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Evaluating community solar as a measure to promote equitable clean energy access

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Abstract

Rooftop and community solar are alternative product classes for residential solar in the United States. Community solar, where multiple households buy solar from shared systems, could make solar more accessible by reducing initial costs and removing adoption barriers for renters and multifamily building occupants. Here, we test whether existing community solar projects have expanded solar access in the United States. We find that community solar adopters are more likely to live in multifamily buildings than rooftop solar adopters, are more likely to rent, and to a lesser extent tend to earn less income. We do not find that community solar expands access in terms of race. These differences are driven, roughly evenly, by inherent differences between the two solar products and by policies that specifically target low-income community solar adoption. The results suggest that alternative solar products can effectively expand solar access and that policy could augment such benefits.

Introduction

Nearly four million residential electricity customers had adopted rooftop solar photovoltaics in the United States by the end of 2022[1]. Rooftop solar adopters tend to be more affluent than the general population, are less likely to rent, and are less likely to self-identify as a racial minority[2-4]. Rooftop solar adoption inequity reflects various barriers to adoption for low- and moderate-income (LMI) households, such as high up-front costs to purchase solar systems outright (as opposed to leasing), barriers for renters (e.g., split incentives), and barriers for multifamily building occupants (e.g., shared ownership of rooftop spaces)[5]. While adoption inequity is common among emerging technologies[6], rooftop solar adoption inequity could pose unique challenges to clean energy transitions and grid decarbonization[7,8]. A growing number of policies seek to ensure equitable access to solar adoption[9].

Previous research suggests that alternative solar products can expand access to solar. Specifically, the development of solar leasing models with minimal up-front costs has driven a more equitable expansion of rooftop solar[10,11], and the recent emergence of solar loans may similarly address up-front cost barriers. However, existing rooftop solar products remain largely inaccessible to renters and families living in multifamily housing[12,13]. Another alternative class of solar products in the United States is community solar, wherein multiple customers buy output from a single solar system[14]. Like leasing, community solar typically entails no or minimal up-front costs. Unlike rooftop solar, community solar poses no specific barriers to adoption for renters or multifamily building occupants. As a result, community solar is often theorized to promote more equitable solar access[13,15-18], and is increasingly integrated into U.S. solar adoption equity policies[9]. The federal Inflation Reduction Act includes tax credits for projects serving

LMI communities or customers, and at least 17 states have incentives or regulations that promote LMI community solar[19-21].

The hypothesis that community solar promotes equitable access thus far lacks empirical evidence[22,23], and there are several reasons to question whether community solar necessarily expands access. LMI participation in community solar can increase costs[13], largely because LMI customers can be more challenging and costly to acquire[24,25]. In the absence of policy mandates to acquire LMI customers, profit-maximizing community solar providers may thus prioritize marketing to relatively affluent customers, consistent with evidence from rooftop solar markets[26]. Further, bill management and customer turnover represent substantial costs to community solar providers[27]. Community solar providers thus face economic incentives to minimize the number of customers by maximizing energy sold per customer. Community solar providers often reduce costs by reserving a large share of project capacity for a large non-residential anchor tenant[13]. For the remaining capacity, community solar providers may prioritize relatively large energy users over lighter energy users, such as LMI households and multifamily building occupants. Providers may also perceive renters as more costly insofar as renters pose a higher turnover risk.

In this study, we explore whether existing community solar projects have expanded solar access by analyzing the demographic profiles of rooftop and community solar adopters. We analyze household-level data to explore how the two customer groups vary in terms of median income levels, housing tenure (whether adopters own or rent their homes), housing type (single or multifamily), and race. We organize our study around two research questions: 1) How do community solar adopters compare demographically to rooftop solar adopters? and 2) How much of any demographic differences are attributable to the inherent features of community solar as a product versus policies that promote community solar participation by LMI households specifically?

Before proceeding to the results, we emphasize that our analysis is retrospective. Community solar is projected to grow rapidly and state policies effectively guarantee that future community solar projects will differ substantially from the existing projects analyzed in our study. Our results should be interpreted primarily as retrospective, though we cautiously discuss the implications of our results for the future of the community solar market.

Rooftop and community solar adopter demographics

We draw on multiple sources to build adopter-level rooftop and community solar data sets (see Table 1 and Methods, for summary statistics see Supplementary Table 1). The community solar data represent customers of community solar projects as defined by the U.S. Department of Energy: solar projects where financial benefits flow to multiple customers within a defined geographic area. We use modeled demographic data to identify income levels, housing type and tenure, and the primary race of every adopter in the data set. We analyze race by bifurcating households into those whose primary modeled race was non-Hispanic White and those whose primary race was Black, Hispanic, Asian, or other, which we collectively refer to as "Non-White or Hispanic." Modeled incomes and race are available for all records, while modeled housing type and tenure are incomplete. The sample sizes associated with each variable in each analysis are described in figure captions. We estimate comparative statistics of adopter demographics using Wilcoxon tests (comparison of median incomes) or Pearson Chi-squared tests (comparisons of categorial variables). We estimate all statistics based on comparisons within states to ensure sample independence. We focus our analyses on 11 states where we have at least 100 records for both adopter types (Table 2). The 11 states include some of the largest community and rooftop solar markets in the United States. Still, we recognize that this limited geographic sample implies that our results can not necessarily be perfectly extrapolated to the U.S. community solar market as a whole. For that reason, we emphasize results that are consistent across the states within our sample.

We explore differences in demographic characteristics using one-sided tests for the following hypotheses:

1. Community solar adopters earn less, on average, than rooftop solar adopters;
2. Community solar adopters are more likely to rent than rooftop solar adopters;
3. Community solar adopters are more likely to live in multifamily buildings than rooftop solar adopters;
4. Community solar adopters are more likely to identify as non-White or Hispanic than are rooftop solar adopters.

Throughout this paper, solid points in figures indicate statistically significant results according to one-sided statistical tests, while empty points indicate insignificant results.

Table 1. Data Sources

Source	Description	N
Rooftop solar		
Solar demographics [2]	Database of rooftop PV adopters with household-level demographic variables	102,974
Community solar		
State program data	Data were obtained directly from state community solar programs in Illinois, Maine, New York, and Oregon. The data represent customers that were actively subscribed as of 2023.	41,323
Sharing the Sun developer data	Data obtained from community solar developers as part of the National Renewable Energy Laboratory's (NREL) Sharing the Sun project. NREL publishes project-level data [28], but subscriber-level data are considered proprietary and are not publicly available. for customers actively subscribed as of 2023.	37,391

Table 2. Solar Sample Sizes and Data Sources by State

State	Community Solar Sample Size	Rooftop Solar Sample Size	Community Solar Data Source(s)

Colorado	398	21,472	NREL
Illinois	21,180	10,774	State of Illinois (Adjustable Block program, Solar For All program), NREL
Maine	19,907	1,322	Central Maine Power Company, Versant Power, NREL
Maryland	7,779	5,582	NREL
Massachusetts	1,814	10,611	NREL
Minnesota	465	4,319	NREL
New Jersey	519	16,077	NREL
New York	23,375	15,565	New York State Energy Research and Development Authority, NREL
Oregon	2,033	10,185	Oregon Energy Trust, NREL
Rhode Island	876	4,881	NREL
Washington, DC	368	2,186	NREL

The data firmly support hypotheses 1-3 defined above (Figure 1). Community solar adopters earn significantly less income and are more likely to rent and live in multifamily buildings than rooftop solar adopters in most states. Weighting the differences by state sample sizes, the data suggest that community solar adopters are about 6.1 times more likely to live in multifamily buildings than rooftop solar adopters, 4.4 times more likely to rent, and earn about 23% less. At the same time, the data suggest that community solar adopters are not demographically representative of the general population. In most states, community solar adopters earn more than average and are less likely to rent and live in multifamily buildings than the general population. That is, community solar expands access relative to rooftop solar but is still inequitable relative to the general population. Differences in race are more ambiguous. The data suggest that community solar adopters are generally less, rather than more, likely to identify as non-White or Hispanic, compared to rooftop adopters. Across all the states in the sample, rooftop solar adopters are about twice as likely than community solar adopters to identify as Asian or Black and about three times as likely to identify as Hispanic (Figure 2).

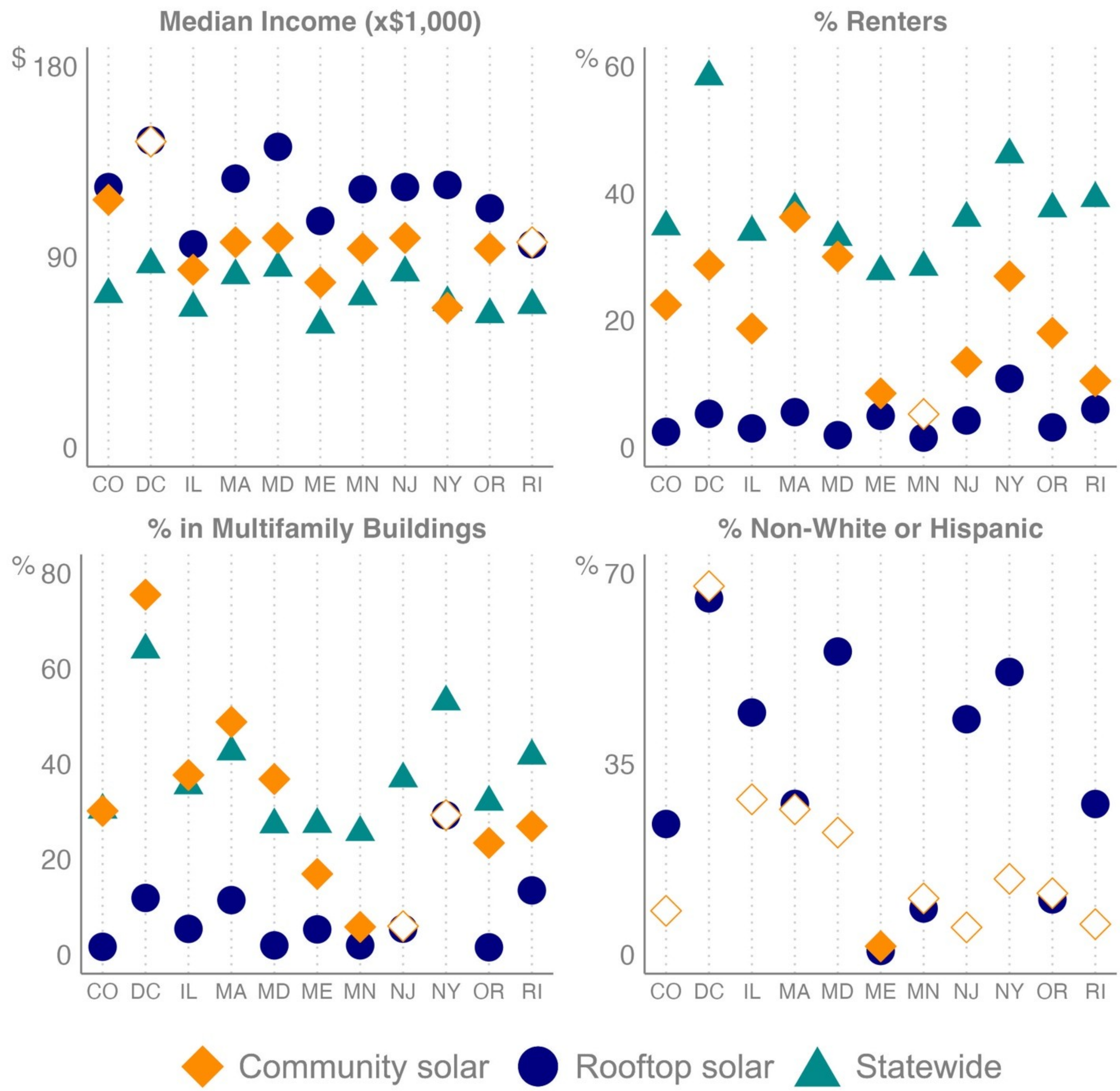

Figure 1. Comparisons of demographic characteristics of community and rooftop solar adopters. Solid diamonds indicate statistically significant ($p<0.05$) results. Statewide estimates for race are omitted for reasons explained in Methods. Sample sizes: income and race N=181,688; % renters N=147,881; % multifamily N=181,672. For numerical results see Supplementary Table 2.

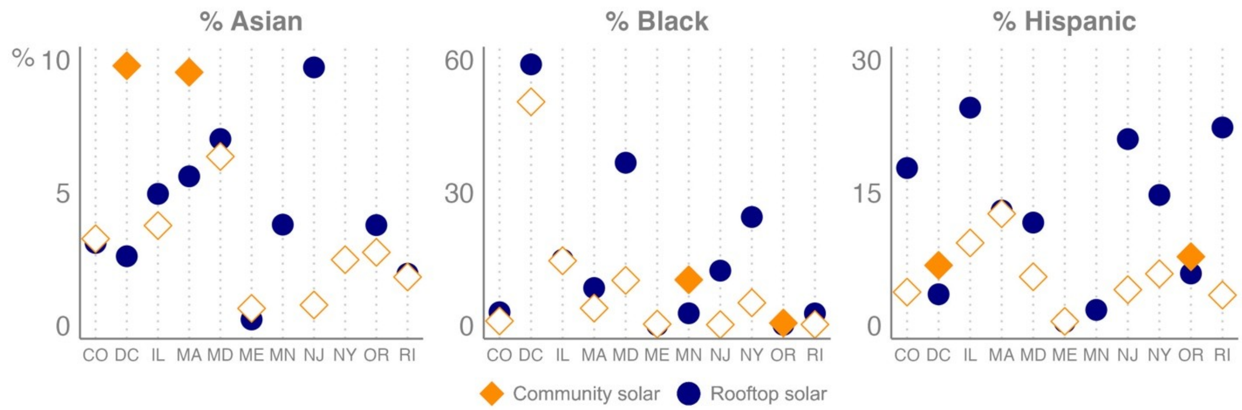

Figure 2. Comparisons of races of rooftop and community solar adopters. Solid diamonds indicate statistically significant ($p<0.05$) results. N=181,688. For numerical results see Supplementary Table 3.

We use a conditional probability model to compare how the different demographic factors explain household adoption decisions (see Methods). The models are not designed to be causal. Rather, the models describe the relative power of each demographic factor in predicting whether a household is a community or rooftop solar adopter, conditioned on the other factors. The model suggests that the strongest predictors of adoption choices are race and housing tenure, while housing type and income have roughly equal predictive power (Figure 3). The conditional model helps isolate statistical associations between demographic factors and adoption decisions from associations driven by confounding correlations among demographic factors. In the data set, multifamily building occupants are about 8.8 times more likely to rent than are single-family occupants ($t=116.3$, two-sided), and households earning less than state median income are about 3.6 times more likely to rent ($t=76.1$, two-sided). The relatively large conditional coefficient for housing tenure suggests that some of the observed differences in housing type and income (see Figure 1) stem from these underlying correlations. That is, multifamily building occupants and low-income households are more likely to adopt community solar partly because those households are more likely to rent. Further, we use Akaike Information Criterion (AIC) scores to assess the prediction accuracy of model variations including different combinations of the demographic factors (Figure 4). The AIC scores likewise suggest that race and housing tenure are the most predictive variables.

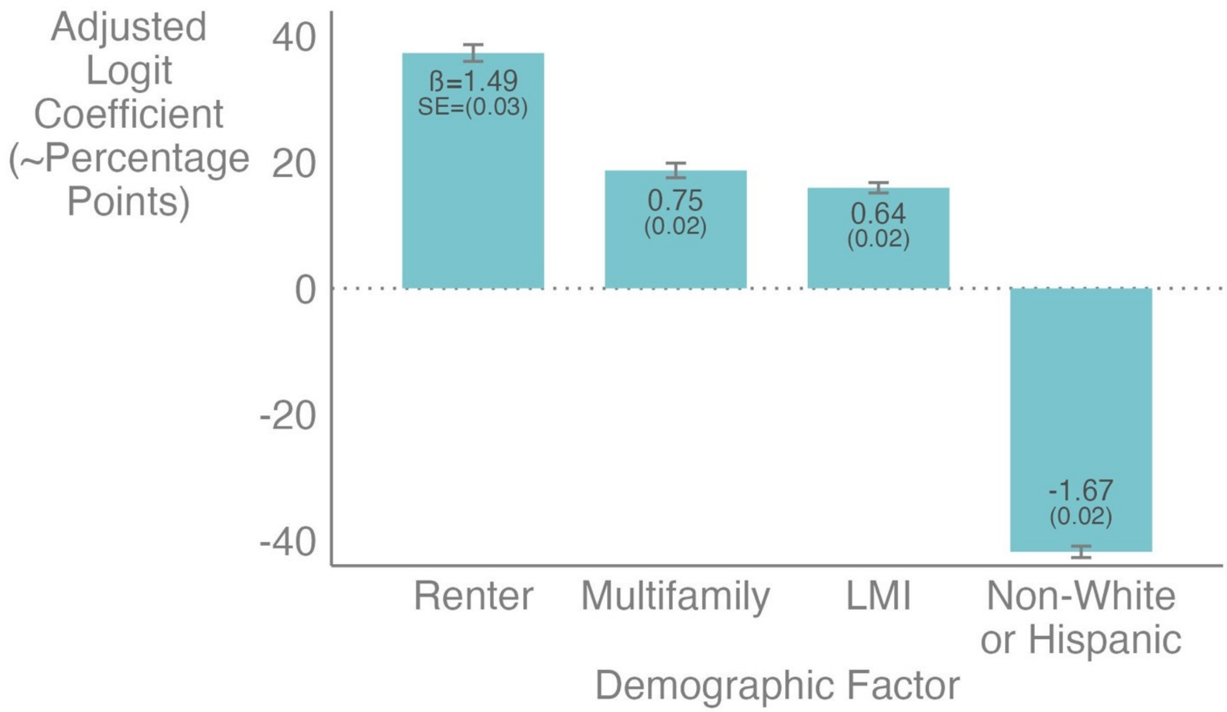

Figure 3. Conditional associations between demographic factors and solar adoption choices. Results based on coefficients from model defined in Equation (1) in Methods. LMI for the purposes of this figure refers to households earning less than the state's median income. For simplicity, we convert the coefficients to percentage point terms using the approximation of multiplying the coefficients (ß) by 100 then dividing by four. N=147,874. Bars represent 95% confidence intervals.

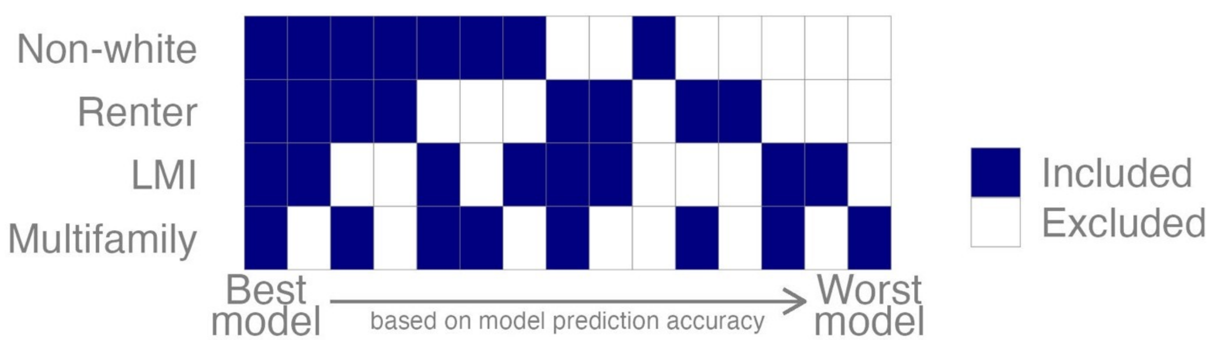

Figure 4. Prediction accuracy from different model variations. Plot depicts different combinations of variables included in the conditional probability model. Combinations to the left have the highest prediction accuracy based on Akaike Information Criterion scores (see Methods). N=147,874.

Overall, the results suggest that community solar primarily expands solar access in terms of housing tenure and type and secondarily in terms of income. This interpretation stems from the relatively larger differences in housing tenure and type as opposed to income as illustrated in Figure 1, and the relatively strong predictive power of housing tenure in the conditional models. This result has a reasonable explanation. As discussed in the Introduction, the emergence of rooftop solar leasing has partly addressed adoption cost barriers, but rooftop solar remains nearly inaccessible to renters and multifamily building occupants. As a result, rooftop solar leasing and community solar may address income-related (cost) barriers in similar ways, but community solar is unique in removing barriers for renters and multifamily building occupants. To further explore this hypothesis, we separately identified rooftop solar system owners and lessees in the five states where leasing is allowed, and the data allowed us to identify lessees. In three of the five states, rooftop solar lessee incomes more closely resemble the typical incomes of community solar adopters than rooftop solar system owners (Figure 5). However, in those same three states rooftop solar lessees are not substantially more likely to rent or live in multifamily housing. As expected, the data suggest that rooftop solar leasing addresses income barriers to adoption but does not effectively address housing barriers. The renter and multifamily housing market is thus the clearest market niche for community solar to address.

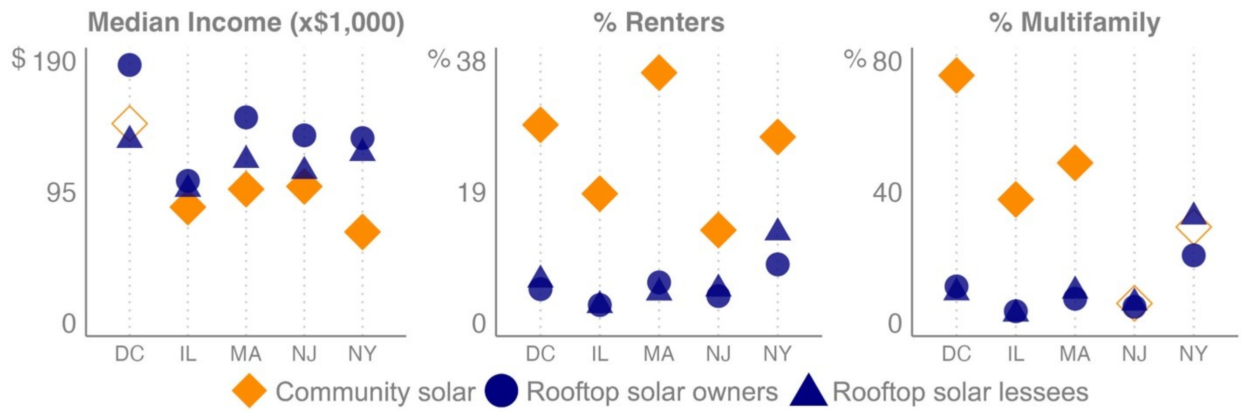

Figure 5. Comparisons of demographic characteristics across three solar products. Solid diamonds indicate statistically significant ($p<0.05$) differences between community solar adopters and rooftop solar lessees. Sample sizes: income and race N=88,563; % renters N=71,007; % multifamily N=88,549. For numerical results see Supplementary Table 4.

Inherent and policy impacts

The preceding analyses demonstrate that community solar adopters differ demographically from rooftop solar adopters. These differences could reflect some combination of differences between the two solar products—what we refer to as "inherent impacts"—and differences between rooftop and community solar policies—what we refer to as "policy impacts." Those policies typically target low-income households and take the form of either additional financial incentives or, in the case of community solar, carve-outs that require some minimum percentage of low-income subscribers[21]. Isolating inherent from policy impacts would be useful for understanding how effectively community solar promotes access without additional policy support and how impactful policies have been in further promoting solar access through community solar.

We analyze inherent and policy impacts by testing for demographic differences among adopters that participated in LMI community solar programs (program participants) and those who did not (non-participants). We can only precisely distinguish participants from non-participants in three states: Illinois, Massachusetts, and Oregon (see Methods). Demographic differences between non-participant community solar and rooftop solar adopters provide evidence of inherent impacts, given that LMI policies did not directly affect non-participants. Demographic differences between participant and non-participant community solar adopters provide evidence of policy impacts. The accuracy of that evidence depends on reasonable assumptions around the share of participants who would have otherwise adopted community solar, also known as free riding (see Methods).

Participants earn significantly less and are more likely to rent and live in multifamily housing than non-participants. Participants are also significantly more likely to identify as non-White or Hispanic than non-participants. Limiting the data (N=7,492) to adopters earning less than 80% of their states' median income (a common threshold for identifying LMI households), participants are about 1.8 times more likely to identify as non-White or Hispanic than non-participants (t=14.0, two-sided). These differences suggest that LMI programs are reaching a distinct population of LMI households than those adopting without program benefits.

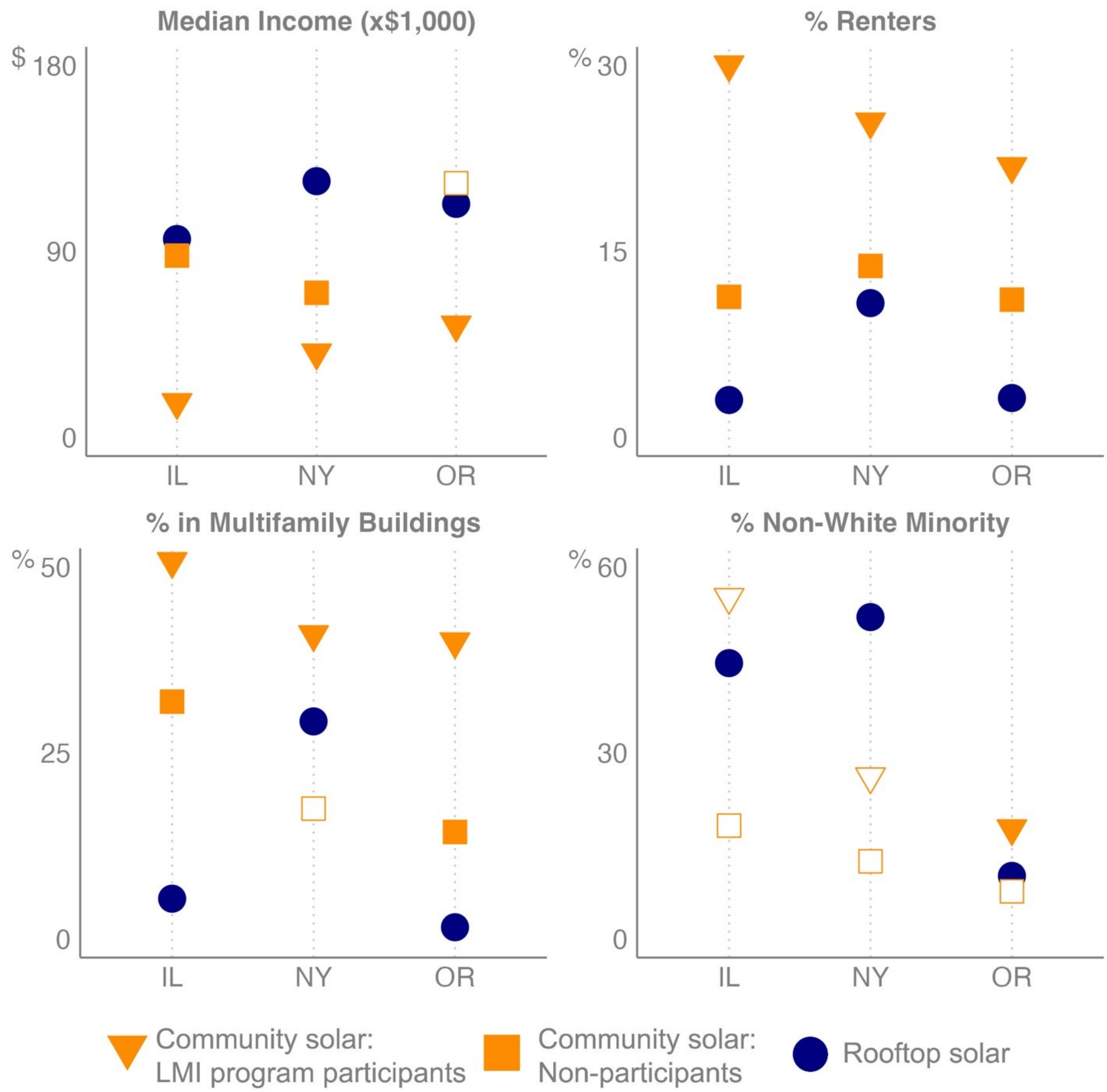

Figure 6. Demographic characteristics in community solar and rooftop solar subsamples. Solid points indicate statistically significant ($p<0.05$) differences. Sample sizes: income and race N=58,300; % renters N=44,950; % multifamily N=58,286. For numerical results see Supplementary Table 5.

The analysis likewise provides evidence of the inherent impacts of community solar on adopter demographics in most cases. Non-participant community solar adopters earn significantly less than rooftop solar adopters in Illinois and New York, indicative of inherent impacts. However, non-participant community solar adopters earn slightly more in Oregon, suggesting that income differences in Oregon are fully explained by policy. Differences in housing type and tenure remain significant for non-participants in Illinois and Oregon (consistent with inherent impacts) but are rendered insignificant in New York. However, New York has exceptionally high rates of rooftop solar renters and multifamily building occupants relative to other states, and the multifamily difference is insignificant in New York for the full sample (see Figure 1).

To generate rough estimates of the contributions of inherent and policy impacts, we calculate the effects of removing participants on overall demographic differences. For instance, in Illinois, the median income difference between all community and rooftop solar adopters is $13k, while the median income difference between non-participants and rooftop adopters is $8k, such that policy accounts for about $5k or 38% of the difference (assuming minimal free riding). Under that approach, if free riding is trivial, the results suggest that policy explains around 67% of income differences between community and rooftop solar adopters, 43% of the differences in housing tenure, and 23% of the differences in housing type, on average across the three states. The fact that policy appears to contribute more to income differences is not surprising given that the policies evaluated here target income levels. Thus, broadly speaking, the data suggest that policy impacts are the primary driver of income differences, while inherent impacts are the primary driver of differences in housing type, and both impacts contribute roughly evenly to differences in housing tenure.

It is worth reiterating that our rough estimation of policy impacts is based on a retrospective analysis of a relatively small sample of LMI programs. While our results suggest that LMI community solar policies have been impactful, the results cannot necessarily be extrapolated to future LMI community solar policies which are increasingly ambitious in scope and scale[29].

Outside of the states explored in the preceding analysis we cannot precisely distinguish participants from non-participants. However, as a robustness check, we obtain similar results based on an analysis of inferred LMI program participation (see Methods and Supplementary Figure 1).

Conclusions

Our results suggest that existing community solar projects are expanding solar access in the United States to a more demographically diverse population. Specifically, we find that community solar adopters in 11 states are about 6.1 times more likely to live in multifamily buildings, 4.4 times more likely to rent, and earn 23% less than rooftop solar adopters, on average. Community solar has, thus far, been particularly effective at expanding access in terms of housing type and tenure, while a substantial portion of observed income differences can be attributable to the uptake of community solar among multifamily building occupants and renters. Though community solar expands access relative to rooftop solar, community solar adopters tend to earn more than the broader population and are less likely to rent and live in multifamily housing. This outcome is not surprising given the economic incentives that community solar providers face (see Introduction). It is likely that community solar will become more equitable over time, both because of the broad tendency of emerging technologies to diffuse to underserved markets over time[6] and because of increasingly ambitious community solar policies to expand access[29]. We do not find evidence that community solar has, thus far, expanded access to solar in terms of race. Indeed, the data suggest that community solar has been less effective at reaching non-White and Hispanic households than rooftop solar. The reason for these racial differences is unclear. Future research could explore how differences in marketing, customer perceptions, or other factors could explain racial differences across the two solar products.

Our data suggest that inherent differences across the two solar products largely explain historical differences in housing type and tenure between community and rooftop solar adopters. Evidence of inherent impacts on housing type and tenure is generally encouraging from a policy perspective. Inherent impacts suggest that policymakers could expand solar access by creating a basic infrastructure for community solar, such as virtual net metering, even without specific measures to promote equity. We find evidence that the inclusion of specific measures to promote equity can increase LMI adoption and possibly expand access in terms of race. Overall, the results suggest that targeted LMI community solar policy can augment the access benefits of community solar.

We conclude with suggestions for further research. Here, we have identified the impacts of community solar on adopter demographics stemming from policies and broad differences between the products. Future research could explore which specific aspects of different solar products most effectively promote solar access. For instance, do community solar features such as cancelation terms and transferability (whether customers can keep community solar subscriptions when changing addresses) affect adopter demographics? Similarly, future research could analyze how different community solar LMI policies affect adopter demographics. For instance, how do LMI carveouts compare to incentives in expanding access? Finally, our results raise many questions about access to solar across race. Future research could explore why rooftop and community solar appear to be reaching distinct racial communities and why policy appears to be particularly critical for expanding solar access to racial minorities.

Methods

Data. Our data sources are defined in Table 1. We used home addresses to match adopter records at the address level to modeled household-level variables for income, housing type, and housing tenure purchased from Experian. We predicted household-level racial characteristics using the *wru* package in R[30]. The *wru* package estimates continuous probabilities for household race in five categories (Asian, Black, Hispanic, White, other) based on the surname of the household's Census tract and the surname of the head of household. In cases where the surname was unavailable (12% of records), *wru* predicts race based only on the Census tract. Removing these tract-only predictions from the data does not substantially affect the results (see Supplementary Figure 2). We converted the continuous probabilities to a binary non-White or Hispanic variable score based on whether some race other than White was assigned the greatest probability. We compare solar adopter demographics to the general population using state-level demographic statistics from the U.S. Census American Community Survey. However, we omit the statewide comparison for race because the continuous race probabilities estimated by *wru* cannot be meaningfully compared to the self-identified races reported in Census data.

Unconditional demographic differences. We test observed (unconditional) differences for the hypotheses described in the main text. We use Wilcoxon rank-sum tests to test hypotheses for household incomes and Pearson χ^2 tests for the categorical variables (housing tenure, housing type, race). We compare medians because household demographic characteristics are not normally distributed. We make two adjustments to ensure independence between the comparison groups. First, we estimate comparative statistics within states to ensure that the community and rooftop solar data are pulled from the same geographic subsamples. Second, we restrict the rooftop solar adopter data to systems installed in 2022 to account for the fact that our community solar data reflect samples of customers enrolled in community solar in 2022 or 2023. That temporal misalignment matters because rooftop solar adoption has become more demographically equitable over time[2]. Both restrictions are reflected in the sample sizes reported in Table 1.

Conditional probability model. To isolate the relative effects of household demographics on adoption choices we use the following logit model:

$$p(CS) = \alpha + D\beta + S + \varepsilon \tag{1}$$

Where $p(CS)$ is the probability that a household is a community solar adopter (as opposed to a rooftop adopter), D is a vector of dummy variables for the four demographic dimensions, and S is a state random effect. We convert the income variable into a dummy value by bifurcating the records into households that earn more or less than the state median income. The coefficient of interest is β, which represents the statistical association between household demographics and the household's adoption choice. Note that the model is not designed for causal inference. Household adoption choices are likely driven by numerous idiosyncratic factors that could correlate with the demographic factors. The purpose of this model is to compare the relative weights of the β coefficients to understand which demographic dimensions are most strongly associated with household adoption choices. We use state random effects to account for the possibility that community solar has distinct impacts on adopter demographics in different states with distinct policy contexts. In addition to comparing the coefficients, we also implement variations of the model in Equation (1) with different combinations of the demographic factors. We then compare Akaike Information Criterion (AIC) values across those models (see Figure 4). The AIC is a metric that simultaneously measures prediction accuracy while penalizing models with more variables. The AIC comparisons provide another way of comparing the relative contributions of demographic differences to household adoption choices.

Analysis of LMI program participants and non-participants. State programs in Illinois, New York, and Oregon provided identifiers for LMI program participants. Participants may have received financial incentives to participate or were otherwise prioritized for adoption to comply with state LMI carveouts. We analyze evidence of inherent and policy impacts by distinguishing participants from non-participants in each state: Illinois (N=918 participants; 11,143 non-participants), New York (1,363 participants; 6,733 non-participants), and Oregon (718 participants; 1,315 non-participants). For each state, we likewise create subsets of rooftop solar adopters who did not receive any LMI incentives for rooftop solar adoption. The accuracy of that analysis depends on how many participants would have adopted community solar without LMI program benefits, a concept known as free riding. At one extreme, inherent and policy impacts can be precisely identified if free riding is non-existent. However, if free riding is common, then the analysis would tend to understate inherent impacts and overstate policy impacts. There are at least three reasons to assume that free riding is not common in LMI community solar programs. First, evidence that LMI program participants are relatively difficult and costly to acquire[24,25] suggests that participants would not otherwise have adopted. Second, LMI community solar programs use similar eligibility criteria as LMI rooftop solar incentives, and available evidence suggests that free riding in LMI rooftop solar programs is infrequent[31]. Third, as noted in the main text, the data suggest that participants vary significantly from non-participants in terms of race, indicating that LMI program benefits are reaching a distinct population of adopters. Still, some degree of free riding likely exists, meaning that policy impacts are imprecisely identified.

Imputed carveouts. Two states in our data (Colorado and Maryland) have specified percentage point minimum "carveouts" for LMI subscribers. We impute an effective LMI carveout for Massachusetts using data compiled in the LIFT Solar Toolkit. The LIFT Solar Toolkit identifies project capacity reserved for LMI subscribers. We divide the reserved LMI capacity by the total, cumulative community solar capacity deployed in the state based on data from Connelly[25]. As a point of reference, the same method yielded an imputed carveout of 5.9% in Colorado, close to the state's mandated carveout of 5%. For all three states we isolate the bottom end of the community solar adopter income distribution in proportion to the carveout. For instance, Colorado requires that LMI households account for at least 5% of community solar customers, such that in that state we isolate the 5% of community solar adopters with the lowest incomes as "below" the carveout. In effect, this represents the most optimistic assumption for the efficacy of the LMI carveout and would thus tend to minimize any residual inherent impact. The results of this analysis are provided in Supplementary Figure 1, where points "below carveout" represent adopters below the implied carveout on the income distribution, and "above carveout" points represent adopters above those implied carveouts.

Limitations. Two limitations noted in the main text are worth expanding upon. First, we analyze a geographically restricted sample of 11 states. While these 11 states represent relatively active community and rooftop solar markets, our analysis excludes important rooftop solar markets, notably California and Hawaii, and some emerging community solar markets, notably Florida and Georgia. We also recognize that our analysis of policy impacts is based on a further restricted sample of 3 states. For this reason, we emphasize results that are consistent across states rather than individual results within states, which may be less safely extrapolated. Second, all our community solar data are cross-sections of households that were actively subscribed at the time the data were generated. With those cross-sectional data, we lack insights into trends in community solar adoption over time. This limitation shaped our analysis of inherent and policy impacts. We have used the practical method of comparing cross-sections of community solar adopter demographics between policy program participants and non-participants. As noted, our method only precisely identifies policy impacts under the strict assumption of no free riding in community solar LMI programs. While available evidence suggests that free riding is infrequent, free riding is likely non-zero and thus our policy impacts are imprecisely identified. An ideal approach—a suggestion for future research— would be to more precisely identify policy impacts through econometric analysis of changes in community solar adoption trends before and after policy implementation.

Data availability

This work was performed using proprietary, household-level data that cannot be shared. However, elements of the rooftop solar data are publicly available from the Lawrence Berkeley National Laboratory: https://emp.lbl.gov/projects/solar-demographics-trends-and-analysis. Other aggregated data will be made available upon reasonable request from the authors.

Code availability

Code will be provided on a publicly accessible web page upon acceptance.

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References

1 **Davis, M. *et al.*** US Solar Market Insight: 2022 Year in Review. (Wood Mackenzie, 2023).

2 Forrester, S., Barbose, G., O'Shaughnessy, E., Darghouth, N. & Crespo Montañés, C. Residential Solar-Adopter Income and Demographic Trends: November 2022 Update. (Lawrence Berkeley National Laboratory, Berkeley, CA, 2022).

3 Sunter, D., Castellanos, S. & Kammen, D. Disparities in rooftop photovoltaics deployment in the United States by race and ethnicity. *Nature Sustainability* **2**, 71-76 (2019). https://doi.org:10.1038/s41893-018-0204-z

4 Lukanov, B. & Krieger, E. Distributed solar and environmental justice: Exploring the demographic and socio-economic trends of residential PV adoption in California. *Energy Policy* **134**, 110935 (2019). https://doi.org:10.1016/j.enpol.2019.110935

5 Heeter, J., Sekar, A., Fekete, E., Shah, M. & Cook, J. J. Affordable and Accessible Solar for All: Barriers, Solutions, and On-Site Adoption Potential. (National Renewable Energy Laboratory, Golden, CO, 2021).

6 Attanasio, O. P. & Pistaferri, L. Consumption Inequality. *Journal of Economic Perspectives* **30**, 3-28 (2016).

7 Welton, S. & Eisen, J. Clean Energy Justice: Charting an Emerging Agenda. *Harvard Environmental Law Review* **43**, 307-371 (2019).

8 Bidwell, D. & Sovacool, B. Uneasy tensions in energy justice and systems transformation. *Nature Energy* (2023).

9 Zhou, S., Gao, X., Wellstead, A. M. & Min Kim, D. Operationalizing social equity in public policy design: A comparative analysis of solar equity policies in the United States. *Policy Studies Journal* **2023**, 1-32 (2023).

10 Drury, E. *et al.* The transformation of southern California's residential photovoltaics market through third-party ownership. *Energy Policy* **42**, 681-690 (2012). https://doi.org:10.1016/j.enpol.2011.12.047

11 O'Shaughnessy, E., Barbose, G., Wiser, R., Forrester, S. & Darghouth, N. The impact of policies and business models on income equity in rooftop solar adoption. *Nature Energy* **6**, 84-91 (2021).

12 Malhotra, R. in *Proceedings of the American Solar Energy Society National Conference.* (eds Ashok Kumar Ghosh & Carly Rixham) (Springer).

13 Goyette, K. L. Community Solar Policy and the Low- and Moderate-Income Customer. *Natural Resources & Environment* **36**, 13-16 (2021).

14 Funkhouser, E., Blackburn, G., Magee, C. & Rai, V. Business model innovations for deploying distributed generation: The emerging landscape of community solar in the U.S. *Energy Research & Social Science* **10**, 90-101 (2015). https://doi.org:10.1016/j.erss.2015.07.004

15 Hausman, N. How Community Solar Can Benefit Low- and Moderate-Income Customers. (World Resources Institute, 2022).

16 Heeter, J., Bird, L., O'Shaughnessy, E. & Koebrich, S. Design and Implementation of Community Solar Programs for Low- and Moderate-Income Customers. (National Renewable Energy Laboratory, Golden, CO, 2018).

17 Abbott, S., Tyson, M., Popkin, M. & Farthing, A. Community Solar+: How the Next Generation of Community Solar Can Unlock New Value Streams and Help Communities Pursue Holistic Decarbonization. (Rocky Mountain Institute, 2022).

18 Michaud, G. Perspectives on community solar policy adoption across the United States. *Renewable Energy Focus* **33**, 1-15 (2020).

19 IREC. Shared Renewables Policy Catalog. (Interstate Renewable Energy Council, 2020).

20 NREL. Equitable Access to Community Solar: Program Design and Subscription Considerations. (National Renewable Energy Laboratory, Golden, CO, 2021).

21 Xu, K., Sumner, J., Dalecki, E. & Burton, R. Expanding Solar Access: State Community Solar Landscape. (National Renewable Energy Laboratory, Golden, CO, 2023).

22 Chwastyk, D., Leader, J., Cramer, J. & Rolph, M. Community Solar Program Design Models. (Smart Electric Power Alliance, 2018).

23 Gallucci, M. in *YaleEnvironment360* (Yale School of the Environment, 2019).

24 Lydersen, K. in *Canary Media* (2023).

25 Connelly, C. U.S. Community Solar Market Outlook: 2023. (Wood Mackenzie, Boston, MA, 2023).

26 O'Shaughnessy, E., Barbose, G., Wiser, R. & Forrester, S. Income-targeted marketing as a supply-side barrier to low-income solar adoption. *iScience* **24**, 103137 (2021).

27 Ramasamy, V. *et al.* U.S. Solar Photovoltaic System and Energy Storage Cost Benchmarks, With Minimum Sustainable Price Analysis: Q1 2023. (National Renewable Energy Laboratory, Golden, CO, 2023).

28 Chan, G., Heeter, J. & Xu, K. in *NREL Data Catalog* (ed National Renewable Energy Laboratory) (Golden, CO, 2022).

29 Connelly, C. Demystifying LMI incentives for community solar projects. (Wood Mackenzie, 2023).

30 wru: Who are you? Bayesian Prediction of Racial Category Using Surname, First Name, Middle Name, and Geolocation (2022).

31 O'Shaughnessy, E. Rooftop solar incentives remain effective for low- and moderate-income adoption. *Energy Policy* **163**, 112881 (2022).