-1.25^{***}	-1.30^{***}	-1.22^{***}
				(0.08)	(0.08)	(0.08)
Constant	-0.69^{***}	-0.87^{***}	-6.49^{***}	-8.21^{***}	-11.41^{***}	-8.77^{***}
	(0.06)	(0.07)	(0.08)	(0.09)	(0.15)	(0.19)
Observations	51,868	51,646	47,853	47,715	47,608	47,608
R^2	0.02	0.06	0.40	0.47	0.46	0.47
Adjusted R^2	0.02	0.06	0.40	0.47	0.46	0.47
Residual Std. Error	1.38 (df = 51866)	1.36 (df = 51640)	1.10 (df = 47844)	1.03 (df = 47702)	1.04 (df = 47595)	1.03 (df = 47594)
F Statistic	$1,315.56^{***}$ (df = 1; 51866)	617.44^{***} (df = 5; 51640)	$4,030.16^{***}$ (df = 8; 47844)	$3,528.95^{***}$ (df = 12; 47702)	$3,443.85^{***}$ (df = 12; 47595)	$3,257.69^{***}$ (df = 13; 47594)
Note:						*p<0.05; **p<0.01; ***p<0.001

DeepSolar – Logit – Homeowner

	Dependent variable:					
	DeepSolar Residential Installations					
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Total Number of Units + 1)	0.41***	0.48***	0.50***	0.68***	0.78***	0.76***
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Majority-Black		-0.76***	-0.76***	-0.45***	-0.36***	-0.33***
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Majority-Asian		0.90***	-0.28	-0.04	-0.07	-0.06
		(0.13)	(0.14)	(0.16)	(0.16)	(0.16)
Majority-Hispanic		0.48***	-0.38***	0.14**	-0.06	0.12*
		(0.03)	(0.04)	(0.05)	(0.05)	(0.05)
No Majority		0.34***	-0.10**	-0.02	-0.12**	-0.05
		(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
Average Daily Solar Radiation			1.13***	1.14***	1.13***	1.13***
			(0.02)	(0.02)	(0.02)	(0.02)
Average Residential Electricity Price			0.002	0.001	-0.001	-0.002
			(0.01)	(0.01)	(0.01)	(0.01)
Total Number of State-Level Residential Solar Incentives			0.10***	0.09***	0.07***	0.07***
			(0.003)	(0.003)	(0.003)	(0.003)
Median Age				-0.04***	-0.03***	-0.03***
				(0.002)	(0.002)	(0.002)
% with Bachelor's or Higher				3.09***		1.95***
				(0.07)		(0.09)
ln(Median Income + 1)					1.40***	0.76***
					(0.03)	(0.04)
% of Population in Owner-Occupied Housing				0.37***	-1.19***	-0.49***
				(0.06)	(0.07)	(0.08)
% of Limited English Proficient Population				-1.21***	-1.16***	-1.17***
				(0.19)	(0.19)	(0.19)
Constant	-1.93***	-2.48***	-8.00***	-8.85***	-23.04***	-16.87***
	(0.08)	(0.11)	(0.17)	(0.19)	(0.37)	(0.46)
Observations	72,537	71,940	66,357	66,166	66,019	66,019
Log Likelihood	-40,758.47	-39,755.20	-34,112.90	-32,310.83	-32,236.56	-31,997.34
Akaike Inf. Crit.	81,520.94	79,522.40	68,243.81	64,647.66	64,499.12	64,022.67
Note:				*p<0.05; **p<0.01; ***p<0.001		

Sunroof – Logit – Homeowner

	Dependent variable:					
	Sunroof Residential Installations					
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Total Number of Units + 1)	0.37***	0.37***	0.38***	0.49***	0.50***	0.52***
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Majority-Black		-0.83***	-0.74***	-0.30***	-0.41***	-0.34***
		(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
Majority-Asian		0.47***	-0.56***	-0.02	-0.001	0.01
		(0.11)	(0.11)	(0.13)	(0.13)	(0.13)
Majority-Hispanic		0.01	-0.83***	-0.08	-0.25***	-0.05
		(0.03)	(0.04)	(0.05)	(0.05)	(0.05)
No Majority		0.06*	-0.33***	0.07*	-0.01	0.08*
		(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
Average Daily Solar Radiation			1.19***	1.12***	1.13***	1.12***
			(0.02)	(0.02)	(0.02)	(0.02)
Average Residential Electricity Price			-0.07***	-0.06***	-0.06***	-0.06***
			(0.01)	(0.01)	(0.01)	(0.01)
Total Number of State-Level Residential Solar Incentives			0.11***	0.12***	0.12***	0.12***
			(0.003)	(0.004)	(0.004)	(0.004)
Median Age				-0.01***	-0.01***	-0.004*
				(0.002)	(0.002)	(0.002)
% with Bachelor's or Higher				1.36***		1.72***
				(0.06)		(0.09)
ln(Median Income + 1)					0.30***	-0.23***
					(0.03)	(0.04)
% of Population in Owner-Occupied Housing				1.10***	0.82***	1.26***
				(0.04)	(0.05)	(0.05)
% of Limited English Proficient Population				-1.44***	-1.68***	-1.53***
				(0.18)	(0.18)	(0.18)
Constant	-2.02***	-1.98***	-6.91***	-8.54***	-11.25***	-6.56***
	(0.10)	(0.12)	(0.18)	(0.21)	(0.33)	(0.41)
Observations	51,868	51,646	47,853	47,715	47,608	47,608
Log Likelihood	-32,808.87	-32,252.91	-27,275.16	-26,470.71	-26,583.64	-26,390.22
Akaike Inf. Crit.	65,621.73	64,517.83	54,568.31	52,967.42	53,193.27	52,808.45
Note:				*p<0.05; **p<0.01; ***p<0.001		

DeepSolar – OLS – Homeowner

	Dependent variable:					
	DeepSolar Residential Installations					
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Total Number of Units + 1)	0.27***	0.38***	0.39***	0.47***	0.54***	0.53***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Majority-Black		-0.62***	-0.50***	-0.09***	0.003	0.01
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Majority-Asian		1.26***	-0.29***	0.10	0.05	0.05
		(0.06)	(0.05)	(0.05)	(0.05)	(0.05)
Majority-Hispanic		0.49***	-0.64***	-0.005	-0.06**	-0.02
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
No Majority		0.43***	-0.19***	0.12***	0.07***	0.09***
		(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Average Daily Solar Radiation			1.30***	1.30***	1.28***	1.28***
			(0.01)	(0.01)	(0.01)	(0.01)
Average Residential Electricity Price			0.03***	0.03***	0.03***	0.03***
			(0.002)	(0.002)	(0.002)	(0.002)
Total Number of State-Level Residential Solar Incentives			0.11***	0.11***	0.09***	0.10***
			(0.001)	(0.001)	(0.001)	(0.001)
Median Age				-0.02***	-0.01***	-0.01***
				(0.001)	(0.001)	(0.001)
% with Bachelor's or Higher				1.32***		0.41***
				(0.02)		(0.04)
ln(Median Income + 1)					0.76***	0.61***
					(0.01)	(0.02)
% of Population in Owner-Occupied Housing				1.18***	0.33***	0.50***
				(0.02)	(0.03)	(0.03)
% of Limited English Proficient Population				-1.52***	-1.42***	-1.42***
				(0.08)	(0.08)	(0.08)
Constant	-0.42***	-1.28***	-8.01***	-9.06***	-16.87***	-15.43***
	(0.04)	(0.06)	(0.07)	(0.08)	(0.14)	(0.19)
Observations	72,537	71,940	66,357	66,166	66,019	66,019
R^2	0.03	0.07	0.43	0.49	0.50	0.50
Adjusted R^2	0.03	0.07	0.43	0.49	0.50	0.50
Residual Std. Error	1.46 (df = 72535)	1.43 (df = 71934)	1.13 (df = 66348)	1.07 (df = 66153)	1.06 (df = 66006)	1.06 (df = 66005)
F Statistic	2,167.05*** (df = 1; 72535)	1,029.12*** (df = 5; 71934)	6,182.15*** (df = 8; 66348)	5,209.23*** (df = 12; 66153)	5,434.81*** (df = 12; 66006)	5,036.43*** (df = 13; 66005)
Note:						*p<0.05; **p<0.01; ***p<0.001

Sunroof – OLS – Homeowner

	Dependent variable:					
	Sunroof Residential Installations					
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Total Number of Units + 1)	0.28***	0.31***	0.31***	0.35***	0.38***	0.37***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Majority-Black		-0.76***	-0.55***	-0.14***	-0.13***	-0.11***
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Majority-Asian		0.73***	-0.45***	0.02	0.01	0.01
		(0.06)	(0.05)	(0.05)	(0.05)	(0.05)
Majority-Hispanic		-0.04*	-0.98***	-0.24***	-0.31***	-0.25***
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
No Majority		0.10***	-0.37***	0.03	-0.01	0.02
		(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
Average Daily Solar Radiation			1.24***	1.22***	1.21***	1.21***
			(0.01)	(0.01)	(0.01)	(0.01)
Average Residential Electricity Price			-0.03***	-0.03***	-0.03***	-0.03***
			(0.003)	(0.003)	(0.003)	(0.003)
Total Number of State-Level Residential Solar Incentives			0.10***	0.11***	0.10***	0.10***
			(0.002)	(0.002)	(0.002)	(0.002)
Median Age				0.001	0.003***	0.002
				(0.001)	(0.001)	(0.001)
% with Bachelor's or Higher				0.76***		0.54***
				(0.03)		(0.04)
ln(Median Income + 1)					0.35***	0.16***
					(0.01)	(0.02)
% of Population in Owner-Occupied Housing				0.98***	0.58***	0.81***
				(0.03)	(0.03)	(0.04)
% of Limited English Proficient Population				-1.79***	-1.79***	-1.76***
				(0.08)	(0.08)	(0.08)
Constant	-0.69***	-0.87***	-6.49***	-7.65***	-11.19***	-9.34***
	(0.06)	(0.07)	(0.08)	(0.09)	(0.17)	(0.22)
Observations	51,868	51,646	47,853	47,715	47,608	47,608
R^2	0.02	0.06	0.40	0.45	0.45	0.45
Adjusted R^2	0.02	0.06	0.40	0.45	0.45	0.45
Residual Std. Error	1.38 (df = 51866)	1.36 (df = 51640)	1.10 (df = 47844)	1.05 (df = 47702)	1.05 (df = 47595)	1.05 (df = 47594)
F Statistic	1,315.56*** (df = 1; 51866)	617.44*** (df = 5; 51640)	4,030.16*** (df = 8; 47844)	3,288.81*** (df = 12; 47702)	3,270.19*** (df = 12; 47595)	3,043.48*** (df = 13; 47594)
Note:						*p<0.05; **p<0.01; ***p<0.001

DeepSolar – OLS – Single-Family Home – IHS Transform

	Dependent variable:					
	DeepSolar Residential Installations					
	(1)	(2)	(3)	(4)	(5)	(6)
asinh(Total Number of Units)	0.30***	0.43***	0.44***	0.62***	0.67***	0.67***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Majority-Black		-0.75***	-0.61***	-0.14***	-0.01	-0.004
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Majority-Asian		1.42***	-0.35***	0.04	-0.01	-0.01
		(0.07)	(0.06)	(0.06)	(0.06)	(0.06)
Majority-Hispanic		0.57***	-0.72***	-0.01	-0.13***	-0.03
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
No Majority		0.48***	-0.22***	0.14***	0.08***	0.12***
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Average Daily Solar Radiation			1.48***	1.40***	1.42***	1.40***
			(0.01)	(0.01)	(0.01)	(0.01)
Average Residential Electricity Price			0.03***	0.04***	0.03***	0.03***
			(0.003)	(0.003)	(0.003)	(0.003)
Total Number of State-Level Residential Solar Incentives			0.12***	0.12***	0.11***	0.12***
			(0.002)	(0.002)	(0.002)	(0.002)
Median Age				-0.01***	-0.02***	-0.01***
				(0.001)	(0.001)	(0.001)
% with Bachelor's or Higher				1.87***		0.97***
				(0.03)		(0.04)
asinh(Median Income)					0.86***	0.55***
					(0.01)	(0.02)
% Detached Single Family Homes				1.28***	0.68***	0.93***
				(0.02)	(0.02)	(0.02)
% of Limited English Proficient Population				-1.11***	-0.98***	-0.94***
				(0.09)	(0.09)	(0.09)
Constant	-0.45***	-1.54***	-9.16***	-11.25***	-20.53***	-17.41***
	(0.05)	(0.08)	(0.08)	(0.10)	(0.16)	(0.21)
Observations	72,537	71,940	66,357	66,166	66,019	66,019
R^2	0.03	0.07	0.41	0.48	0.49	0.49
Adjusted R^2	0.03	0.07	0.41	0.48	0.49	0.49
Residual Std. Error	1.69 (df = 72535)	1.66 (df = 71934)	1.33 (df = 66348)	1.25 (df = 66153)	1.24 (df = 66006)	1.23 (df = 66005)
F Statistic	2,150.79*** (df = 1; 72535)	1,029.64*** (df = 5; 71934)	5,840.56*** (df = 8; 66348)	5,190.03*** (df = 12; 66153)	5,300.95*** (df = 12; 66006)	4,976.52*** (df = 13; 66005)
Note:						*p<0.05; **p<0.01; ***p<0.001

Sunroof – OLS – Single-Family Home – IHS Transform

	Dependent variable:					
	Sunroof Residential Installations					
	(1)	(2)	(3)	(4)	(5)	(6)
asinh(Total Number of Units)	0.31***	0.35***	0.35***	0.48***	0.50***	0.51***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Majority-Black		-0.91***	-0.67***	-0.16***	-0.19***	-0.15***
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Majority-Asian		0.83***	-0.53***	-0.03	-0.03	-0.03
		(0.07)	(0.06)	(0.06)	(0.06)	(0.06)
Majority-Hispanic		-0.04	-1.12***	-0.28***	-0.40***	-0.27***
		(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
No Majority		0.12***	-0.42***	0.05**	-0.01	0.05*
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Average Daily Solar Radiation			1.44***	1.32***	1.33***	1.32***
			(0.01)	(0.01)	(0.01)	(0.01)
Average Residential Electricity Price			-0.04***	-0.03***	-0.04***	-0.03***
			(0.003)	(0.003)	(0.003)	(0.003)
Total Number of State-Level Residential Solar Incentives			0.12***	0.13***	0.13***	0.13***
			(0.002)	(0.002)	(0.002)	(0.002)
Median Age				0.01***	0.01***	0.01***
				(0.001)	(0.001)	(0.001)
% with Bachelor's or Higher				1.18***		1.13***
				(0.03)		(0.05)
asinh(Median Income)					0.39***	0.03
					(0.02)	(0.02)
% Detached Single Family Homes				1.21***	0.91***	1.20***
				(0.02)	(0.02)	(0.03)
% of Limited English Proficient Population				-1.49***	-1.56***	-1.46***
				(0.10)	(0.10)	(0.10)
Constant	-0.80***	-1.07***	-7.53***	-9.72***	-13.79***	-10.34***
	(0.07)	(0.09)	(0.10)	(0.11)	(0.19)	(0.24)
Observations	51,868	51,646	47,853	47,715	47,608	47,608
R^2	0.02	0.06	0.39	0.46	0.46	0.46
Adjusted R^2	0.02	0.06	0.39	0.46	0.46	0.46
Residual Std. Error	1.63 (df = 51866)	1.60 (df = 51640)	1.30 (df = 47844)	1.23 (df = 47702)	1.23 (df = 47595)	1.23 (df = 47594)
F Statistic	1,275.05*** (df = 1; 51866)	621.02*** (df = 5; 51640)	3,891.31*** (df = 8; 47844)	3,409.18*** (df = 12; 47702)	3,320.14*** (df = 12; 47595)	3,145.90*** (df = 13; 47594)
Note:						*p<0.05; **p<0.01; ***p<0.001

DeepSolar – OLS – Homeowner – IHS Transform

	Dependent variable:					
	DeepSolar Residential Installations					
	(1)	(2)	(3)	(4)	(5)	(6)
asinh(Total Number of Units)	0.30^{***}	0.43^{***}	0.44^{***}	0.55^{***}	0.63^{***}	0.62^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Majority-Black		-0.75^{***}	-0.61^{***}	-0.14^{***}	-0.03	-0.02
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Majority-Asian		1.42^{***}	-0.35^{***}	0.09	0.03	0.04
		(0.07)	(0.06)	(0.06)	(0.06)	(0.06)
Majority-Hispanic		0.57^{***}	-0.72^{***}	0.02	-0.05^{*}	0.001
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
No Majority		0.48^{***}	-0.22^{***}	0.13^{***}	0.07^{***}	0.09^{***}
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Average Daily Solar Radiation			1.48^{***}	1.48^{***}	1.45^{***}	1.45^{***}
			(0.01)	(0.01)	(0.01)	(0.01)
Average Residential Electricity Price			0.03^{***}	0.03^{***}	0.03^{***}	0.03^{***}
			(0.003)	(0.003)	(0.003)	(0.003)
Total Number of State-Level Residential Solar Incentives			0.12^{***}	0.12^{***}	0.11^{***}	0.11^{***}
			(0.002)	(0.002)	(0.002)	(0.002)
Median Age				-0.02^{***}	-0.01^{***}	-0.02^{***}
				(0.001)	(0.001)	(0.001)
% with Bachelor's or Higher				1.61^{***}		0.55^{***}
				(0.03)		(0.04)
asin(Median Income)					0.92^{***}	0.71^{***}
					(0.01)	(0.02)
% of Population in Owner-Occupied Housing				1.31^{***}	0.30^{***}	0.52^{***}
				(0.03)	(0.03)	(0.04)
% of Limited English Proficient Population				-1.69^{***}	-1.58^{***}	-1.57^{***}
				(0.09)	(0.09)	(0.09)
Constant	-0.45^{***}	-1.54^{***}	-9.16^{***}	-10.56^{***}	-20.63^{***}	-18.54^{***}
	(0.05)	(0.08)	(0.08)	(0.10)	(0.18)	(0.24)
Observations	72,537	71,940	66,357	66,166	66,019	66,019
R^2	0.03	0.07	0.41	0.47	0.48	0.49
Adjusted R^2	0.03	0.07	0.41	0.47	0.48	0.49
Residual Std. Error	1.69 (df = 72535)	1.66 (df = 71934)	1.33 (df = 66348)	1.26 (df = 66153)	1.25 (df = 66006)	1.25 (df = 66005)
F Statistic	$2,150.79^{***}$ (df = 1; 72535)	$1,029.64^{***}$ (df = 5; 71934)	$5,840.56^{***}$ (df = 8; 66348)	$4,952.07^{***}$ (df = 12; 66153)	$5,162.23^{***}$ (df = 12; 66006)	$4,790.55^{***}$ (df = 13; 66005)
Note:						*p<0.05; **p<0.01; ***p<0.001

Sunroof – OLS – Homeowner – IHS Transform

	Dependent variable:					
	Sunroof Residential Installations					
	(1)	(2)	(3)	(4)	(5)	(6)
asinh(Total Number of Units)	0.31***	0.35***	0.35***	0.41***	0.44***	0.44***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Majority-Black		-0.91***	-0.67***	-0.18***	-0.18***	-0.15***
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Majority-Asian		0.83***	-0.53***	0.03	0.02	0.02
		(0.07)	(0.06)	(0.06)	(0.06)	(0.06)
Majority-Hispanic		-0.04	-1.12***	-0.25***	-0.33***	-0.25***
		(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
No Majority		0.12***	-0.42***	0.03	-0.01	0.03
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Average Daily Solar Radiation			1.44***	1.41***	1.40***	1.41***
			(0.01)	(0.01)	(0.01)	(0.01)
Average Residential Electricity Price			-0.04***	-0.04***	-0.04***	-0.04***
			(0.003)	(0.003)	(0.003)	(0.003)
Total Number of State-Level Residential Solar Incentives			0.12***	0.13***	0.12***	0.12***
			(0.002)	(0.002)	(0.002)	(0.002)
Median Age				0.0003	0.003***	0.001
				(0.001)	(0.001)	(0.001)
% with Bachelor's or Higher				0.92***		0.67***
				(0.03)		(0.05)
asinh(Median Income)					0.42***	0.17***
					(0.02)	(0.02)
% of Population in Owner-Occupied Housing				1.13***	0.66***	0.94***
				(0.03)	(0.04)	(0.04)
% of Limited English Proficient Population				-2.12***	-2.12***	-2.08***
				(0.10)	(0.10)	(0.10)
Constant	-0.80***	-1.07***	-7.53***	-9.03***	-13.54***	-11.06***
	(0.07)	(0.09)	(0.10)	(0.11)	(0.21)	(0.28)
Observations	51,868	51,646	47,853	47,715	47,608	47,608
R^2	0.02	0.06	0.39	0.44	0.44	0.45
Adjusted R^2	0.02	0.06	0.39	0.44	0.44	0.45
Residual Std. Error	1.63 (df = 51866)	1.60 (df = 51640)	1.30 (df = 47844)	1.25 (df = 47702)	1.25 (df = 47595)	1.25 (df = 47594)
F Statistic	1,275.05*** (df = 1; 51866)	621.02*** (df = 5; 51640)	3,891.31*** (df = 8; 47844)	3,179.28*** (df = 12; 47702)	3,156.20*** (df = 12; 47595)	2,940.37*** (df = 13; 47594)
Note:						*p<0.05; **p<0.01; ***p<0.001