DOCKETED	
Docket Number:	16-OIR-06
Project Title:	Senate Bill 350 Disadvantaged Community Advisory Group
TN #:	229647
Document Title:	Distributed solar and environmental justice
Description:	Exploring the demographic and socio-economic trends of residential PV adoption in California
Filer:	Rosemary Avalos
Organization:	California Energy Commission
Submitter Role:	Public Adviser
Submission Date:	9/4/2019 10:47:49 AM
Docketed Date:	9/4/2019

Energy Policy 134 (2019) 110935

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

Distributed solar and environmental justice: Exploring the demographic and socio-economic trends of residential PV adoption in California

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ARTICLE INFO

Keywords:
Rooftop solar
Photovoltaics
Environmental justice
CalEnviroScreen
Energy justice
Distributed energy resources

ABSTRACT

The rapid growth of distributed solar adoption in California provides an opportunity to lower electricity bills for the adopters and realize additional community benefits, including grid resilience and lower grid emissions. It is unclear, however, whether this transition is occurring equitably across the state's various demographic and socioeconomic groups and whether historically disadvantaged environmental justice (EJ) communities have been able to exploit the bill savings and other associated benefits of rooftop solar. Here we analyze the cumulative and annualized (spatial and temporal) rates of PV adoption across California and compare those with data from the state's cumulative impact EJ methodology (CalEnviroScreen). We find persistently lower levels of PV adoption in disadvantaged communities, suggesting clear distributive and equity impacts of existing PV support policies, and indicating that the benefits bypass some of the state's most vulnerable populations. The analysis reveals strong correlation of solar adoption with not only socioeconomic variables, but also with health, environmental and demographic indicators, contributing to our growing understanding of the role these factors play in household clean-energy adoption trends. The results provide a baseline from which to develop more effective policies, strategically design incentives, and track the efficacy of existing solar programs that target disadvantaged communities.

1. Introduction

Residential photovoltaic (PV) adoption in the US has seen a dramatic increase over the past couple of decades. The state of California leads the nation, both in terms of total number of small-scale PV systems deployed — over 610,000 installations up to 20 kW (kW) in size as of 2018 — and the number of such installations per capita, averaging about one array for every 65 California residents (The OpenPV Project, 2018). The high rate of distributed solar adoption in California has been fueled by a combination of factors: aggressive statewide renewable energy policies aimed at reducing greenhouse gas emissions, strong incentive programs such as the California Solar Initiative (CSI), state and federal PV income tax credits and rebates, net energy metering (NEM) compensatory mechanisms, high solar resource potential throughout the state, falling PV costs, and last but not least, electricity prices that are among the highest in the nation. State government policies, as well as general consumer preferences for cleaner energy, are rapidly transforming the California energy landscape — generation from small-scale solar has grown from 3% to 6.6% of total in-state generation in just the last four years (Electricity Data Browser, 2018). As the state keeps moving towards a power sector with lower overall greenhouse gas and criteria pollutant emissions, it is also upending the traditional paradigm of electricity generation and distribution by providing some consumers with the opportunity to produce electricity at the point of consumption. However, important questions still remain about whether this transition is occurring equitably across the state's various demographic and socioeconomic groups and whether historically disadvantaged environmental justice communities have been able to capitalize on the bill savings and other associated benefits of distributed solar.

The levelized cost of energy from renewable energy resources has fallen precipitously in recent years (Lazard Ltd, 2018). Early adopter regions of renewable technologies such as California and Germany, however, have faced the unfortunate side effect of increased electricity prices for consumers (Rockzsfforde and Zafar, 2015; Grösche and Schröder, 2014; Jenkins et al., 2016). High residential utility costs can place a disproportionate burden on low-income households. A study by the American Council for an Energy Efficient Economy (ACEEE) found that the median US energy burden, defined as the percent of annual income spent on energy utility bills (electric, gas or other heating fuels), was 3.5% across all major US cities, while the median low-income household's energy burden was more than twice that at 7.2% (Drehobl

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https://doi.org/10.1016/j.enpol.2019.110935
Received 18 April 2019; Received in revised form 5 August 2019; Accepted 10 August 2019

and Ross, 2016). In a large fraction of the cities surveyed, the lowest quarter of low-income households, i.e. the poorest residents, experienced an even greater energy burden of over 14%, substantially higher than the 3.5% average for all US households. Energy burden disparities are often articulated through terms like fuel poverty and energy insecurity, which reflect the inability of a household to meet basic energy needs (Bednar et al., 2017; Hernández, 2013). Concerns related to fuel poverty and energy insecurity constitute the foundation of a growing field of scholarship on energy (in)justice, which revolves around the idea that fuel poverty violates the basic principle of distributive justice (Jenkins et al., 2016; Reames, 2016; Gross, 2007; Sovacool et al., 2016).

Additional environmental, health, and demographic factors often interplay with the socioeconomic aspects of energy insecurity. Evidence suggests that other social stressors besides poverty, including racial discrimination, crime, malnutrition, substance abuse, and numerous environmental and health stressors are often present in communities of lower socioeconomic status (Morello-Frosch et al., 2011; Cushing et al., 2018). Research is also beginning to show how the cumulative effects of these social and environmental vulnerabilities can work in concert to produce both health and equity disparities (Solomon et al., 2016). As a result, regulatory agencies have started to consider new cumulative impact methodologies that incorporate social equity, health and environmental data in policy decision-making (U.S. Environmental Protection Agency, 2017; California Climate Invest, 2019). One such methodology is CalEnviroScreen (CES) introduced by the California Office of Environmental Health Hazard Assessment (OEHHA) in 2013 (CalEPA, 2017). CES is a database and a geospatial mapping tool that integrates environmental burden and socioeconomic data on the census tract level in California. The state of California uses CES to identify disadvantaged communities (DACs) in the state, defined as the census tracts that score in the top 25% statewide on the CalEnviroScreen 3.0 metric. These are the 25% of California communities that suffer the most from a combination of socioeconomic, health and environmental burdens. The CES methodology now plays a key role in directing resources from the California Cap-and-Trade program to support clean energy investments in environmental justice (EJ) communities (535 Disadvantaged Comm, 2019), with several new statewide initiatives serving as the vehicles for these funds (Solar on Multifamily Affo, 2019; Expanding Solar in Disadv, 2019).

Residential PV adoption can help lower electricity bills for low-income households and make energy expenses more stable from month to month. In addition, environmental justice communities, which are affected by multiple environmental, health and socioeconomic stressors, may see multiple benefits (Cushing et al., 2018). For example, 84% of the peaker power plants in California are sited in locations that have higher than average CES scores, and close to half of these plants are located in disadvantaged communities (top 25% of CES scores) (Krieger et al., 2016). Deployment of rooftop solar in such communities, especially when paired with storage to reduce electricity consumption during peak hours, has the potential to not only lower electricity bills for the adopters, but to also yield co-benefits such as lower air pollutant emissions by displacing local marginal fossil fuel electricity generation in transmission-constrained load pockets (Krieger et al., 2016). Low-income households face numerous barriers to accessing solar power and its economic benefits, including high upfront costs, lack of access to financial instruments, lack of information, language and behavioral barriers, split incentives between owners and tenants (many low-income households are renters), and others. Several state programs in California were initiated with the goal of lowering or removing some of those barriers (Multifamily Affordable So, 2018; Single-Family Affordable, 2018; California Energy Commission, 2016). The emergence of third-party financing models has also provided an avenue to spur PV deployment among low-income households (Drury et al., 2012). To date, however, no studies have rigorously examined PV adoption rates in EJ communities, analyzed the role of various EJ indicators in PV adoption, or evaluated the cumulative effects of state programs developed to help these communities. To improve the effectiveness of targeted policies, a more in-depth evaluation of the spatial and temporal dynamics of solar adoption in vulnerable populations is needed. The aim of this paper is to fill this gap by providing a comprehensive assessment of the role that EJ, demographic, and socioeconomic factors play in the uptake of solar PV in disadvantaged communities in California.

A significant portion of the research on residential PV diffusion to date has focused on equity issues related to PV policy incentives in countries like Australia (Macintosh and Wilkinson, 2011; Simpson and Clifton, 2016), Germany (Grösche and Schröder, 2014) and the US (Griffith et al., 2014), behavioral and policy reasons for adoption vs. non-adoption of clean energy technologies (Braito et al., 2017; Caird et al., 2008; Kemp and Volpi, 2008; Wilson and Dowlatabadi, 2007; Li and Yi, 2014), or on developing predictive models of consumer behavior (Robinson and Rai, 2015; Rai and Robinson, 2015; Sultan et al., 2016). In recent years, econometric, agent-based, regression and other models have identified key demographic, socioeconomic, and behavioral variables that influence domestic PV diffusion, including income, education, age, ethnicity, family size, owner occupancy, peer effects, and of course, access to financial resources (Kwan, 2012; Sommerfeld et al., 2017; Coffman et al., 2018; Sardianou and Genoudi, 2013; Islam and Meade, 2013; Bollinger and Gillingham, 2012). Models have also looked at the spatial dynamics of PV adoption (Kwan, 2012; Sharshing, 2017; Aklin et al., 2018; Yu et al., 2018). A 2014 study of PV diffusion in California explored how several types of geospatial data, including less-commonly studied variables like house age, number of rooms, and heating source, vary regionally at various spatial scales across the state, and found that regression models using small subsets of geospatial information may be just as predictive as models using hundreds of geospatial variables, but that their predictive powers also depend on the level of spatial resolution and regional characteristics (Davidson et al., 2014). This and other geospatial studies did not explore the temporal dynamics of residential PV adoption. A recent analysis by the Lawrence Berkeley National Lab (LBNL) examined income trends among US residential solar adopters with an emphasis on low- and moderate-income (LMI) residents (Barbose et al., 2018). The report revealed that the median income of residential solar adopters is $32K higher than that of other households, and $13K higher compared to owner-occupied households only, but also showed that PV adoption has been trending towards more moderate-income households in recent years. As evidenced by some of the studies referenced above, however, income may not be the only strong driver behind disparities in PV adoption. Importantly, the relative impact of the various demographic and socioeconomic variables is still not well understood, and, to the best of our knowledge, no studies have investigated simultaneously the geospatial and temporal influences of individual and combined EJ indicators within the framework of disadvantaged communities to examine the viability of current EJ methodologies and the policies aimed at helping these communities.

In this paper, we utilize project-level data for the vast majority of residential PV systems in California using LBNL's *Tracking the Sun* database. We chose the state of California for this analysis because: 1) it has the largest number of small-scale PV installations to date and the highest rate of PV adoption per capita in the US; 2) has some of the highest levels of income inequality in the country as well as significant environmental pollution disparities across the state; and 3) has developed a unique and robust environmental justice cumulative impact methodology (CalEnviroScreen) that the state uses to direct clean energy funding streams. We identify key variables within CES and quantify their relative influence on solar adoption both independently and using the combined CES score. We explore geospatial variations of solar adoption on the census tract level and regionally across utility territories, as well as temporal variations of solar adoption within and outside of disadvantaged communities in California over the past 20 years. We aim to answer several key questions: 1) How is distributed solar adoption in California correlated with various socioeconomic and EJ indicators? 2) How have the geospatial, demographic and socioeconomic trends of PV uptake changed over time? 3) What role have state programs designed to help low-income and disadvantaged communities played in solar deployment trends? 4) What are the policy implications of the answers to these questions and what do they say about the EJ methodology used in California (CalEnviroScreen) and its application to climate investments? Our results indicate that EJ communities in California have experienced disproportionately low levels of PV adoption. These low levels of uptake continue to persist to the present day, despite fairly aggressive state policies and a number of solar incentive programs aimed at targeting low-income and disadvantaged communities. Our analysis reveals strong correlation between solar adoption rates and socioeconomic/demographic indicators such as poverty, education, linguistic isolation and housing burden. It also reveals correlation between solar deployment and health/environmental EJ indicators such as asthma rates, cardiovascular disease, low birthweight births and traffic density. These findings contribute to our growing understanding of the role that demographic, socioeconomic, health and environmental factors play in household uptake of clean energy technologies and offer an opportunity to more effectively shape future incentives and policies to successfully target disadvantaged communities in California. They also provide a framework for supporting the equitable deployment of residential solar PV systems and other distributed clean energy technologies nationwide.

2. Data and methodology

This work relies primarily on two data sources. PV deployment data were obtained from the most recent edition of LBNL's Tracking the Sun 2018 database (Darghouth and Barbose, 2018). The dataset includes project-level data for the vast majority of grid-connected non-utility scale PV systems installed nationwide through 2017. LBNL collects the data from state incentive programs, large utilities, state utility regulators and other organizations. For California, our data include 695,620 individual systems within the three largest investor-owned utility (IOU) territories in the state Pacific Gas and Electric (PG&E), Southern California Edison (SCE), and San Diego Gas and Electric (SDG&E). The dataset also contains an additional 50,915 PV systems installed in the two largest public utility service territories in the state: the Los Angeles Department of Water and Power (LADWP) and the Sacramento Municipal Utility District (SMUD). Since individual PV system addresses are not publicly available, LBNL provided us with a list containing the census tract code for each PV installation. This allowed us to aggregate various types of data, including total number of installations, total installed capacity (in kW), customer segment (residential, commercial, government, nonprofit, school, non-residential), and others on the census tract level. It also allowed us to associate the tract-level PV information with the CES 3.0 dataset, which is similarly aggregated on the census tract level. We did not include data for LADWP in our analysis because LADWP data were available to us on the zip code level only.

OEHHA's CalEnviroScreen 3.0 is the other primary data source for this analysis. The CES methodology develops an EJ score for each census tract in California based on its state percentile values for 20 different socioeconomic, demographic and environmental indicators. Using percentiles produces a relative, rather than an absolute scale for the pollution impacts and vulnerabilities in California communities, but this approach allows for the aggregation of multiple indicators that are otherwise measured in non-comparable units. The 20 CES indicators are grouped into two broad categories: (1) Population Characteristics, which include five socioeconomic factors (educational attainment, housing burden, linguistic isolation, poverty, unemployment) and three sensitive populations variables (asthma emergency room visits, cardiovascular disease emergency room visits, percent low birthweight births); and (2) Pollution Burden, which includes seven exposure indicators (ozone and $PM_{2.5}$ concentrations, diesel PM emissions, drinking water contamination, pesticide use, toxic releases, traffic density) and five environmental indicators (cleanup sites, groundwater threats, hazardous waste, impaired water bodies, and solid waste sites) (CalEPA, 2017). The five indicators comprising the Environmental Effects component are weighted one-half when combined with the seven indicators comprising the Exposures component. The overall CES score for each census tract is calculated by (1) averaging the state percentiles of the 12 Pollution Burden indicators and separately averaging the percentiles of the eight Population Characteristics indicators; (2) scaling each of these results to a maximum score of ten; (3) multiplying the population and environmental scores to create an EJ score with a maximum value of 100; and (4) calculating the state percentile of these EJ scores for each census tract. The communities that score in the top 25% of census tracts statewide on this metric and the tracts that do not have an overall CES score but are in the top 5% in the Pollution Burden category are designated as Disadvantaged Communities by the state of California.

We also utilize data from the American Community Survey (ACS) to obtain the 5-year-average (2012–2016) median household income for each census tract. The ACS is a statistical survey conducted by the US Census Bureau that samples a small percent of the US population every year to provide demographic, social and economic data on various communities in the US. ACS provides 1-, 3- and 5-year rolling data but the 5-year ACS data are based on larger survey samples and are considered more reliable.

Due to the distributed nature of small-scale solar systems, in this work we use installed PV capacity per capita as the dependent variable to represent PV adoption rates (or PV deployment density). We use regression and correlational analysis to correlate solar deployment with various demographic, socioeconomic and environmental factors on the census tract level. For parts of the analysis we log-transform the installed PV per capita and use that as the dependent variable in order to produce more normally distributed model residuals.

3. Results and discussion

In this section, we examine the overall geospatial and EJ distribution of PV adoption in California, deployment rates by utility service territory, and the temporal dynamics of solar uptake since 1998. We also correlate PV deployment with predictor variables such as overall CES score, overall Population Characteristics and Pollution Burden scores, as well as several individual indicators from the CES methodology and ACS, including median household income, education level, poverty, unemployment, linguistic isolation, $PM_{2.5}$, asthma rates and others.

3.1. Spatial and EJ analysis

The geospatial distribution of EJ scores in California and adoption rates of rooftop solar by census tract are compared side-by-side in Fig. 1. Fig. 1a displays the geographic extent of disadvantaged communities in California. The map outlines the broader regional patterns in the state, with most disadvantaged communities located in dense urban areas such as Downtown LA and San Francisco Bay Area (insets), near the smaller metropolitan area of Sacramento, and in the slightly less dense but heavily industrial and agricultural region of the San Joaquin Valley. These communities are colored darker orange on the blue-orange divergent EJ map. Fig. 1b outlines variations in residential PV adoption across census tracts in California. In contrast to the distribution of EJ communities, the geospatial characteristics of rooftop solar (presented on a per capita basis to control for differences in population density) follow a more suburban and rural trajectory. The urban cores of the cities, where most disadvantaged communities are located, reveal relatively low levels of solar uptake, while the outlying

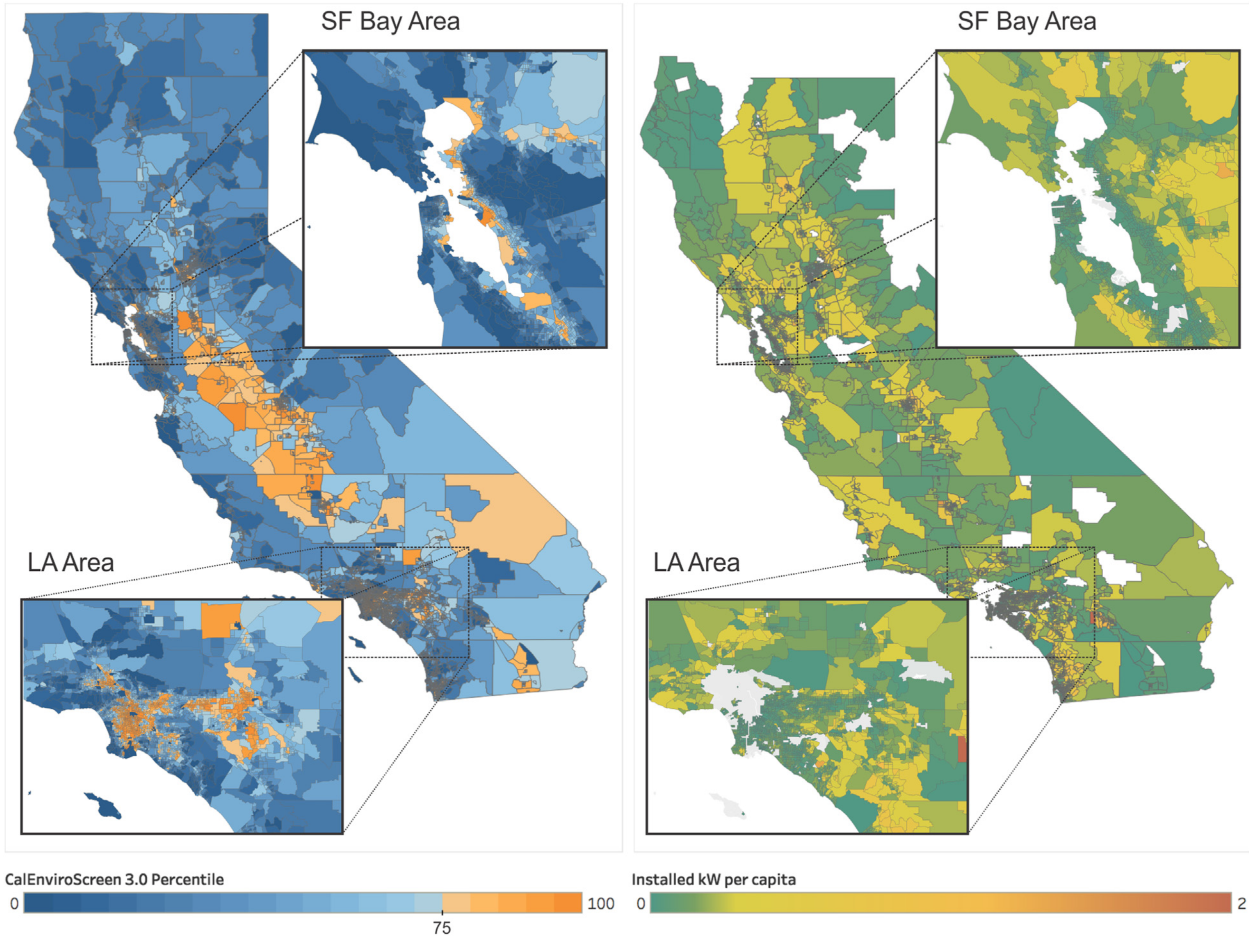

Fig. 1. (a) Geospatial distribution of CES EJ score percentiles in California by census tract. The highest 25% of CES scores are designated as disadvantaged communities (colored orange). (b) Distribution of rooftop solar deployments in California on a green-yellow-orange-red color map. Green indicates lowest rates of solar deployment, yellow-orange indicate medium levels of PV deployment, red indicates highest levels of solar adoption (nearly 2 kW per capita). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

suburbs and rural areas appear to have significantly higher rates of PV adoption. The insets in Fig. 1 illustrate these trends visually for two of the most populous areas in the state: the LA Basin and the San Francisco Bay Area. The census tracts with highest levels of residential PV adoption (colored yellow-red in Fig. 1b) form a spotted band of suburban and rural areas often situated more than 30 miles away from the dense city cores. We note that a large portion of the LA Basin is colored grey on the map due to the unavailability of solar deployment data on the census tract level for LADWP territory. A small number of census tracts overlap both LADWP and SCE territory. In those census tracts, only systems deployed within SCE territory were considered.

CES data are often presented in terms of percentiles rather than CES scores. The percentile rank of each census tract is based on the rank-order of its CES score compared to all other census tracts in the state. Thus, a tract's CES percentile indicates the percentage of census tracts with lower CES scores. In Fig. 2, we plot the cumulative installed PV capacity in kW per capita across the full CES percentile range (0–100) divided into 5% bins. The figure shows rooftop solar deployment data for three major customer segments: residential, commercial and government installations. We excluded non-profit, school and non-residential installations from this figure because they comprise a small percentage of the total kW installed (less than 2% each).

For residential installations, the PV deployment data in Fig. 2 reveals unambiguous tendency towards progressively lower PV adoption levels in communities with higher EJ scores. Rates of residential solar deployment in the most disadvantaged communities, i.e. the census

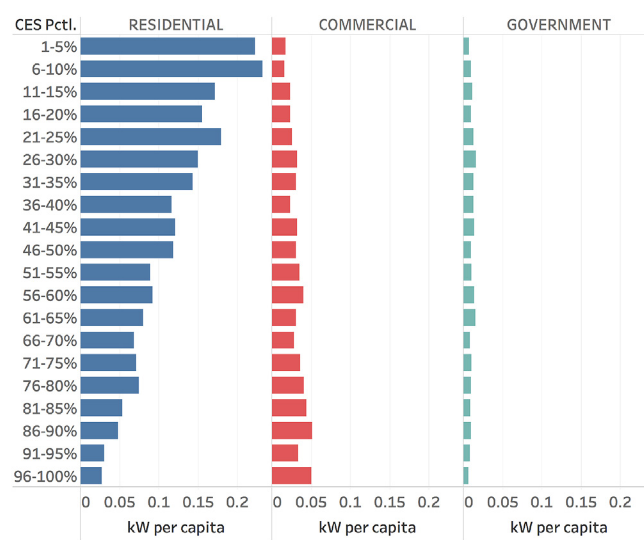

Fig. 2. Total installed rooftop solar (in kW per capita) by CES percentile range divided in 5% bins. Data are shown for three main customer segments: residential (blue), commercial (red), and government (green). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

tracts that rank in the top 5% of CalEnviroScreen, are 8.2 times lower than the adoption rates in the bottom 5% of CES scores (the least disadvantaged communities). To date, only 2.6% of the total residential solar capacity has been installed in the top 10% of CES communities. In contrast, the bottom 10% boast almost 20% of the total residential solar installed to date. The average PV system sizes in the bottom 10% and top 10% CES scores are similar at about 6 kW per system.

In contrast, PV adoption trends for commercial installations are reversed and we see slightly higher installed PV capacity per capita in the higher CES percentile ranges. This finding may be partially attributable to the fact that commercial businesses are often located in industrial and urban areas where environmental burdens are elevated due to high traffic volumes and industrial activities. Government installations reveal a more equal distribution of PV deployment per capita across EJ communities that seems to be largely independent of the EJ score.

The three major IOU territories in California have slightly different solar potential due to their geographic distribution from north to south, with PG&E being the furthest north and SDG&E the southernmost of the three. To account for differences in solar irradiance, as well as for other discrepancies between utilities such as median household income, electricity rates, utility program structures, and percentage of disadvantaged communities, we plot residential solar adoption rates by CES percentile for each of the three main IOU territories. We also include data for the Sacramento Municipal Utility District (SMUD), which is the second largest public utility in California after LADWP. Residential solar adoption rates by utility territory are displayed in Fig. 3.

SDG&E, which tends to serve wealthier populations and contains a smaller percent of disadvantaged communities within its territory, has higher rates of solar adoption per capita in the bottom 25% of CES scores compared to other utilities, but has less PV capacity per capita installed in the top 25% of CES scores (disadvantaged communities). The latter finding is surprising, given that the smaller number of EJ communities in SDG&E territory should, in principle, require less programmatic effort to reach these populations and ensure a more equitable distribution of solar benefits. Only 5.2% of SDG&Es customers live in disadvantaged communities, compared with 30% in SCE, 17.7% in PG&E and 13.3% in SMUD.

In contrast to SDG&E, PG&E and SCE exhibit higher rates of PV adoption in EJ communities, with PG&E claiming the most equitable

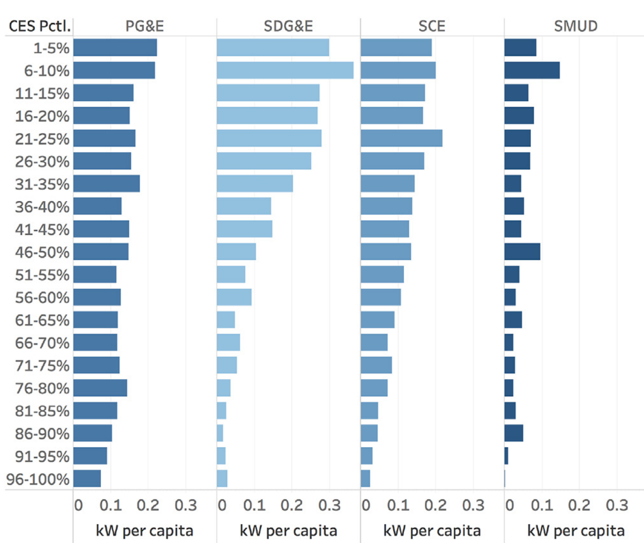

Fig. 3. Residential PV deployment in California (in kW per capita) by CES percentile range. Data shown for four main utility service territories: Pacific Gas and Electric, San Diego Gas and Electric, Southern California Edison, and Sacramento Municipal Utility District.

distribution of the three IOUs. A significant fraction of the solar capacity installed in PG&E territory falls within the middle CES ranges, although the lowest 10% of CES scores, i.e. the least disadvantaged communities, still show the highest installed PV per capita. SMUD appears to have the lowest overall levels of solar adoption of the four utility territories shown in Fig. 3. This may be due to the convergence of multiple factors, including lower median household income in SMUD territory compared to the three IOUs, different population density, lower electricity rates, and the fact that municipal utilities in California are not subject to the same oversight by the California Public Utilities Commission (CPUC) as compared to the IOUs.

3.2. Temporal dynamics of PV adoption

Figs. 1–3 highlight the total capacity per capita installed in California to date. To explore trends in solar adoption over time, we also examine the annual data time series for the years between 1998 and 2017. Fig. 4 details the evolution of residential solar uptake over the second decade of this period: 2008–2017. The last three years in particular show a marked increase in solar deployment across all CES percentiles. In fact, more than sixty percent (62.8%) of the total residential capacity installed between 1998 and 2017 was deployed in the last three years alone. However, despite the availability of PV support policies in the state of California that have specifically targeted low-income residents in affordable housing, such as the California Solar Initiative and its two main low-income components, the Single-Family Affordable Solar Homes (SASH) and the Multifamily Affordable Solar Housing (MASH) programs, lower rates of solar adoption have continued to persist in the higher CES percentiles.

We analyzed the number of installations installed through SASH and MASH and found that the total PV capacity installed through them is less than 5% of the total residential capacity installed in the state to date. This reported PV capacity reflects the direct impact of the two programs (i.e. the number of directly incentivized deployments) but there may be secondary impacts, such as social diffusion peer effects, which are beyond the scope of this work. Both programs have targeted only low-income households, defined as the households with income of less than 80 percent of the area median income. As a result, systems installed through these programs have been sited both within and outside of disadvantaged communities. While we do note somewhat increased levels of solar diffusion in the higher CES percentiles over the last three years of the dataset, the overall rate of deployment in these populations has remained lower compared to communities with low EJ scores, leading to an ever-widening gap in solar installations between the two ends of the CES spectrum.

This point is further illustrated in Fig. 5, where we plot the total installed residential kW per capita in disadvantaged communities (top 25% of CES scores) versus all other CES percentiles. Fig. 5a compares the running total of cumulative PV installations per capita over the twenty-year period between 1998 and 2017. We note that a gap in installed kW per capita starts to open up very early on and continues to grow until present day. By the end of 2017, the total PV capacity per capita installed outside of disadvantaged communities is almost three times that installed inside them.

Fig. 5b compares the annual rate of solar additions in disadvantaged communities (DACs) versus non-DAC communities as their relative weight of the total installed kW per capita for that year. This means that an equal rate of deployment would be at the 50% mark. In 1998, 1999, all new residential solar deployments occurred outside of disadvantaged communities. In the early years after that, the levels of solar adoption per capita outside of disadvantaged communities were nearly ten times greater than the deployment levels in EJ communities. In the last few years of our dataset, the relative weight of total PV capacity per capita installed in disadvantaged communities has shown a steady increase. This trend is in line with observations by Barbose et al. (2018) who report increased PV adoption rates among low- and moderate-

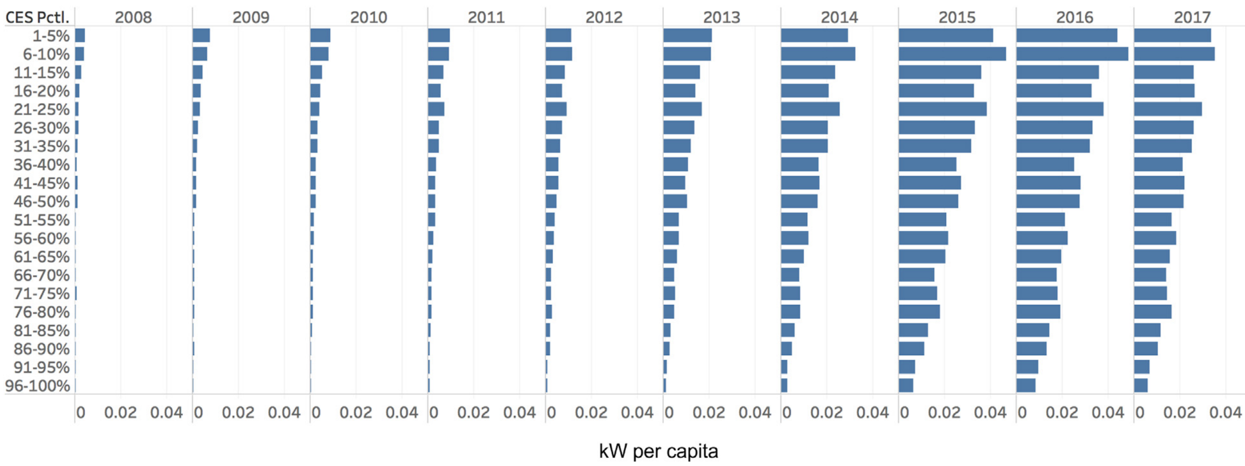

Fig. 4. Installed residential PV in California by year (2008–2017) and by CES percentile range.

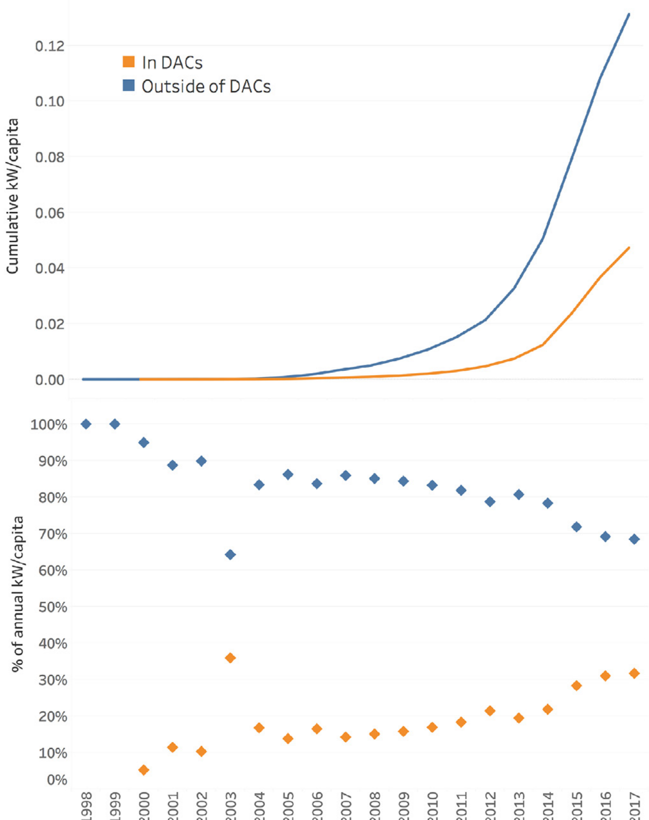

Fig. 5. Installed residential solar in Disadvantaged Communities (DACs) compared to non-DACs. (a) Cumulative running total of installed kW per capita 1998–2017. (b) Relative weight of annual residential solar deployments per capita as percent of the total installed kW per capita for that year. An equal rate of deployment would be at the 50% line. The outlier in 2003 is due to two unusually large residential systems installed in DACs in PG&E territory that year.

income households in recent years. However, even in the last three years of our dataset the kW per capita deployed outside of DACs in California still constitutes the vast majority of installed PV capacity. In 2017, the most recent year in our data, the deployment rate outside of disadvantaged communities was still more than twice the deployment rate in DACs. These numbers suggest that when it comes to distributed solar, the gap between the haves and have-nots in California has continued to increase (albeit at a slower rate) despite aggressigve state policies and a slew of solar incentive programs aimed at targeting low-income communities.

The drivers behind disparities in solar uptake can be complex. As mentioned in the Introduction, previous literature has identified positive association between PV uptake and several socioeconomic and demographic variables, including income, age, education, access to information, perception of risk, neighborhood effects, and others (Wilson and Dowlatabadi, 2007; Kwan, 2012; Barbose et al., 2018; Rai et al., 2016). Home ownership is also a key driver for discrepancies in PV adoption within similar income groups (Barbose et al., 2018).

To evaluate the role of various CES metrics in PV adoption, we explore the relative influence of the overall CES score compared to its two main components that comprise it: Pollution Burden and Population Characteristics. Fig. 6 shows bivariate log-linear scatter plots of the annual installed residential PV capacity per capita across census tracts in California versus each census tract's total CES, Pollution Burden and Population Characteristics scores. Each point on the scatter

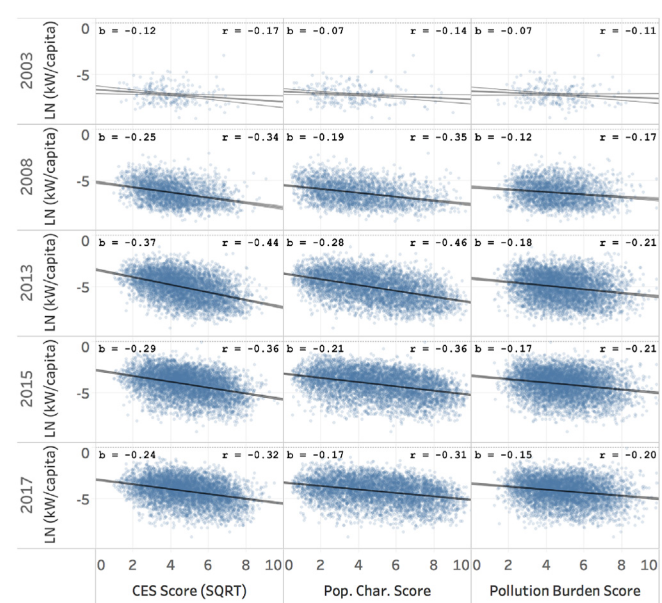

Fig. 6. Bivariate log-linear scatter plots of the residential PV per capita installed in census tracts in California for select years (2003, 2008, 2013, 2015, 2017). Each data point represents a census tract where residential solar was deployed during that year. Data shown as LN (kW/capita) for the total CES score, Population Characteristics Score and Pollution Burden Score. Linear regression models are shown, with b = regression coefficients, r = Pearson correlation coefficients. All are significant at the $p < 0.001$ level.

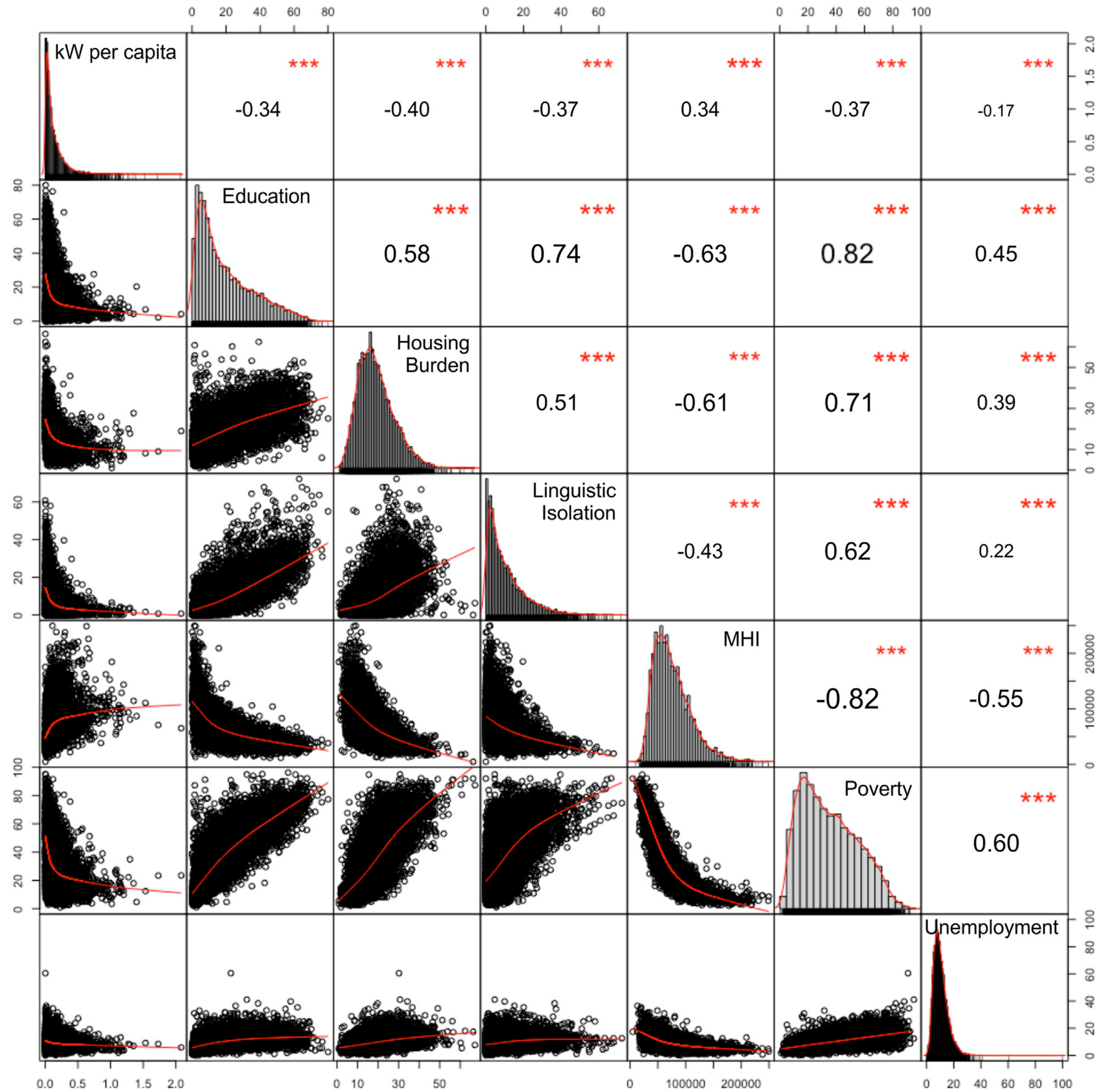

Fig. 7. A correlation matrix for residential solar adoption (kW per capita) and six other independent variables: education, housing burden, linguistic isolation, median household income (MHI), poverty and unemployment. Spearman rank correlation coefficients are displayed to the right of the diagonal. Histogram distributions of the number of census tracts across each variable are shown along the diagonal. Bivariate scatter plots with fitted lines are displayed left of the diagonal. The $p < 0.001$, 0.01 and 0.05 significance levels associated with each coefficient are indicated by three, two, and one stars respectively.

plots represents a single census tract where residential solar was deployed during that year. To illustrate the overall trends over time, we plot the data in five-year intervals early on and then two-year intervals for the most recent years.

We note that census tracts are normally distributed across both the Pollution Burden and Population Characteristics components, which have a score range of 0–10. Census tracts are also normally distributed across the total CES score, calculated by multiplying the Pollution Burden and Population Characteristics components and resulting in a maximum score of 100. We therefore plot the square root of the CES score to obtain a variable directly comparable with the Pollution Burden and Population Characteristics components. Census tracts have a non-normal distribution across the PV deployment variable — a histogram of census tracts ranked by installed PV capacity per capita produces a distribution peaked near the origin (i.e. most census tracts have little residential solar installed), which decays exponentially at higher rates of PV deployment. We therefore log-transformed the installed kW per capita and used this as the new dependent variable to produce more normally distributed model residuals.

The simple linear regressions shown in the scatter plots in Fig. 6 reveal statistically significant inverse dependence (all significant at the $p < 0.001$ level). The inverse trends are strongest for the overall CES score, slightly less so for the Population Characteristics category, and weakest for the Pollution Burden category. Looking at the annual time series of the scatter plots, we note that the negative regression coefficients b increase over time until 2013, after which they become less influential. The same is true for the Pearson correlation coefficients r. They are generally strongest for the Population Characteristics component, slightly less so for the overall CES score, and weakest for the Pollution Burden component, indicating that Pollution Burden is

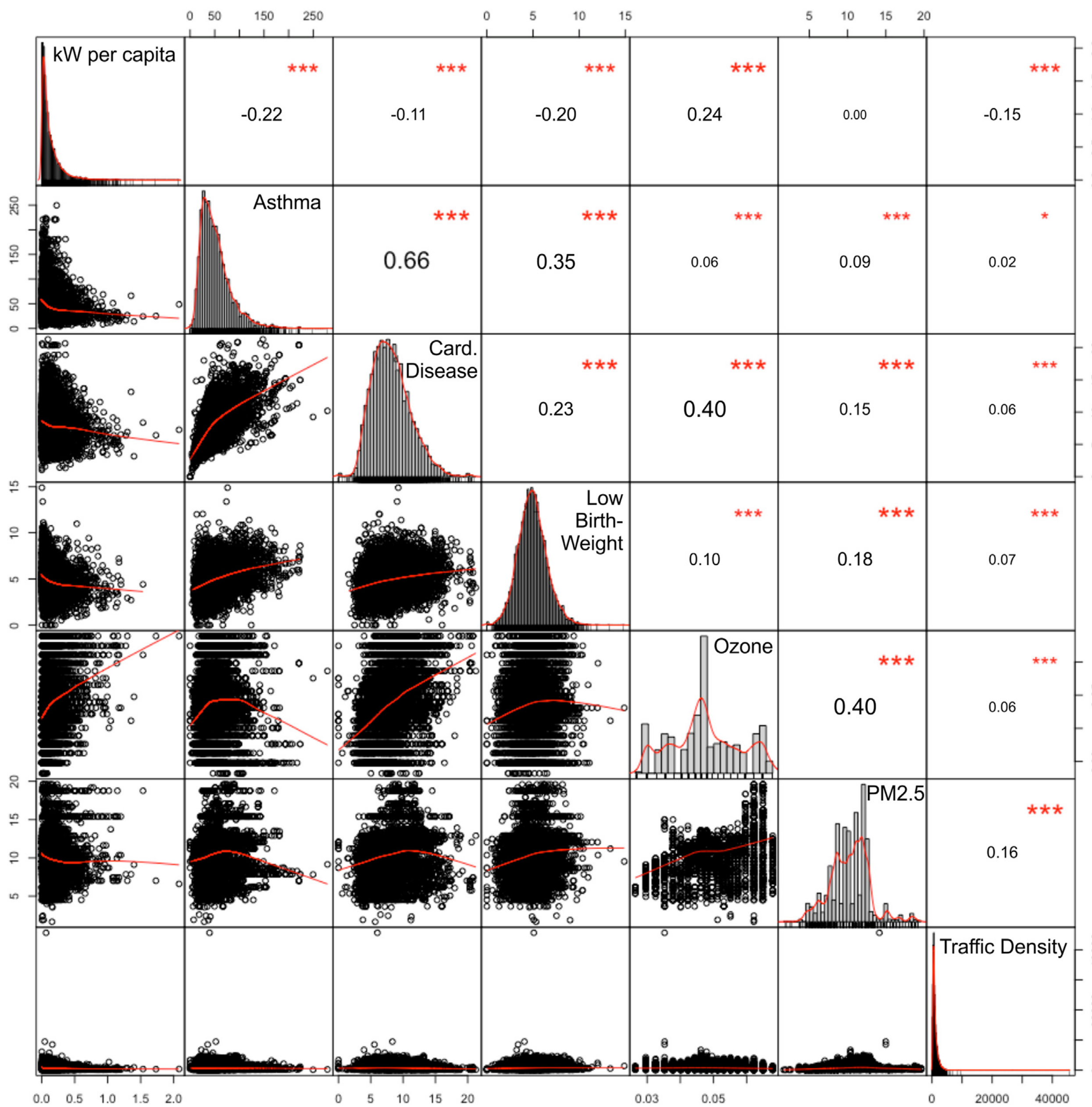

Fig. 8. A correlation matrix for residential solar adoption (kW per capita) and six other independent environmental and health variables: asthma, cardiovascular disease, low birth weight, ozone, $PM_{2.5}$ and traffic. Spearman correlation coefficients are displayed to the right of the diagonal. Histogram distributions of the number of census tracts across each variable are shown along the diagonal. Bivariate scatter plots with fitted lines are left of the diagonal. The $p < 0.001$, 0.01 and 0.05 significance levels associated with each coefficient are indicated by three, two, and one stars respectively.

slightly less influential in predicting residential solar adoption rates (but still statistically significant). The results suggest that the Population Characteristics component and the EJ indicators that comprise it are slightly more influential as predictor variables impacting solar PV uptake than the Pollution Burden indicators. To explore this relationship further, we next look at how individual indicators within these two CES categories correlate with residential solar uptake.

3.3. Correlational analysis

We performed both regression and correlational analysis on the individual indicators in our study to examine not only the explanatory ability of these variables but also their relative weight. An ordinary least squares (OLS) multiple regression model for solar adoption was run on our data using all 20 CES indicators plus the median household income (MHI). Many of these predictor variables, including linguistic isolation, housing burden, MHI, cardiovascular disease, asthma rates, ozone, traffic and others were found to be statistically significant at the $p < 0.001$ level. While regression analysis allows us to control for confounding effects between the explanatory variables, it does not provide clear information about the relative influence of each of the predictor variables on solar adoption rates.

We therefore chose to perform correlational analysis on the two main categories of CES metrics based on the results of the previous section: socioeconomic EJ indicators that comprise the Population Characteristics component in CalEnviroScreen and environmental EJ indicators that comprise the Pollution Burden component. We started by evaluating the Spearman's rank correlation coefficients between residential PV adoption (in kW/capita) and five socioeconomic and demographic variables in the Population Characteristics category:

unemployment, education, housing burden, linguistic isolation and poverty. In CES, the education indicator is defined as the percent of population over age 25 with less than a high school education, housing burden is defined as the percent of households that are both low-income and paying greater than 50% of their income to housing costs, and poverty is defined as the percent of population living below twice the federal poverty level. We also include the 5-year-average (2012–2016) median household income aggregated on the census tract level. The results are summarized in the correlation matrix in Fig. 7 where Spearman's rank correlation coefficients for every pair of variables are displayed. Histogram distributions of the number of census tracts across each variable are also shown along the diagonal, revealing non-normal distributions for all variables. Left of the diagonal are the respective bivariate scatter plots with fitted trend lines, which are generally non-linear. Right of the diagonal are the values of the respective Spearman rank correlation coefficients. The $p < 0.001$, 0.01 and 0.05 significance levels associated with each coefficient are indicated by three, two, and one stars respectively.

All six variables are statistically significant in explaining variations in residential solar adoption across census tracts. Housing burden is the most (inversely) correlated variable with PV adoption (-0.40), followed closely by linguistic isolation (-0.37), poverty (-0.37), low education levels (-0.34) and median household income (0.34). Given the small differences, all five of these variables carry similar weight as predictors, suggesting that a combination of these factors may be more statistically significant in influencing residential solar adoption levels than each of them individually. To test this hypothesis, we generated an index taking the average of the census tract percentiles of the four CES variables most correlated with PV adoption rates — housing burden, linguistic isolation, poverty and education. The Spearman correlation coefficient between the new index variable and kW solar per capita was -0.46 — stronger than for any one of the four variables individually. This correlation is also stronger compared to the overall CES score (-0.34) because the CES score includes the more weakly correlated Pollution Burden component, and compared to the overall Population Characteristics component (-0.37), which contains less correlated indicators such as asthma, cardiovascular disease, and unemployment. Fig. 7 also shows the unemployment indicator, which has a correlation coefficient of -0.17.

As one might expect, Fig. 7 illustrates strong pairwise correlations between all six explanatory variables. The correlation coefficient between median household income and poverty is -0.82, between low education and poverty 0.82, between low education and linguistic isolation 0.74, and between housing burden and poverty 0.71. The weakest (but still statistically significant) correlation is between linguistic isolation and unemployment at 0.22. All coefficients are statistically significant at the $p < 0.001$ level.

In Fig. 8, we also correlate the dependent variable PV deployment per capita with six environmental and health indicators: low birth-weight births, ozone, $PM_{2.5}$, traffic, asthma and cardiovascular disease. Five of these variables are statistically significant factors in explaining variations in residential solar adoption between census tracts but with somewhat weaker correlation compared to the demographic and socioeconomic indicators in the Population Characteristics category. The respective correlation coefficients are 0.24 for ozone, -0.22 for asthma, -0.20 for low birth weight, -0.15 for traffic and -0.11 for cardiovascular disease. $PM_{2.5}$ does not end up being a statistically significant predictor variable for residential solar adoption.

3.4. Data significance and limitations

Previous research on the factors influencing solar uptake has focused primarily on socioeconomic considerations and has identified income and home ownership as key explanatory variables for PV adoption (Macintosh and Wilkinson, 2011; Coffman et al., 2018; Barbose et al., 2018). Our analysis suggests that other variables, including linguistic isolation and education, may be more significant predictors of solar uptake than median household income (at least for data aggregated on the census tract level). Housing burden, linguistic isolation, poverty, education and income all carry nearly equal weights in predicting residential solar adoption rates.

The results also highlight the interrelationship between explanatory variables and indicate that examining combinations of socioeconomic factors using cumulative impact analyses is important for developing a more complete picture of the barriers to solar adoption. The index averaging the census tract percentiles of the CES variables most correlated with PV adoption revealed higher correlation with solar deployment than any of the comprising individual variables. The data also suggest that environmental and pollution burden indicators in the CES methodology (including asthma rates, cardiovascular disease, low birthweight births and traffic density) are statistically significant predictors of solar adoption, albeit slightly less so compared to socioeconomic indicators.

We should emphasize the fact that correlations do not necessarily imply causations. There are numerous confounding demographic and socioeconomic factors that can influence the rates of rooftop solar adoption that were not taken into account in this study. Some of these include degree of home ownership, rural versus urban areas, social diffusion peer effects, and others. We also did not try to account for potential endogeneity effects. We note that home ownership is to some extent reflected in the housing burden CES indicator. We also explored the effects of population density (qualitatively) by arranging census tract data into population density bins and comparing urban versus rural PV adoption rates — we found no significant trends related to the EJ distributional aspects of solar adoption based on population density. The correlations examined in this study, however, do highlight areas where more attention may be needed and where barriers for solar adoption might still exist (e.g. linguistic isolation and education).

Recent studies have indicated that race and ethnicity are important factors for solar adoption in vulnerable communities (Sunter et al., 2019). Research confirms that racial disparities in rooftop PV adoption remain significant even after accounting for income and home-ownership differences (Sunter et al., 2019). Race is no longer used as an indicator in CalEnviroScreen (it was removed after the first iteration of the methodology in order to render CES more practical for state entities prohibited from including racial considerations in their decision-making processes) and, although linguistic isolation can sometimes serve as a proxy for race and ethnicity, the influence of race on solar adoption is not necessarily well represented by this indicator and other population characteristic variables in CES (Liévanos, 2018). The absence of a dedicated race indicator in CalEnviroScreen 3.0 is a limitation, given that CES is used to allocate a quarter of California's carbon Cap-and-Trade funds towards marginalized communities in the state.

We note that the census tract histograms and scatter plots for ozone and $PM_{2.5}$ in Fig. 8 exhibit a peculiar striated pattern. This is an artifact in CES due to the unavailability of hyperlocal data on the census tract level for these two criteria pollutants, which highlights another important limitation in the CES methodology. The low granularity of regional air pollution data means that modeling is generally required to interpolate pollutant concentrations for individual census tracts. Because the models are anchored by a small number of regional air monitoring stations, many census tracts tend to get the same criteria pollutant CES scores, resulting in the striated patterns for ozone and $PM_{2.5}$ seen in Fig. 8. This indicates that data accuracy for these two metrics is not satisfactory at the community level. Collecting hyperlocal pollution data for ozone and $PM_{2.5}$ and achieving higher spatial resolution (ideally on the census tract level) has the potential to considerably improve the CES methodology and in particular the CalEnviroScreen Pollution Burden component.

Geospatial granularity is also an important consideration when analyzing solar data at different geographic aggregation scales. Because clean energy deployment data are not always available on the census tract level, we ran parts of our analysis for data aggregated on the ZIP code level to test for the effects of lower geospatial granularity on the general findings of this paper. We averaged census tract CES scores within zip codes to obtain a score for each zip code area (this introduces some level of uncertainty because zip code and census tract boundaries do not always align). We then re-ranked zip codes based on their calculated CES scores to obtain a new set of CES percentiles and a new set of disadvantaged communities based on zip code percentiles. We found that the lower granularity of zip code data did change the specific values of correlation coefficients but that the overall trends of solar adoption in EJ communities in California were still captured reasonably well and remained statistically significant. This implies that findings of this study should hold for analyses performed on the zip code level as well, suggesting that zip code data may be sufficiently granular to identify broad trends for the purposes of future research.

Conversely, more granular data on the household level would be highly informative and would allow researchers to explore whether trends observed in this work are mostly community-based or mostly household-based. For instance, solar uptake in education-limited households may be similar across all communities, or worse in communities with low educational levels across the board. Pointers in either direction could inform future policy designs and indicate whether PV support policies should be aimed at identifying disadvantaged communities or disadvantaged households in particular.

3.5. Discussion

The results of this study illustrate an important point about residential solar adoption in California: that there are clear distributive and equity impacts of PV support policies (e.g. net energy metering) and that the benefits of residential PV adoption in California are largely accruing within less-disadvantaged communities and bypassing some of the most vulnerable populations in the state. In addition, the data imply that current climate incentives and state investments in clean energy may not be aligned with equity considerations and environmental pollution trends. Indeed, we should flag a potential concern that has already been raised in previous studies: that in some cases climate incentives can actually be detrimental to equity and public health goals because of increased energy burdens on disadvantaged populations through higher energy prices (Simpson and Clifton, 2016), and because of potentially exacerbated local air pollution due to more frequent ramping of fossil fuel peaker power plants to compensate for the intermittent nature of solar power generation. Peaker power plants in California are disproportionately located in EJ communities (Krieger et al., 2016).

These considerations are important, because residential solar carries the potential to not only address energy disparities by lowering electricity bills through net energy metering and feed-in tariffs, but to also bring additional environmental and health co-benefits to populations that are affected by numerous socioeconomic, environmental and health stressors. The somewhat weaker correlation between pollution/environmental indicators and PV adoption does not necessarily imply that California should ignore communities where EJ scores are elevated primarily as a result of environmental burdens. Rather, we would argue that the rationale for directing investments towards those communities would be slightly different, including targeted support for overburdened populations, or achieving health and pollution-reduction cobenefits rather than focusing solely on the climate and socioeconomic benefits of PV adoption. As mentioned earlier, deployment of distributed solar in combination with efficiency and storage in EJ communities can improve resilience and help displace local fossil fuel generation (Krieger et al., 2016). Delayed participation by disadvantaged communities in this process can exacerbate the disparities between them and other populations in the state.

In line with previous findings, our results suggest that economic burdens — such as housing burden and poverty rates — are likely significant barriers to solar adoption. In addition, our breakdown of population characteristic metrics suggests that linguistic isolation and low education levels are also highly anticorrelated with solar adoption. Reversing the trends in solar adoption may therefore require both an increase in financial support for low-income populations as well as strategies to specifically target linguistically isolated communities and those with lower levels of education. Ensuring the participation of low-income and linguistically isolated customers in community solar programs can be challenging, and program designs and subscription policies may need to be adjusted compared to standard community solar models by, for example, encouraging affordable housing facilities to serve as subscribers for their tenants, or by using prepaid subscriptions subsidized through state funding, or investing in increased customer outreach, etc. Various third-party financing mechanisms have also proven successful in recent years. In fact, more than two thirds of the SASH and MASH residential installations to date have been financed through third-party financial models.

Future research may need to address limitations in this study related to social diffusion effects, urbanization levels, degree of household ownership, and the lack of high-resolution air pollution data on the census tract level in CES. Future work should also track the impact and effectiveness of new solar support policies and programs for DACs and look at specific programs or strategies that have been particularly effective at reducing inequalities in certain IOUs territories like PG&E. It would be valuable to utilize household-level data to explore whether trends observed in this study are predominantly community-based or household-based. It would also be valuable to explore the distributive justice landscape of other clean energy technologies such as energy storage and energy efficiency.

4. Conclusions and policy implications

The rooftop solar industry in California has experienced dramatic growth in the past four years. In the context of this accelerating deployment, it is critical to evaluate the impacts of PV incentives in the broader context of climate, environmental, public health and equity goals, and improve these policies to maximize the multiple economic, air quality, environmental justice and community resilience benefits that rooftop PV has to offer. As the solar industry continues to grow and solar-adopting states like California continue to refine their next steps in energy policy, it is important that this development is both inclusive and just in order to maximize this resource potential as well as the number of people that have access to its benefits.

In this paper, we analyzed distributed solar adoption in California in the context of environmental justice communities and the applicability of cumulative impact methodologies such as CalEnviroScreen to climate investments in clean energy technologies. We found significantly lower levels of PV adoption in communities that are disadvantaged and suffer from a combination of socioeconomic, health and environmental burdens. We have shown that without intervention, the solar adoption gap between EJ and other communities will likely continue to increase. This underscores the importance of state programs aimed at reaching disadvantaged communities in California.

The state has already taken steps to correct its course. Cap-and-Trade funding streams have been established for several new programs designed to target EJ populations in the state: the new Solar on Multifamily Affordable Housing program (SOMAH) is funded at substantially higher levels compared to the previous MASH program; a new SASH program for disadvantaged communities (DAC-SASH) will target single family low-income homes located in DACs; and two Green Tariff programs — for DACs and for community solar respectively — will provide electricity bill discounts for low-income customers who live in DACs and for community solar projects located in and serving disadvantaged communities. These programs can provide important incentives for solar growth in EJ communities but are still in their nascent stage. Because net energy metering has been one of the most influential policy drivers in support of rooftop solar adoption in California, it is still unclear whether the new programs will have a significant impact on decreasing inequities in solar access and ensuring that solar co-benefits such as bill savings reach all customers. The effectiveness of the programs should be carefully monitored in the near future and this paper provides a baseline from which to track their efficacy.

Community solar may prove to be an attractive policy instrument for increasing access to solar and reducing solar burdens. Cap-and-Trade funds may ultimately need to be directed towards this sort of solution if individual residential barriers in disadvantaged communities continue to prove challenging. However, community solar may be most viable in urban neighborhoods where significant industrial or commercial rooftop space is available nearby to use for project installations or in more rural EJ areas with readily available land, whereas different policy solutions may be needed in dense urban areas with many apartments and little rooftop space. In such areas, Community Choice Aggregations with carve-outs for LMI customers may be the best option to provide clean energy from resources that are not necessarily located in the vicinity of those neighborhoods.

The results of this analysis may hold policy implications for other non-solar distributed energy resources, including energy efficiency, storage, and demand response (DR) programs. The solar deployment trends examined here highlight the need to design effective incentives for storage and DR while these technologies are still in the early stages of adoption to ensure that their growth does not follow similar inequitable deployment trends. The strategies used to overcome barriers to solar deployment in low-income and disadvantaged communities will likely be effective for other distributed energy technologies, as well as other states and contexts outside of California.

This study also provided insights into the relative influence of various CES indicators on the levels of residential solar adoption. The results confirm the importance of socioeconomic factors such as housing burden, poverty levels and income but also highlight the significance of demographic variables such as linguistic isolation and education, as well as the relevance of health and environmental burden indicators such as traffic pollution, cardiovascular disease and asthma rates. The combination of all these indicators is ultimately important in determining the cumulative barriers to and understanding the drivers behind participation in the adoption of clean energy technologies. Failure to account for these various effects may misdirect efforts to promote environmental health and equity in vulnerable EJ communities that are most in need of regulatory and investment interventions.

For policy makers, our results highlight the value of cumulative impact methodologies like CES. The implications largely rest in the distributive impacts of clean energy technology adoption as a result of energy rate-based compensatory mechanisms and other incentives, and in the question of how to bring the multiple benefits of clean energy technologies to the broadest possible set of customers. The examples that California sets in this regard will hold lessons for other regions in the US in the years to come. While California continues to lead the nation in solar adoption, it should do so by also addressing these important equity issues.

Acknowledgements

The authors are grateful to the Energy Foundation (G-1710-26985) and the 11th Hour Project of the Schmidt Family Foundation (G-1707-57004) for grants in partial support of this research. We thank Naim Darghouth and LBNL for providing the census tract codes for all California PV systems in the Tracking the Sun dataset. We also thank Naim Darghouth, Arjun Makhijani, Joan Casey, Jesse Burkhardt and Annelise Dillon for helpful comments and input on the manuscript draft, as well as feedback from three anonymous reviewers. Any errors remain our own.

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