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ANALYSIS

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Disparities in rooftop photovoltaics deployment in the United States by race and ethnicity

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The rooftop solar industry in the United States has experienced dramatic growth—roughly 50% per year since 2012, along with steadily falling prices. Although the opportunities this affords for clean, reliable power are transformative, the benefits might not accrue to all individuals and communities. Combining the location of existing and potential sites for rooftop photovoltaics (PV) from Google's Project Sunroof and demographic information from the American Community Survey, the relative adoption of rooftop PV is compared across census tracts grouped by racial and ethnic majority. Black- and Hispanic-majority census tracts show on average significantly less rooftop PV installed. This disparity is often attributed to racial and ethnic differences in household income and home ownership. In this study, significant racial disparity remains even after we account for these differences. For the same median household income, black- and Hispanic-majority census tracts have installed less rooftop PV compared with no majority tracts by 69 and 30%, respectively, while white-majority census tracts have installed 21% more. When correcting for home ownership, black- and Hispanic-majority census tracts have installed less rooftop PV compared with no majority tracts by 61 and 45%, respectively, while white-majority census tracts have installed 37% more. The social dispersion effect is also considered. This Analysis reveals the racial and ethnic injustice in rooftop solar participation.

As prices of solar photovoltaics (PV) continue to decline[1], accelerated adoption of solar PV is expected among utilities, businesses and communities[2]. In fact, techno-economic analyses project that PV total annual installed capacity in the United States will amount to 16 GW within the next 5 years given the attractive economic value proposition[3].

Growth to date can be attributed in part to top-down approaches, such as enacted public policies and alternative financing mechanisms, that have gradually led to customers understanding the benefits of solar PV[4]. In a similar vein, bottom-up approaches, such as the social diffusion effect, have been identified as significant drivers in catalysing solar PV adoption[5]. An example of the diffusion effect takes place when a 'seed' customer installs rooftop PV and, by consequence, influences their neighbours to also install solar, creating an adoption chain within a radius of influence[6,7].

However, this expected growth contrasts with current deceleration reports by many distributed solar PV companies across the United States[8], despite historically low PV installation prices[1]. Studies suggest that this can be explained by multiple factors[9], including a potential saturation of medium-to-high-income customers having already adopted rooftop PV[3], and in some instances, a wide disparity in willingness to acquire PV given electric grid price competitiveness[10]. Although reports have elucidated the income distribution of owners[11], sample sizes have been limited, and details on the customer demographics are not reported.

In response, there have been federal and state efforts to encourage low-income participation in rooftop PV. The Renew300 Initiative aims to install 300 MW of solar PV (enough to power 50,000 homes) on federally assisted housing in programmes such as the US Department of Housing and Urban Development's rental housing portfolio, US Department of Agriculture's Office of Rural Development Multi-Family Housing Programs, and rental housing supported by the Low-Income Housing Tax Credit[12]. The US Department of Housing and Urban Development also broadened the applicability of Section 108 Community Development Block Grants to support renewable energy[13]. Several states have developed policies to further include low-income individuals. California has the Solar on Multifamily Affordable Housing Program[14] and New Solar Homes Partnership[15]. Massachusetts' Solar Carve-Out II programme and the Solar Massachusetts Renewable Target programme provide tiered benefits based on income[16]. New York offers Affordable Solar Initiatives and Affordable Solar Predevelopment and Technical Assistance[13]. California, Colorado, New York and Oregon have incorporated low-income carve-outs into their community solar policies[17]. Many states have integrated rooftop solar into their low-income weatherization assistance programmes[13]. Despite the efforts in the United States to encourage participation from low-income communities, those specifically targeting racial and ethnic minorities are still missing.

Distributional energy justice considers both the physically unequal allocation of energy access and associated environment benefits and burdens, as well as the uneven distribution of their associated financial and economic responsibilities. In an international context, distributional energy justice concerns, such as the siting of energy infrastructure and access to low-cost energy services, have been raised. Large-scale, centralized renewable energy projects have been documented in some instances to displace populations or alter ecosystems[18–22]. On the other side of the spectrum, policies aimed at increasing small-scale distributed energy access, such as the ones in Germany through their Energiewende, have resulted in financial burden on lower-income communities, where these are reported to have been paying higher relative shares of their

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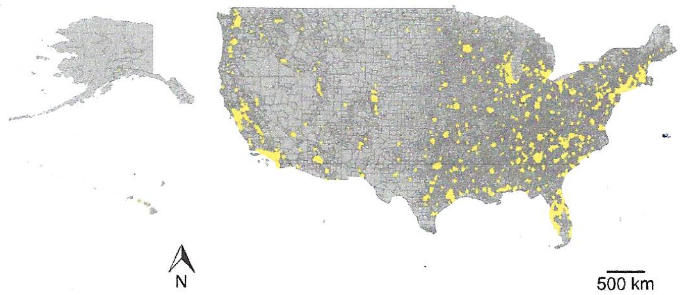

Fig. 1 | Census tracts analysed in the United States for solar rooftop adoption, median household income, home ownership and racial composition. The analysed region (yellow) contains 58% of the national technical potential for rooftop PV annual energy generation.

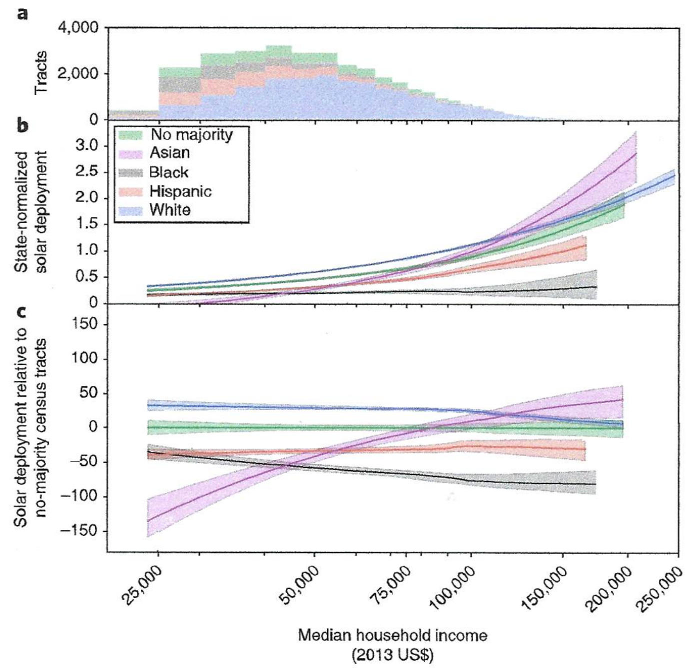

Fig. 2 | Relationship between household income and rooftop PV installation by race and ethnicity. a, Histogram of the distribution of census tracts analysed at intervals of US$5,000. **b,c**, Rooftop PV installations relative to the available rooftop PV potential and normalized by state as a function of the median household income for majority census tracts in absolute values (**b**), and normalized relative to the rooftop PV adoption of no majority census tracts (**c**). Each colour represents a majority race or ethnicity in the census tract. Dark continuous curves represent the results of the LOWESS method applied to all data in each racial and ethnic majority group. Lighter shading represents the 90% CIs based on 1,000 bootstrap replications of each racial and ethnic majority group. Note that the *x* axes are plotted on a base 10 logarithmic scale.

total income for energy costs[20]. Similar examples of solar rooftop PV economic benefits disproportionately advantaging higher-income communities can be found in several locations around the world[20,23].

Furthermore, in instances where societal sectors perceive climate change threats and recognize the importance of low carbon approaches in everyday life activities (for example, clean energy sources, as we posit), the lack of economic resources and property ownership have been stated as main contributors for inaction[24]. These factors therefore constitute an uneven equity scenario for some segments of the population, commonly only grouped by income.

The aim of our study is to understand the energy justice landscape from a distributional perspective (that is, the distribution of access to benefits, such as access to lower-cost electricity, income from feed-in tariffs and avoided costs from tax credits) in small-scale distributed renewable energy systems by evaluating the installation of solar rooftop PV. We hypothesize that PV adoption is not hindered by economic resources nor property ownership only. To test this hypothesis, we analyse solar rooftop PV deployment, correcting for both median household income and property ownership, to elucidate the role of racial and ethnic compositions in detail—a variable that gains relevance in a multi-racial and multi-ethnic society that aims to aggressively deploy clean energy technologies.

To gain insight into the disparity in solar rooftop PV adoption, we combined high-resolution PV rooftop georeferenced maps with census demographics data. We used information on the existence and potential of rooftop PV on more than 60 million buildings across all 50 US states from Google's Project Sunroof (https://www.google.com/get/sunroof/data-explorer/) to quantify the relative rooftop PV deployment. Variations across states, such as available solar resources[25], incentive programmes and policies (http://www.dsireusa.org/), electricity prices[26] and state racial compositions[27], were mitigated by normalizing the rooftop PV adoption by the average solar adoption of all census tracts in each state. To evaluate the social demographic characteristics at the census tract level, median household income and racial composition from the 2009–2013 5-year American Community Survey (ACS)[27] were merged with the Project Sunroof data. Figure 1 shows the geographic coverage of this analysis. We categorized census tracts as majority and strong majority, corresponding to any census tract in which more than 50 or 75%, respectively, of the population self-identified as the same race or ethnicity. Tracts where no single racial or ethnic group comprises more than 50 or 75% of the population are categorized as no majority and no strong majority, respectively. To investigate the role of race and ethnicity, we used the locally weighted scatterplot smoothing (LOWESS) method to fit local relationships between household income and home ownership to rooftop PV adoption for each racial and ethnic majority group.

Of all the challenges in terawatt-scale PV[2], a critical and largely understudied one is that of equity and inclusivity. We posit that additional demographic variables, such as racial composition, can provide social insights into adoption patterns for rooftop PV, and can be used to better target top-down approaches to increase solar deployment and improve energy justice conditions.

Evaluation of racial bias in rooftop PV installations

Household income. The differences in the fitted LOWESS curves denote disparity in the deployment of rooftop PV based on racial composition across different income levels (Fig. 2). Overall, black- and Hispanic-majority census tracts have deployed less rooftop solar than the other census tracts in their state (Fig. 2b), and are disadvantaged on average 69 and 30%, respectively, compared with no majority tracts (Fig. 2c). In contrast, white-majority census tracts show an advantage over no majority census tracts with an increase in rooftop PV adoption of 21% on average. While on average Asian-majority census tracts show a disadvantage of 2%, it is interesting to note that low-income Asian-majority census tracts exhibit a relative disadvantage in rooftop PV adoption, whereas high-income Asian-majority census tracts show a relative advantage compared with no majority tracts. Similar results were found for strong majority communities (Supplementary Fig. 1).

The value of one's income is related to the local cost of living. Using county-level cost-of-living estimates from the Living Wage Calculator[28], we subtracted the local cost of living from the census tract median household income to calculate the local surplus

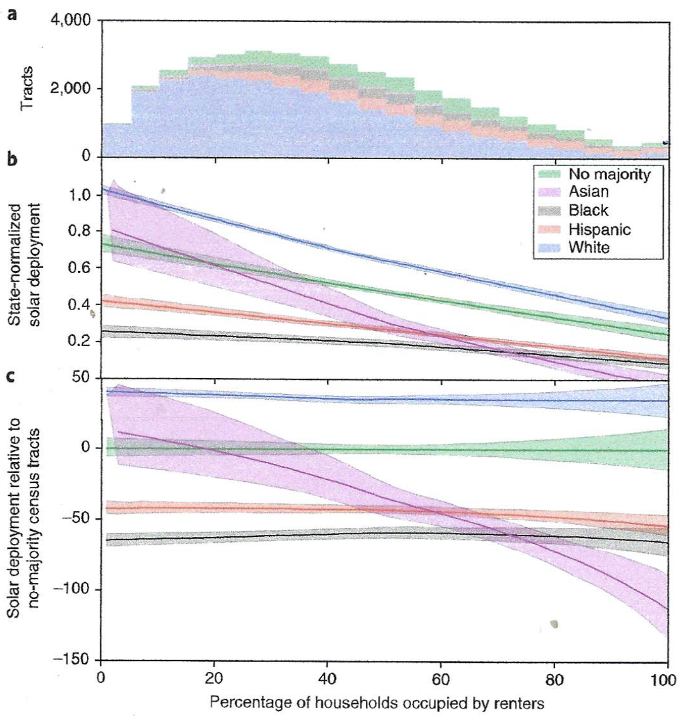

Fig. 3 | Relationship between home ownership and rooftop PV installation by race and ethnicity. **a**, Histogram of the distribution of census tracts analysed at intervals of 5%. **b**,**c**, Rooftop PV installations relative to the available rooftop PV potential and normalized by state as a function of renter-occupied households for majority census tracts in absolute values (**b**), and normalized relative to the rooftop PV adoption of no majority census tracts (**c**). Each colour represents a majority race or ethnicity in the census tract. Dark continuous curves represent the results of the LOWESS method applied to all data in each racial and ethnic majority group. Lighter shading represents the 90% CIs based on 1,000 bootstrap replications of each racial and ethnic majority group.

income. The analysis was repeated using the surplus income, and comparable results were found (Supplementary Fig. 2). While this analysis cannot address one's willingness to pay to install rooftop PV, it provides a proxy for one's ability to pay to install rooftop PV.

Home ownership. People who identify as belonging to a racial or ethnic minority group are disproportionately more likely to rent their home. In 2016, 58% of black and 54% of Hispanic household heads rented their home, compared with only 28% of white household heads[29]. The split-incentive problem for rooftop PV occurs in landlord–tenant relationships[30]. The landlord accepts the risk and up-front cost of rooftop solar, yet the benefits of energy cost savings are reaped by the tenants, often hindering adoption. To determine whether the racial bias seen in Fig. 2 was the result of racial biases in home ownership, we repeated the analysis with the median household income replaced by the percentage of renter-occupied households. Figure 3b shows the expected trend of decreased solar deployment as the percentage of renter-occupied households increases. However, when we considered the solar deployment of each racial and ethnic majority group relative to no majority census tracts, we found uniform racial bias across all percentages of renter occupancy, except for Asian-majority census tracts, as seen in Fig. 3c. Once again, black- and Hispanic-majority census tracts have deployed less rooftop PV than the other census tracts in their state, and are disadvantaged on average 61 and 45%, respectively, compared with

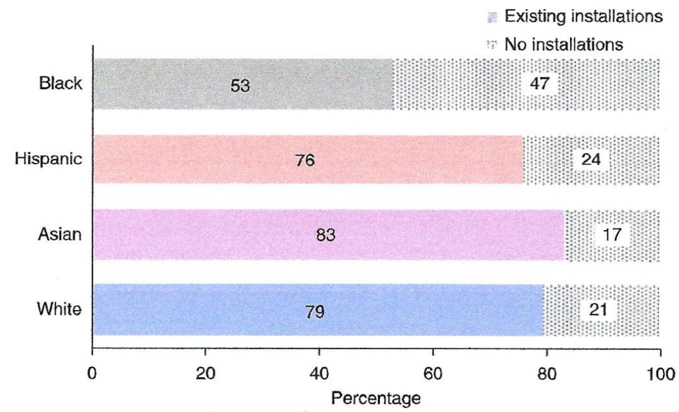

Fig. 4 | Percentages of each census tract with and without existing rooftop photovoltaic installations. In the census tracts listed, at least 50% of the population self-identified as a single race or ethnicity.

no majority tracts (Fig. 3c). White-majority census tracts show an average advantage over no majority census tracts of 37% on average (Fig. 3c).

Social diffusion effect. Communities that lack any rooftop PV installations (also known as 'seed' rooftop PV customers) are prone to a delayed future solar adoption[7]. We found that 47% of black-majority census tracts do not have any existing solar installations, representing in some cases more than double that for the corresponding white-, Asian- and Hispanic- majority census tracts (Fig. 4). The trend was consistent when disaggregated by income decile for both majority and strong majority black census tracts (Supplementary Figs. 3 and 4).

After excluding census tracts without existing rooftop PV installations, we repeated the analysis and found that the rooftop PV deployment for black-majority census tracts increased substantially for those tracts with a median household income below the 2013 national median (US$52,250; ref. [27]). In fact, the 90% confidence interval (CI) for the black-majority census tracts shows greater installation of rooftop PV than the 90% CI for the no majority communities for median household incomes below the national average (Fig. 5c). Within a small portion of the household income range, the 90% CI for the black-majority census tracts shows greater installation of rooftop PV compared with the 90% CI for the white-majority census tracts. In contrast, the Hispanic-majority census tracts showed disparity comparable to that in Fig. 2. Negligible difference can be seen in the results for the Hispanic-majority census tracts regardless of whether the analysis included (Fig. 2b,c) or excluded (Fig. 5b,c) census tracts without existing rooftop PV installations. The trend was similar for strong majority census tracts (Supplementary Fig. 5).

Conclusions

We found racial/ethnic differences in the adoption of rooftop PV, even after accounting for median household income and household ownership. When correcting for median household income, majority black, Hispanic and Asian census tracts showed on average significantly less rooftop PV installation relative to no majority census tracts by 69, 30 and 2%, respectively. In contrast, white-majority census tracts showed on average 21% more rooftop PV deployment across all income levels compared with no majority census tracts. When correcting for household ownership, black- and Hispanic-majority census tracts have installed less rooftop PV compared with no majority tracts by 61 and 45%, respectively, while white-majority census tracts have installed 37% more.

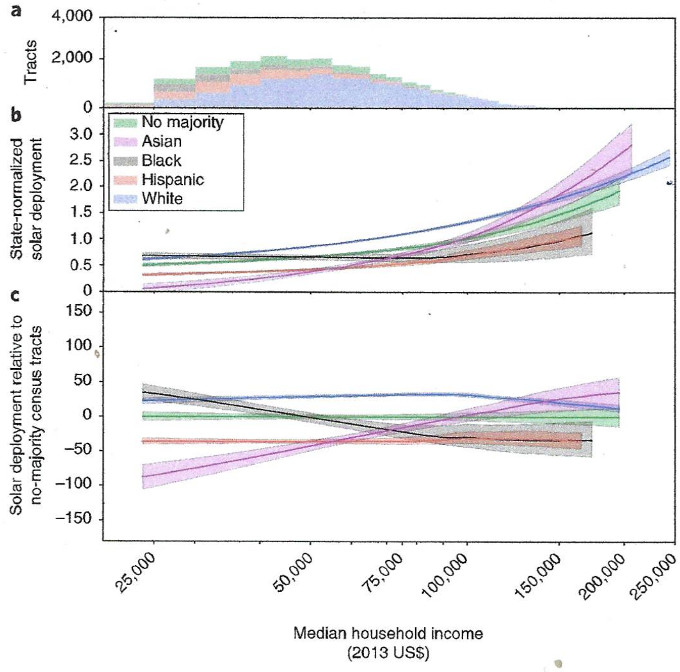

Fig. 5 | Relationship between household income and rooftop PV installation after excluding census tracts without existing rooftop PV installations by race and ethnicity. a, Histogram of the distribution of census tracts analysed at intervals of US$5,000. **b**,**c**, Rooftop PV installations relative to the available rooftop PV potential and normalized by state as a function of the median household income for majority census tracts with existing rooftop PV in absolute values (**b**), and normalized relative to the rooftop adoption of no majority census tracts (**c**). Each colour represents a majority race or ethnicity in the census tract. Dark continuous curves represent the results of the LOWESS method applied to all data in each racial and ethnic majority group. Lighter shading represents the 90% CIs based on 1,000 bootstrap replications of each racial and ethnic majority group. Note that the *x* axes are plotted on a base 10 logarithmic scale.

Additionally, black-majority communities suffer from a disproportional lack of initial deployment, or 'seeding'. In contrast, Hispanic-majority census tracts have more similar seeding patterns to white- and Asian-majority census tracts (Fig. 4), yet deploy significantly less rooftop PV than those census tracts (Figs. 2 and 5). Since rooftop PV adoption is significantly influenced by spatial neighbouring effects, we hypothesize that the Hispanic-majority census tracts may have been undergoing a delayed seeding process, presumably resulting in their observed lower state-normalized rooftop PV deployment levels. Time, social interactions and population group similarities have been found to be intrinsically related in epidemiology studies[31], and propagation behaviours from initial 'seed' groups could similarly apply to rooftop PV propagation. Ultimately, extended time-series rooftop PV adoption data could strengthen an analysis to elucidate the evolution of adoption rates.

In addition, potential low diversity in the renewable energy workforce in terms of race[32] could be hindering proper PV technology diffusion to black and Hispanic communities. The lack of racial diversity is particularly pronounced in management and senior executive positions in solar firms, where in the United States over 80% of these positions are held by white people[33]. While this paper focuses on distributional injustices, the cause for this uneven deployment might be more complex and point to procedural (inclusion of citizens in the decision-making process of accessing energy) injustices, too[23].

The root causes of the differences between black- and Hispanic-majority census tracts (Figs. 2 and 5) are difficult to predict and fully explain, and can also have social-psychological attributions[34] that require further validation. Interestingly, when communities of colour are initially seeded—or have first-hand access to rooftop PV technologies—the deployment significantly increases compared with other racial/ethnic groups for median household income below the national average. These results suggest that appropriately 'seeding' racial and ethnic minority communities may mitigate energy injustice in rooftop PV adoption.

As the rooftop PV industry grows, and states discuss next steps for their energy policies[35], it is important for this development to be inclusive to maximize its potential, and provide equal and just access to the economic benefits of rooftop PV. While the benefits of rooftop PV vary regionally, examples of these benefits include lower cost of electricity, tax credits, feed-in tariffs and rebates. Delayed participation by a community can exacerbate disparity gaps relative to other communities that may increase with time. While this paper provides evidence of the already apparent racial disparity in rooftop PV adoption, without intervention, the disparity gap would probably increase. Our results highlight a more profound adoption characteristic that might shift the focus to more specialized government interventions and adaptive business models to fully achieve the national rooftop PV potential. How well we understand and address the barriers to participation in rooftop PV will determine whether or not the solar industry can achieve racial inclusivity and maximize adoption.

Methods

To gain insight into the disparity in solar rooftop PV adoption, we merged the Project Sunroof data (https://www.google.com/get/sunroof/data-explorer/) and the 2009–2013 5-year ACS[27] by matching census tracts between the two datasets. We used the highly spatially resolved dataset from Project Sunroof (https://www.google.com/get/sunroof/data-explorer/), which contains more than 60 million buildings across all 50 US states and over a range of approximately 4 years starting in 2012, to quantify the number of buildings with existing rooftop PV systems relative to the total number of buildings that could support rooftop PV, according to Project Sunroof's methodology[36], in each census tract. To evaluate the social demographic characteristics, we used tract-level data on the median household income and the percentage of the population that self-identifies as: (1) Asian (no Hispanic origin); (2) black (no Hispanic origin); (3) Hispanic; and (4) white (no Hispanic origin). Other races and ethnicities included in the 2009–2013 ACS were excluded from this analysis given their low percentages. While there is both uncertainty in the reported tract-level values in the 2009–2013 5-year ACS data and variation within the census tract[37], national high-resolution information at the individual household level is not currently available.

Census tracts where (1) Project Sunroof data do not cover at least 95% of the buildings, (2) there are invalid data entries or (3) the median annual household income is below the 2013 poverty threshold of $23,834 for a 4-person household[38] were excluded, leading to a total of 34,156 census tracts used (Fig. 1). Project Sunroof estimates the annual energy generation potential for rooftop PV in these census tracts to be 829 TWh yr^{-1} (https://www.google.com/get/sunroof/data-explorer/). The National Renewable Energy Laboratory estimates the total nationwide technical potential for rooftop PV to be 1,432 TWh yr^{-1} (ref. [39]). Therefore, the region considered in this analysis contains 58% of the national technical potential for rooftop PV.

Census tracts (CTs) were categorized by how well they reach their rooftop PV potential. The number of buildings with installed PV systems in each census tract ($N_{\mathrm{ExistingRooftopPV}}$) was divided by the total number of buildings in that tract (N_{CT}), as shown in equation (1):

$$\mathrm{SolarDeployment}_{\mathrm{CT}} = \frac{N_{\mathrm{ExistingRooftopPV}}}{N_{\mathrm{CT}}} \quad (1)$$

where both the numerator and denominator entries were obtained from the Project Sunroof dataset (https://www.google.com/get/sunroof/data-explorer/), following their detection algorithm and criteria to identify appropriate potential rooftop space for PV deployment[36].

Variations across states, such as available solar resources[25], incentive programmes and policies (http://www.dsireusa.org/), electricity prices[36] and state racial compositions[27], were mitigated by normalizing the census tract solar deployment performance by the population (P)-weighted census tract solar deployment performance average in each state, as shown in equation (2). Hence, any value greater than 1 indicates that the census tract has installed more rooftop PV relative to the state average installation, and the opposite is the case for values less than one:

$$\text{StateNormalizedSolarDeployment}_{\text{CT}} = \frac{\text{SolarDeployment}_{\text{CT}}}{\sum_{\text{CT}_{\text{State}}} \frac{P_{\text{CT}}}{P_{\text{State}}} \text{SolarDeployment}_{\text{CT}}} \quad (2)$$

To investigate the role of race and ethnicity, we categorized census tracts as majority and strong majority, corresponding to any census tract in which more than 50 or 75%, respectively, of the population self-identified as the same race or ethnicity. Each census tract was grouped by the race or ethnicity that the population most self-identified as.

To correct for variations due to income, the median annual household income was plotted against the state-normalized solar deployment for all majority and strong majority census tracts. High variability and a large number of outliers made it difficult to directly observe and compare a relationship between income and solar adoption. To more easily compare the results across different groups, we applied the LOWESS (locally-weighted scatterplot smoothing) method to fit local linear relationships between household income and rooftop PV adoption. The primary advantage of the LOWESS method is that it does not require a specification of a global function that would fit all of the data. The LOWESS method was implemented using the Python package statsmodels[40]. The smoothing parameter, f, was varied between 0.2 and 0.8 and then chosen based on the value of f that minimized the sum of the residuals squared. The selected values of f can be found in Supplementary Tables 1–3. The bootstrap method was applied with 1,000 bootstrap replications for each racial and ethnic group, to establish 90% CIs of the LOWESS method[41]. At increments of US$50 on the median annual household income, the bootstrap replications in both the 5th and 95th percentile were selected and plotted.

Variations due to home ownership and the social diffusion effect were analysed following a similar method. To evaluate the influence of home ownership, we applied the bootstrapped LOWESS method to the fraction of households occupied by renters[29] plotted against the state-normalized census tract solar deployment for each racial and ethnic group (Fig. 3). To explore the influence of the social diffusion effect, the fraction of census tracts with no existing rooftop PV installations was calculated for each racial and ethnic group, both overall (Fig. 4) and by income decile (Supplementary Figs. 3 and 4). We repeated the bootstrapped LOWESS method excluding census tracts without existing rooftop PV installations (Fig. 5 and Supplementary Fig. 5).

Data availability

The data that support the findings of this study are available from Google Project Sunroof (https://www.google.com/get/sunroof/data-explorer/) and the 2009–2013 5-year ACS[27]. The computer codes used for this study are available online at https://github.com/DeborahSunter/Rooftop-PV-Deployment-Disparities.

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D.A.S. and S.C. designed and performed the research, analysed the data and wrote the paper. D.M.K. supervised the research, guided the study and edited the paper.

Competing interests
The authors declare no competing interests.

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