Exploring the potential of non-residential solar to tackle energy injustice

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ABSTRACT

Despite the observed disparities in U.S. residential solar deployment, there is limited insight into whether these disparities exist for the non-residential sector. We use DeepSolar, a comprehensive photovoltaic database constructed with satellite imagery, to assess solar deployment equity based on the U.S. Justice40's disadvantaged community measure. We find that disadvantaged communities have less non-residential solar (-38%), however, this disparity is notably higher for residential solar (-67%). Across-state variations are consistent for residential solar (-81% to -49%), yet highly heterogeneous for non-residential solar (-66% to +34%). Using scenarios to explore the potential for microgrids powered by solar on building rooftops larger than 1,000 square meters, we estimate that 63% of disadvantaged communities could meet at least 20% of annual residential electricity demand. Our research argues for a new focus on non-residential solar as a way to strengthen resilience and accelerate local deployment of clean energy resources to promote energy justice.

INTRODUCTION

The widespread diffusion of Distributed Energy Resources (DERs) is foundational for building a resilient and decarbonized energy system. Deployment of DERs, such as solar photovoltaics (PV) and battery storage, can mitigate grid strain, promote the adoption of electric vehicles, reduce fossil fuel dependence, and can be further coordinated with smart infrastructure – all critical to the ongoing energy transition[1–3]. However, who bears the costs and who reaps the benefits of this transition are key considerations when designing a future energy system that is equitable in its accessibility and distribution of societal benefits and burdens[4,5]. There already are indications that the distribution of solar PV deployment may not always be equitable – for example, previous research has identified sociodemographic disparities in residential rooftop solar adoption[6–9]. Communities with higher proportions of racial and ethnic minorities, lower household incomes, and those designated as vulnerable or disadvantaged, have lower residential solar penetration, giving rise to a gap in solar equity[9,10]. However, whether this same equity gap exists for the

adoption of non-residential solar has remained largely unexplored with few exceptions[7] even though it has the potential to be a driving force in building a just, decarbonized, and reliable future energy system[11].

Non-residential solar, for the purposes of our research, is defined to include all solar installations that are not residential or utility-scale. Therefore, non-residential solar includes installations on commercial or industrial buildings and/or properties such as factories, warehouses, retail stores, or office buildings, as well as community solar systems located on multifamily housing units and installations located on other building types such as educational and government facilities. Such systems are usually larger than residential systems yet smaller than utility-scale, i.e., their direct current (DC) capacity tends to fall within the 10 to 1,000 kW range. Typically, non-residential solar systems are interconnected to the grid via the distribution rather than the transmission network and have the potential to provide benefits to the local grid and surrounding community. Some of the benefits may be in terms of overall net load reductions at the substation level, as non-residential electricity demand accounts for the largest share of U.S. electricity consumption (61%)[12]. Other benefits could be realized through improved population health as the phasing out of carbon-intensive energy generation lowers pollution levels[13]. Non-residential solar can also be coordinated with other DERs like battery storage to increase resilience to disruptive events that trigger demand spikes or damage power infrastructure (e.g., heat waves, wildfires, storms, flooding, etc.)[14]. Concepts such as community microgrid planning, which can impart localized resilience against grid outage events while also reducing everyday energy costs, are gaining traction[15–17]. Distributed electricity generators, including solar installed on residential and non-residential rooftops, are essential components for keeping microgrids running[14,18]. Such community microgrids could provide discounted electricity to low-income households and thereby reduce financial energy burdens in disadvantaged communities[19]. This could accelerate the decarbonization of the residential sector via electrification, by making it financially feasible to shift from cooking and heating with natural gas to electric systems powered by renewables.

To investigate the potential of non-residential solar for ensuring equity in access to renewable and affordable electricity, we ask the following four questions: (1) How equitable is the distribution of solar deployment on non-residential buildings compared to residential buildings across communities in the United States?; (2) How has solar deployment evolved over time?; (3) Which community characteristics are associated with solar deployment?; (4) What are the potential benefits of increased non-residential solar deployment in disadvantaged communities? To answer these questions, we apply a community-level environmental justice measure developed by the U.S. Federal Government: disadvantaged communities[20] (DACs; Justice40). One-third (33%) of the U.S. population live in DACs and approximately 36% of census tracts, including all lands of Federally Recognized Tribes, are classified as disadvantaged. Through its Justice40 initiative, the U.S. government pledges that 40% of the benefits of certain Federal investments will flow to these communities. Census tracts are classified as disadvantaged if they are below an income threshold and are designated as overburdened (due to climate change, energy, health, housing, legacy

pollution, transportation, or water and wastewater-related burdens) or if they are below an education threshold and face workforce development-related burdens. Additionally, all Federally Recognized Tribes are classified as disadvantaged as well as census tracts that are surrounded by disadvantaged communities and are below an income threshold[21].

We find substantial disparities in solar deployment between DACs and non-DACs. This solar equity gap is 77% larger for the residential sector compared to the non-residential sector, and the size of this gap is highly heterogeneous across states for the non-residential sector. During our entire observation period (2006-2016; 2022) the absolute gap widened every year and the overall percentage difference stayed within a range of 45-56% fewer installations in DACs than in non-DACs. In terms of census tract characteristics, non-residential solar deployment is associated with higher solar irradiance, a larger population, lower population density, more land area, and an increased number of particularly large buildings. Finally, we explore the potential of deploying solar on available rooftop space of large buildings as part of community microgrids and we find that 63% of disadvantaged census tracts can meet at least 20% of annual residential electricity demand through rooftop solar installations on buildings with footprints larger than 1,000 square meters. Our results suggest that encouraging more non-residential solar deployment using targeted policy initiatives to ensure that this resource is shared by the community may be an effective lever for tackling energy injustice.

MAIN TEXT

The solar equity gap

[Figure 1]

We first compare relative percentage differences in non-residential, residential, and combined solar deployment across disadvantaged communities (DACs) and non-disadvantaged communities (non-DACs) (Fig. 1). We find that non-residential solar deployment is 38% lower in DACs as compared to non-DACs, which can be broken down into the number of systems (36% lower) and average system size (3% lower). In contrast, residential solar deployment is much more disparate: it is 67% lower in DACs than in non-DACs, i.e., the solar equity gap is 77% larger for the residential sector. Similar to the non-residential sector, this gap is mostly due to fewer buildings with solar installations rather than differences in system size. Combining residential and non-residential solar deployment, we find an equity gap of 56%. This gap is decomposed into 62% fewer buildings with solar installations and 17% larger systems in DACs. The combined number of buildings with solar installations closely aligns with the residential sector because most buildings (94%) are classified as residential. The large difference between DACs and non-DACs in combined system size is driven by the larger share of non-residential solar installations within DACs.

To investigate whether the non-residential equity gap stems from variations in building use types between DACs and non-DACs we analyzed solar deployment on various building types including retail chains, warehouses, banks, hospitals, fire stations, factories, and educational facilities (Supplementary Note 2). We observe an average equity gap of -29% across these building types, which suggests that differences in building use cannot solely explain the observed non-residential equity gap.

State-level variation of the solar equity gap

[Figure 2]

We next analyze state-level variation in the solar equity gap displayed as the relative percentage difference in solar deployment between DACs and non-DACs (Fig. 2). We focus on states with at least 2,000 non-residential solar installations. The solar equity gap in the non-residential sector varies strongly across states: Pennsylvania has the largest gap with 66% less solar in DACs, whereas Utah and Hawaii have no equity gap. In fact, non-residential solar deployment in these states is higher in DACs than in non-DACs, which can be explained by observed variables (Supplementary Note 4 and Supplementary Table 6). The residential sector is much more homogenous with the equity gap varying between 81% in New York and 49% in Missouri. The size of residential and non-residential equity gaps are not strongly related – a large residential gap is not indicative of a large non-residential gap and vice versa. Finally, the combined equity gap

ranges from -70% in Pennsylvania (largest) to -34% in Missouri (smallest). Our findings suggest that non-residential solar deployment may be more sensitive to state-specific characteristics than residential solar.

Temporal trends in solar deployment and the solar equity gap

[Figure 3]

Against the backdrop of falling prices for solar photovoltaic panels and extensive government subsidies[22], solar deployment experienced strong growth over the last 16 years (Fig. 3). Starting at a low base in 2006, solar deployment increased rapidly thereafter with a compounded average growth rate (CAGR) of more than 50% until 2011. Initially, deployment was highest in the non-residential sector, which dominated deployment in non-DACs until 2014 and which remained the dominant sector in DACs throughout our observation period. Between 2011 and 2016, the residential sector grew substantially with CAGRs of 41% in non-DACs and 50% in DACs, as compared to CAGRs of approximately 20% for non-residential solar across both community types. The annualized growth rate was 15% for the non-residential and 18% for the residential sector between 2016 and 2022, leading to more than a doubling of deployed capacity in this most recent period.

This strong growth of solar deployment was paralleled by only small changes in the relative percentage differences between DACs and non-DACs. In 2006, solar deployment in DACs was 48% lower than in non-DACs, and by 2022 this gap had grown to 56%. While the gap was always considerably larger in the residential sector, it has decreased from its peak of 80% in 2008 to 67% in 2022. This may reflect the effectiveness of policy interventions that target low and medium-income households[23]. In contrast, the non-residential gap increased from 24% in 2006 to 38% in 2022.

Drivers of solar deployment

To explore factors related to solar deployment, we fit negative binomial count regression models that use census tract characteristics and policy interventions to explain the number of buildings with solar installations. Our focus lies on installation count rather than footprint size because the equity gap is primarily driven by differences in the number of installed systems.

[Table 1]

The disadvantaged community indicator is negative and highly significant for both sectors, indicating that the independent variables do not fully explain the equity gap. Solar irradiance — measured as average annual Global Horizontal Irradiance (GHI) — is positively associated with solar deployment for both sectors, although only statistically significant (i.e., p-value <0.05) for

the residential sector. Population is positively associated, whereas population density is negatively associated, reflecting that deployment is generally higher in more populated census tracts but not in high-density areas such as urban centers. Additionally, census tract area is positively associated with non-residential deployment while negatively associated with residential deployment. We also find that electricity rates are positively associated with solar deployment in general, as the profitability of solar investments increases with rising electricity rates. We further utilize building-level assessments of footprint size and estimate separate coefficients for the number of buildings in six groups that range from buildings with footprints below 50 square meters to buildings with footprints larger than 1,000 square meters. We observe a strong association between residential solar deployment and the number of buildings with footprints between 100 and 300 square meters – corresponding to the approximate size range of a single-family home. Non-residential solar installations have the strongest correlation with the number of buildings with much larger footprints, such as industrial plants, retail malls, and large warehouses. Furthermore, we controlled for two types of policy interventions: count of regulatory policies such as interconnection, net metering, and renewable portfolio standards and count of financial incentives such as tax benefits, feed-in tariffs, and programs for energy credits, grants, rebates, and financing. While both types of policy interventions are positively associated with non-residential and residential solar deployment, financial incentives are more strongly associated with non-residential deployment. This likely reflects the effectiveness of rebates, solar renewable energy credits, and tax benefits for encouraging non-residential solar[24,25]. However, we only analyze correlations, thus, our results should not be interpreted causally.

Non-residential solar potential in disadvantaged communities

To provide a high-level estimate of non-residential solar potential in disadvantaged communities, we analyze available rooftop space on buildings with footprints that are larger than 1,000 square meters (henceforth *large buildings*; see Supplementary Figure 6 for illustrative aerial images of such buildings). Specifically, we calculate the cumulative footprint of such large buildings at the census tract level and derive solar potential under various scenarios (Fig. 4). Our focus is on large buildings because they are highly associated with existing non-residential solar deployment and their rooftops often allow for the installation of high-capacity solar systems, potentially enabling economies of scale in project coordination as well as system installation and maintenance. Such solar systems could benefit residents indirectly by reducing net electric load behind the substation, or directly, if microgrids are constructed to supply low-income and renter populations with discounted solar electricity.

The cumulative footprint of large buildings exceeds 30,000 square meters in most communities. Typically only a fraction of a building's rooftop can be covered with solar panels due to HVAC systems, limited solar irradiance (e.g., due to shading and roof tilt), roof weight capacity, as well as other factors. Empirically, the footprint of non-residential solar installations on large buildings ranges from 5% (25th percentile) to 29% (75th percentile), with an average of 20% of the building's

footprint. However, this may not reflect the maximum solar potential of these buildings' rooftops since net metering policies incentivize building owners to limit system size to match their electricity demand. We distinguish between three scenarios for the fraction of large building footprints feasible for solar deployment: 10%, 25%, and 40%. We assume 200 W DC solar system capacity per square meter and retrieve monthly solar generation potential (kWh AC per kW DC) for each census tract. We then compare solar generation potential to residential household electricity demand[26,27], which we observe for each state and month, and find that many DACs have sufficient space on large buildings to deploy substantial solar capacity. Supplementary Note 7 details our assessment approach and discusses the main analysis components. At a footprint utilization rate of 25% (10%; 40%), we find that 63% (29%; 77%) of DACs have the potential to deploy enough solar generation capacity on large buildings to meet more than 20% of annual residential electricity demand. This potential-to-demand ratio tends to be highest in spring and lowest in winter — for example, a system that supplies 20% of annual electricity demand would on average supply 30% in May, while only supplying 13% in January. With regards to geographic variation, solar electricity generation potential is highest in southwestern states such as New Mexico, Arizona, and Nevada and lowest in northern states such as Alaska, Washington, and Oregon[28]. However, we find that solar investments can be financially attractive in some states with comparatively low solar resources such as Alaska, New York, New Hampshire, and Vermont because of high residential electricity rates. Levelized cost of electricity (LCOE) from non-residential solar PV systems range from 6.4 cents per kWh in New Mexico to 10.9 cents per kWh in Alaska, whereas residential electricity rates range from 7.9 cents per kWh in Maine to 37.4 cents per kWh in Hawaii. For 93% of disadvantaged communities, LCOE from non-residential solar PV systems are below residential electricity rates (Supplementary Note 8).

However, solar PV systems should ideally be coupled with appropriate battery storage to match electricity generation, which is highest during afternoon hours, with demand, which typically peaks in the evening. Such batteries may also benefit communities during power outages or planned interruptions such as Public Safety Power Shutdown (PSPS) events, especially if the batteries can be utilized to power critical infrastructure such as medical facilities, fire and police stations, as well as local supermarkets and community centers[19]. A typical battery with 600W storage capacity per kW of solar PV capacity would increase total system cost by 50% and would increase LCOE by 4 cents per kWh on average (Supplementary Note 8).

[Figure 4]

DISCUSSION

Our research reveals solar equity gaps in both non-residential and residential sectors, although this gap is markedly less pronounced for the non-residential sector. However, when examining the

solar equity gap per state, there are substantially higher levels of heterogeneity in non-residential solar compared to residential solar. Upon further exploration, we found that certain community characteristics, such as population, area, and building footprint size, as well as policy interventions, are associated with non-residential solar deployment. We then explored the potential of non-residential rooftop solar deployed on large buildings and found that 63% of disadvantaged communities have the potential to meet at least 20% of annual residential electricity demand. These envisioned community solar installations would provide additional benefits such as strengthening local distribution grid resiliency and decreasing the need for fossil fuel-powered peaker plants, which are often sited in or nearby disadvantaged communities[29].

Given that installing residential solar is often only feasible for certain subsets of the population, namely those who live in owner-occupied single-family homes, policies that promote residential solar may be less effective in closing the equity gap as they must also contend with existing inequalities in income, housing, health, energy access, as well as known disparities in solar adoption related to race and ethnicity[9]. This might explain why a large solar equity gap remains in the residential sector despite various incentive programs targeting low and medium-income households. While the installation of solar systems on non-residential buildings may also require alignment of various stakeholders, such as real-estate developers, owners, tenants, and facility managers, non-residential systems tend to be quite large and the associated economies of scale could prove advantageous. Therefore, we expect some of the adoption-related obstacles to be comparatively smaller – or at least different – in the non-residential context, suggesting non-residential solar deployment as an additional and to date relatively unexplored avenue for promoting energy justice and benefitting surrounding communities through access to renewable energy.

Local populations can benefit from non-residential solar deployment because it improves the resilience of non-residential buildings to power outages, which can help preserve access to important services (e.g., educational, medical, and government facilities) and goods (e.g., grocery and hardware stores). Furthermore, non-residential solar can reduce the net load at the substation level, hence reducing the burdens on electricity distribution infrastructure and provide benefits to residential households in terms of increased grid resilience. Non-residential solar could also be integrated into community microgrids and directly supply nearby residential homes with clean and low-cost electricity. Through community solar subscriptions, households that may not be able to install a solar system on their home could reap the bill-stability and energy-cost-reduction benefits that are enjoyed by solar adopters. When paired with sufficient battery storage capacity, such integrated systems could prove particularly valuable during power supply interruptions at the transmission level, as they could have the potential to enable communities to be electricity self-sufficient for a limited time. This could mitigate some of the negative effects of unplanned outages and planned shutoffs, making them less disruptive for communities. This partial self-sufficiency could in turn provide additional benefits, such as enabling utilities to lower the risk threshold for

triggering Public Safety Power Shutoffs, which could reduce wildfire risk without leaving communities in the dark.

To promote microgrid development, new approaches may be needed to lower structural and technical barriers and encourage the sharing of locally generated electricity within communities. For example, policies such as feed-in-tariffs could encourage companies to install large solar systems that utilize all available rooftop space. In addition, market-based mechanisms like time-varying compensation could encourage the deployment of battery storage systems that enable the matching of electricity feed-in with local demand patterns. Further incentives may be needed to facilitate the installation of high-capacity battery systems that are capable of supplying communities during large power outages of long duration, but such collective backup systems are economically much more viable than individual solutions[27]. Building codes for commercial buildings could also be updated so that all new construction are required to host, or at least be capable of hosting, sizable rooftop solar systems and on-site storage. In addition to policies and incentives targeted towards non-residential buildings, distribution infrastructure will need to be upgraded to enable microgrid deployment at scale. While our research suggests that these infrastructure upgrades should be targeted towards disadvantaged communities, which are more vulnerable to outage events[30,31], any new development should be constructed in a way that makes it "microgrid ready". To this end, the passage of the Inflation Reduction Act[32] has already made progress in lowering microgrid costs through tax credits for solar, storage, and microgrid controllers which will help enable the potential of non-residential solar to be realized in the future. From a non-governmental perspective, one promising concept could be to evaluate the environmental, social and corporate governance (ESG) performance of large companies based on whether their clean energy assets create benefits to local communities. Asset managers could encourage such corporate social responsibility actions by including them in the assessment frameworks that guide their investment decisions.

Future work can build upon our research in multiple ways. First, we focused on disadvantaged communities, as defined by the Justice40 initiative, and it could be important to understand whether similar or perhaps different disparities in solar deployment are found using other community vulnerability measures, both for the U.S. and elsewhere. Second, the factors that determine the disadvantaged community categorization vary over time and it may be that some communities that are considered disadvantaged today would not have been considered disadvantaged throughout our observation period or vice versa. Therefore, it would be interesting to analyze how the factors that identify a community as disadvantaged have evolved and how such temporal variation affects the equity gap. Third, due to data availability, we are currently unable to observe annual changes in solar deployment for the period between 2016 and 2022. Evaluating how disparities evolved throughout that period, which includes the COVID-19 pandemic, could provide insight into how globally disruptive events impact solar deployment patterns. Fourth, while we explore correlations between policy interventions and solar deployment, due to data

limitations, we were unable to identify causal effects. Understanding the causal mechanisms, and what policies are most effective in promoting non-residential solar adoption and in what context, could prove critical for guiding future policy design that mitigates energy injustice. Finally, our scenario assessment indicates substantial non-residential solar potential in disadvantaged communities, and future research could further explore the feasibility of solar on large buildings and propose guidance for updating building codes to ensure that all new construction is "microgrid-ready".

METHODS

Data sources

To enable our main analysis we extracted and combined data from five distinct sources: (1) rooftop solar installations and the classification of buildings with solar installations into the residential vs. non-residential category are included in the DeepSolar database[33–35]. This database was constructed by applying computer vision techniques to satellite images to identify solar installations over time, estimate their footprint size, and classify the associated building type across the United States. (2) Similarly, Microsoft's Open Buildings dataset[36], which we used to analyze the distribution of building footprints across census tracts, is also based on an application of computer vision techniques to aerial imagery. (3) The classification of census tracts into disadvantaged and non-disadvantaged communities as well as population and area information are provided by the U.S. Council on Environmental Quality in their Climate and Environmental Justice dataset[37]. (4) Geospatial patterns of solar irradiance and electricity rates were extracted through an API from the National Renewable Energy Laboratory (NREL)[38,39]. (5) Finally, we constructed features about policy interventions based on information from the Database for State Incentives for Renewables & Efficiency (DSIRE)[40].

Furthermore, for the robustness checks that we present in the Supplementary Information, we utilized Berkeley Lab's "Tracking the Sun" (TTS) dataset of solar installations[41] in combination with a crosswalk mapping from ZIP codes to U.S. census tracts that is provided by the Department of Housing and Urban Development[42]. For a subset of census tracts in California, the Berkeley Lab provided us with solar deployment data at census tract level, which enabled a direct comparison of results based on DeepSolar and TTS. To analyze disparities in solar deployment by building use type we employed both publicly available data and data derived from public sources. We further utilized grid topology data from Pacific Gas and Electric (PG&E), an investor owned utility from California, to validate our solar potential assessment.

Update of DeepSolar to include 2022 deployment

We updated the DeepSolar database, which previously contained solar deployment data from 2006 to mid-2017, to include new solar deployment information based on aerial images from 2022. In addition to extending the temporal scope of the DeepSolar database, we also expanded its

geographic scope, which now includes all 50 states and the District of Columbia. Similar to the original DeepSolar framework, first we leverage an image classification model to classify whether an image contains a solar panel or not. Second, for images predicted to contain solar, we leverage a semantic segmentation model to further segment the area of solar panels and estimate their sizes. We use Vision Transformer (ViT)[43] as the image classification model and SegFormer[44] as the semantic segmentation model, both of which are trained in a fully-supervised way.

We deploy the framework to approximately 230 million aerial images spanning across the entire United States, resulting in a dataset that reflects comprehensive information regarding photovoltaic installations in the country up to 2022. In this 2022 update we identified a total of 2.3 million buildings with solar installations compared to a total of 927,000 buildings with solar installations in mid-2017. We convert the footprint area of identified solar systems into capacity estimates based on the assumption that one square meter translates into 200W DC capacity. This is based on the efficiency of solar modules, which improved from 15% to 20% and above for commercial wafer-based silicon modules over the last decade[45] and considers that panels in the U.S. should be tilted by approximately 30 to 40 degrees to maximize generation potential[46], therefore their surface area slightly exceeds their footprint.

Descriptive analysis of disparities in solar deployment

We analyze solar deployment on U.S. census tract level and compare deployment in DACs with that in non-DACs based on differences in means. We calculate 95% confidence intervals by applying a bootstrapping method, that is, we resample the dataset 100,000 times and use the 2.5% and 97.5% quantiles of the empirical distribution of sample means as lower and upper bounds. We quantify both absolute and relative magnitude of disparities in solar deployment, which we refer to as the solar equity gap (SEG), defined as follows:

$$SEG_{absolute} = \mu_{non\text{-}DAC} - \mu_{DAC} \quad (1)$$

$$SEG_{relative} = \left(\frac{\mu_{DAC}}{\mu_{non-DAC}} - 1\right) * 100 \quad (2)$$

Here μ refers to the mean of the quantity of interest, including the number of buildings with solar installations, average capacity per solar installation, or their combination – cumulative capacity of all solar-installations.

To confirm the robustness of our results against potential biases in the DeepSolar dataset, we recreated our analysis of disparities in non-residential and residential solar deployment on the "Tracking the Sun" (TTS) dataset from the Berkeley Lab (Supplementary Note 1). This includes a comparison of all 27 states that are covered in TTS, for which we apply a ZIP code to census tract crosswalk because TTS data are published at ZIP code level, as well as a comparison that is based on 6,225 census tracts from California, for which the TTS team provided us with

observations at census tract level. We broadly confirm that relative differences between the non-residential and residential equity gaps are consistent across datasets.

We further assess whether a solar equity gap exists for specific building use types. We find an average equity gap of 28.5% across analyzed building types, which constitutes a substantial difference, albeit being smaller than the overall non-residential gap of 38%. Therefore, we conclude that disparities in non-residential solar deployment not only result from differences in building use types. Additionally, we tested whether our findings are robust to alternative measures of solar deployment. We analyzed disparities in solar deployment in relation to the number of buildings and the total building footprint area at census tract level (Supplementary Note 6). We observe a gap of 44% between DACs and non-DACs in terms of the share of buildings with solar installations and a gap of 36% in terms of the solar footprint as a fraction of total building footprint area (Supplementary Figure 6). When controlling for observed variables, we find that the disadvantaged communities indicator is consistently negative and statistically significant at the 1% level (Supplementary Table 9). This further supports that the census tract level differences in the number of buildings or available rooftop area are not driving the observed equity gap.

Count regression analysis

We estimate negative binomial regression models of installation count on census tract level. The negative binomial distribution models a sequence of independent Bernoulli trials, where each trial succeeds with probability p and fails with probability 1-p. The sequence is observed until the r^{th} success and the random number of failures, X, which occur before the r^{th} success follow a negative ninomial distribution with the following probability mass function:

$$P(X = k) = \frac{k + r - 1}{k}(1 - p)^k p^r \quad (3)$$

The negative binomial distribution can also be parameterized in terms of its mean μ and variance σ^2, with $p = \frac{\mu}{\sigma^2}$ and $r = \frac{\mu^2}{\sigma^2 - \mu}$.

Our focus lies on modeling $\hat{\mu}_i$, i.e., the expected number of buildings with solar installations within census tract i:

$$\hat{\mu}_i = e^{(\alpha_{[state]} + \beta X_i)} \quad (4)$$

Here, $\alpha_{[state]}$ is a state-level fixed effect and β is a vector of regression coefficients for the X_i observed independent variables. Residential and non-residential solar deployment are modeled separately and all independent variables are scaled to lie between zero (for the minimum observed value) and one (for the maximum observed value). Therefore, the exponentiated coefficients quantify how much more solar installations are expected when the respective variable is at its maximum than when it is at its minimum.

To confirm the robustness of our coefficient estimates against model and covariate choices, we test various alternative model specifications (Supplementary Notes 4 & 5). First, we compare our negative binomial models to Poisson models and find that negative binomial models fit the data significantly better (likelihood ratio test yields p-value < 0.001) (Supplementary Table 3). Second, we compare our main specification to five alternative specifications, which include different variables and fixed effects (Supplementary Tables 4 & 5). We thereby confirm that the disadvantaged community indicator is negative and statistically significant (p-value < 0.001) across all tested specifications. Third, we analyze the fixed effects of a model with state and community type fixed effects, which enables us to quantify the portion of the equity gap that is unexplained by observed variables at state level (Supplementary Table 6). For most states we find that the equity gap is not fully explained by observed variables. Fourth, we analyze the association between solar PV deployment and selected sociodemographic characteristics of census tracts (Supplementary Note 5 and Supplementary Tables 7 & 8).

Assessment of solar potential in disadvantaged communities

Our scenario assessment of non-residential solar potential in disadvantaged communities is based on a comparison of non-residential solar generation potential with residential electricity demand for each disadvantaged community. To assess solar generation potential, we estimate non-residential solar capacity potential (kW DC) based on available rooftop area of large buildings (i.e., buildings with a footprint of 1,000 square meters or larger) and monthly solar resources (kWh AC per kW DC). The approach is detailed in Supplementary Note 7. We assess the financial viability of microgrids powered by non-residential solar systems by comparing levelized cost of electricity (LCOE) with prevalent residential electricity rates. LCOE are calculated for standalone solar PV systems and for systems that combine PV with battery storage (Supplementary Note 8). Since we do not have access to grid topology data for the entire United States, we make the simplifying assumption that electricity generation and demand is aggregated at census tract level and there is no pooling of capacity across tracts. We utilize grid topology data from California's investor-owned utility Pacific Gas & Electric (PG & E) to show that this is usually a conservative assumption because most substations serve several census tracts, which creates pooling benefits (Supplementary Note 9).

DATA AVAILABILITY STATEMENT

The complete data analyzed in the current study are not publicly available due to ethical restrictions and the privacy of individual homeowners. However, de-identified versions of the data are made available through the Open Science Framework at https://osf.io/a7n3j/?view_only=d91d76a4946e45c6bcf3237a45b32d15.

CODE AVAILABILITY STATEMENT

The code that is used for data processing, model implementation, and result visualization is made available through the Open Science Framework at https://osf.io/a7n3j/?view_only=d91d76a4946e45c6bcf3237a45b32d15.

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Author contributions

M.W., C.Z., J.F., D.N., A.M., and R.R. conceptualized and designed the research; M.W. performed the research and analyzed the data; R.P. and Z.W. constructed the main dataset; M.W. and C.Z. wrote the initial paper draft. All authors edited and revised the paper. A.M. and R.R. provided funding acquisition support for the research.

Competing interests

The authors declare no competing interests.

Tables

	Model 1: non-residential	**Model 2: residential**
Independent variables	Coefficient [95% confidence interval] (clustered standard error; t-statistic; P value)	Coefficient [95% confidence interval] (clustered standard error; t-statistic; P value)
Disadvantaged community indicator	-0.2 [-0.28; -0.12] (0.04; -4.91; <0.001)	-0.45 [-0.52; -0.38] (0.04; -12.08; <0.001)
Solar irradiance (avg. GHI)	0.97 [-0.32; 2.27] (0.66; 1.48; 0.14)	2.15 [0.16; 4.14] (1.02; 2.11; 0.034)
Population (log)	0.91 [0.49; 1.33] (0.21; 4.25; <0.001)	5.95 [5.03; 6.87] (0.47; 12.69; <0.001)
Population density	-2.29 [-7.08; 2.51] (2.45; -0.94; 0.349)	-23.56 [-30.81; -16.31] (3.7; -6.37; <0.001)
Area (log)	1.67 [1.05; 2.29] (0.32; 5.26; <0.001)	-1.7 [-2.35; -1.06] (0.33; -5.21; <0.001)
Electricity rate	2.85 [0.31; 5.4] (1.3; 2.2; 0.028)	10.55 [8; 13.09] (1.3; 8.13; <0.001)
Number of buildings (log) with footprint in square meters …		
… below 50	-0.18 [-0.58; 0.23] (0.21; -0.86; 0.388)	-0.24 [-0.83; 0.35] (0.3; -0.8; 0.421)
… between 50 and 100	1.07 [0.68; 1.47] (0.2; 5.37; <0.001)	-0.64 [-1.19; -0.1] (0.28; -2.3; 0.021)

… between 100 and 300	-1.43 [-1.9; -0.96] (0.24; -5.97; <0.001)	6.18 [5.49; 6.88] (0.36; 17.36; <0.001)
… between 300 and 500	1.71 [1.24; 2.17] (0.24; 7.17; <0.001)	1.39 [0.65; 2.14] (0.38; 3.65; <0.001)
… between 500 and 1,000	1 [0.43; 1.57] (0.29; 3.44; <0.001)	-0.03 [-0.24; 0.18] (0.11; -0.31; 0.758)
… larger 1,000	2.55 [2.24; 2.86] (0.16; 15.95; <0.001)	-0.71 [-0.94; -0.48] (0.12; -6.12; <0.001)
Number (log) of solar regulatory policies	4.92 [1.81; 8.03] (1.59; 3.1; 0.002)	4.01 [1.93; 6.09] (1.06; 3.78; <0.001)
Number (log) of solar financial incentives	4.55 [2.59; 6.51] (1; 4.55; <0.001)	2.71 [1.37; 4.06] (0.68; 3.96; <0.001)
Fixed effects	state	state
Observations	72,143	72,143
Pseudo R2	0.15	0.18
BIC	222,176	478,949
Overdispersion parameter	1.27	1.69

Table 1: Negative binomial regression results quantifying the association of census tract characteristics and policy interventions with solar deployment. Dependent variables are the number of buildings with solar installations that are classified as non-residential (Model 1) and residential (Model 2). Both models include state-level fixed effects and standard errors are clustered at the state-level. All independent variables are normalized to the [0,1] interval so the coefficients represent the difference in effect size when the corresponding variable is at its maximum (coded as 1) vs. minimum (coded as 0). Included electricity rates as well as regulatory policy and financial incentive information vary for the non-residential vs. residential model (see Supplementary Note 3 for summary statistics of the included variables). A total of 596 census tracts (0.8% of all census tracts) are dropped because we did not observe all explanatory variables (590 census tracts) or for lack of within-state heterogeneity (6 census tracts from Alaska). P-values are based on a two-sided t-test.

Figure Legends/Captions

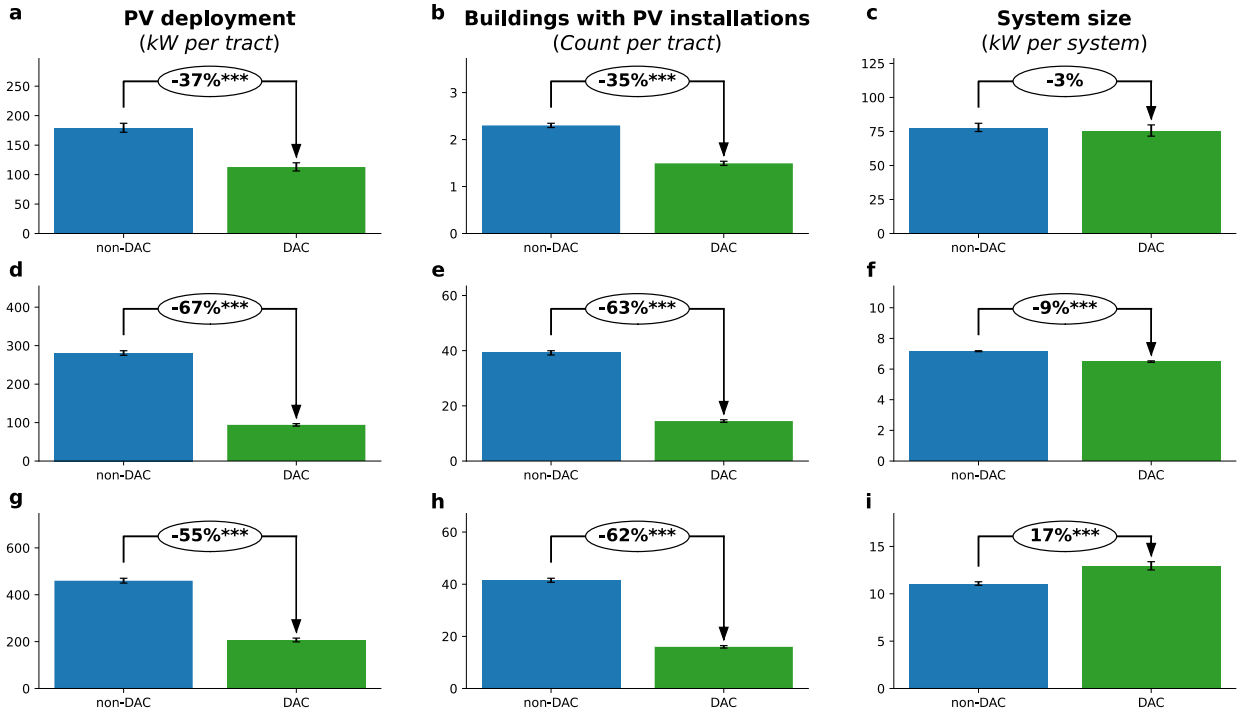

Fig. 1: Disparities in non-residential and residential solar deployment. The solar equity gap for non-residential (**a-c**), residential (**d-f**), and combined (**g-i**) solar resources at the community level for the United States. The equity gap is the percentage difference in means between Disadvantaged Communities (DAC) and non-Disadvantaged Communities (non-DAC) identified by the U.S. government's Justice40 initiative at the U.S. census tract level. We analyze solar deployment for 72,739 census tracts, out of these 26,372 (36%) are classified as disadvantaged, and 46,367 (64%) are classified as not disadvantaged. The average (mean) values across census tracts are displayed as vertical bars and 95% confidence intervals estimated via bootstrapping are indicated by black error bars. Significance levels are * p<0.05, **p<0.01, and ***p<0.001 based on two-sided hypothesis tests of difference in means.

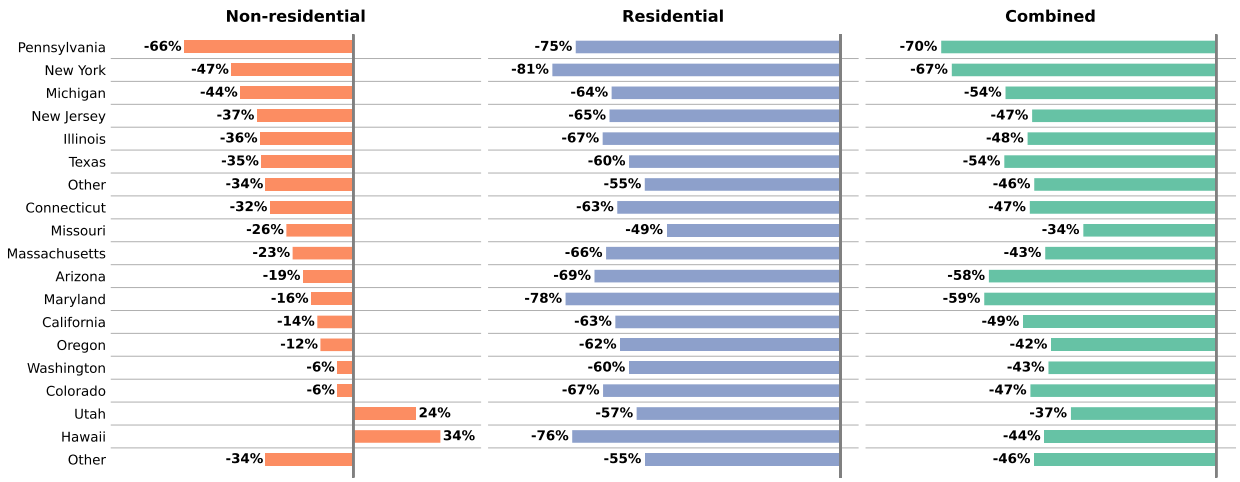

Fig. 2: State-level variation of the solar equity gap. Disparities in non-residential, residential, and combined solar resources for communities by state. All states that have less than 2,000 non-residential solar installations are aggregated into "Other". The equity gap is defined as the percentage difference in solar deployment (kW solar PV capacity per census tract) between Disadvantaged Communities (DAC) and non-Disadvantaged Communities (non-DAC) identified by the U.S. government's Justice40 initiative. We analyze solar deployment for 72,739 census tracts, out of these 26,372 (36%) are classified as disadvantaged, and 46,367 (64%) are classified as not disadvantaged.

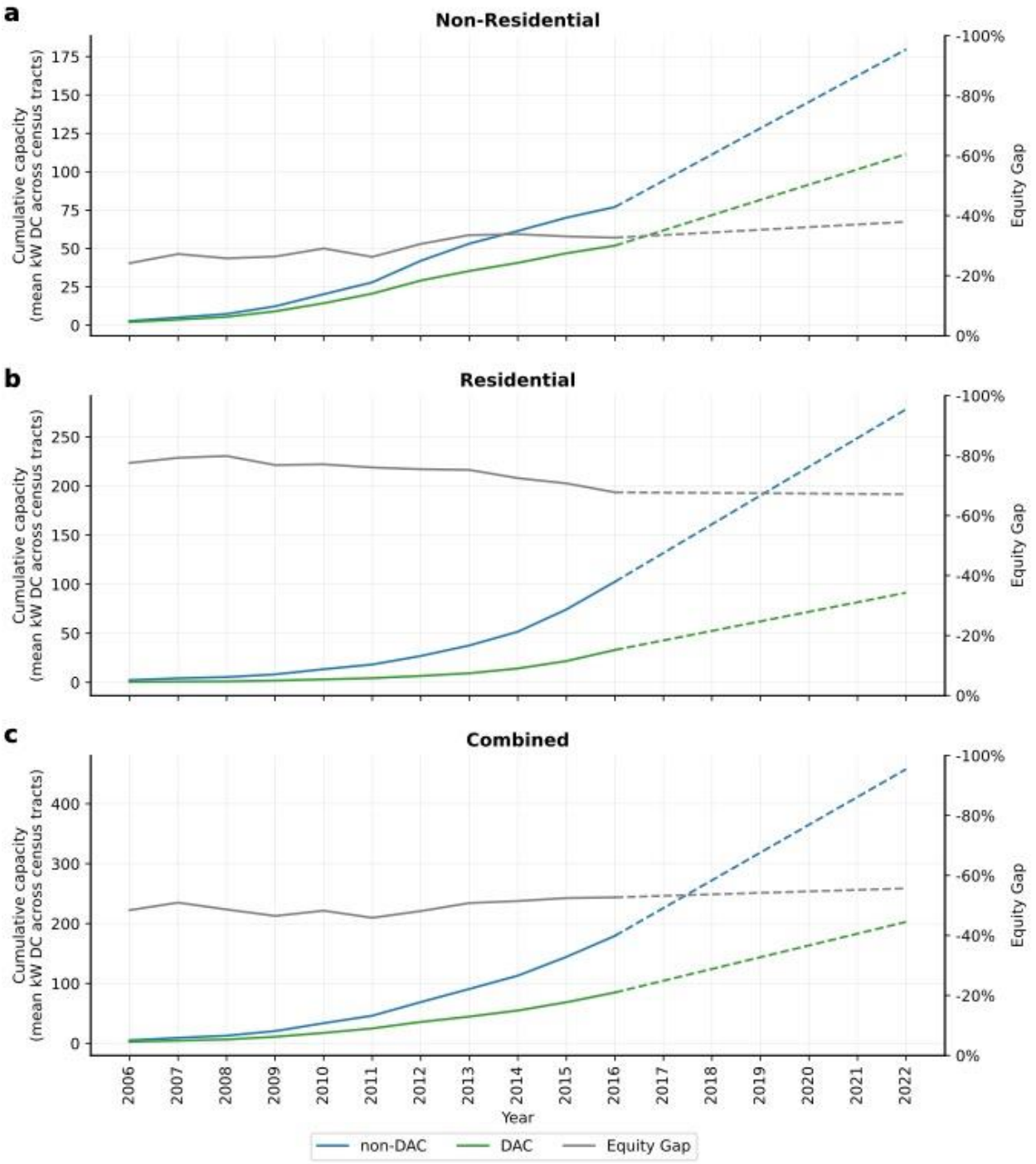

Fig. 3: Temporal trends in solar deployment and the solar equity gap from 2006 – 2016; 2022. The equity gap is defined as the difference between Disadvantaged Communities (DAC) and non-Disadvantaged Communities (non-DAC) identified by the U.S. government's Justice40 initiative. We analyze solar deployment for 72,739 census tracts, out of these 26,372 (36%) are classified as disadvantaged, and 46,367 (64%) are classified as not disadvantaged. We assess solar deployment in 2022 and for every year from 2006 to 2016. Deployment growth between 2016 and 2022 is linearly interpolated, as indicated by dashed lines.

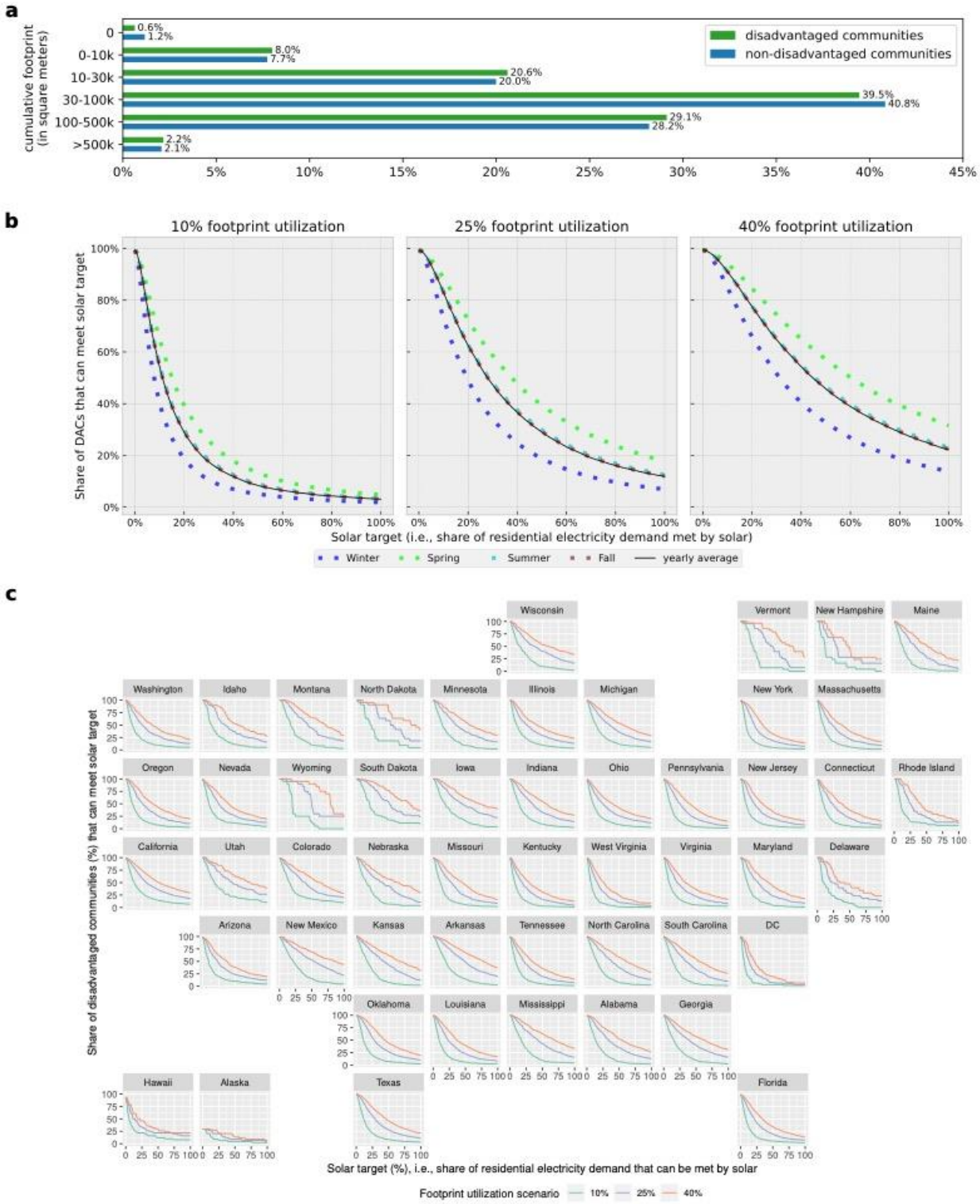

Fig. 4: Scenarios assessing the non-residential solar potential in disadvantaged communities. **a**, Empirical distribution of the cumulative footprint of large buildings (i.e., buildings with footprints above 1,000 square meters) across census tracts for disadvantaged and non-

disadvantaged communities. **b**, the solar target refers to the share of residential electricity demand that can be met by solar installations on large buildings (x-axis) and the share of disadvantaged communities that have enough large building rooftop space to meet a given solar target (y-axis). The share of a large building's footprint that can be covered by solar panels is varied across the three scenarios (10%; 25%; 40%), denoted as footprint utilization. Separate lines are plotted for each season as well as the yearly average. **c**, Breakdown by state of the solar target (x-axis) and share of disadvantaged communities that can achieve it on average throughout a year (y-axis) for each footprint utilization scenario.

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