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## LETTER

## Characterizing local rooftop solar adoption inequity in the US

## OPEN ACCESS

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## Abstract

Residential rooftop solar is slated to play a significant role in the changing US electric grid in the coming decades. However, concerns have emerged that the benefits of rooftop solar deployment are inequitably distributed across demographic groups. Previous work has highlighted inequity in national solar adopter deployment and income trends. We leverage a dataset of US solar adopter household income estimates—unique in its size and resolution—to analyze differences in adoption equity at the local level and identify those conditions that yield more equitable solar adoption, with implications for policy strategies to reduce inequities in solar adoption. The solar inequities observed at the national and state levels also exist at more granular levels, but not uniformly so; some US census tracts exhibit less solar inequity than others. Some demographic, solar system, and market characteristics robustly lead to more equitable solar adoption. Our findings suggest that while solar adoption inequity is frequently attributed to the relatively high costs of solar adoption, costs may become less relevant as solar prices decline. Results also indicate that racial diversity and education levels affect solar adoption patterns at a local level. Finally, we find that solar adoption is more equitable in census tracts served by specific types of installers. Future research and policy can explore ways to leverage these findings to accelerate the transition to equitable solar adoption.

## 1. Introduction

Residential rooftop solar photovoltaics (PV) are slated to play a significant role in the changing US electric grid in the coming decades (US DOE 2021). Households adopting rooftop solar can reduce their electricity bills by displacing the volumetric portion of their retail rate (in \$ kWh<sup>-1</sup>). Electricity rate structures commonly recoup most fixed costs through these volumetric payments, and hence electricity suppliers may need to increase electricity rate levels as a result of solar deployment, effectively shifting costs to non-solar-adopters. Grid cost shifting is common; however, some have argued that solar-driven cost shifts could be regressive as a result of solar adoption inequity: high-income households are more likely to adopt solar than low- and moderate-income (LMI) households (Borenstein 2017, Clastres *et al* 2019, Metcalf 2019, Burger *et al* 2020). Preventing regressive cross-subsidies by accelerating the transition to more equitable rooftop solar adoption is a key piece of the

emerging clean energy justice policy agenda (Eisen and Welton 2019, Carley and Konisky 2020).

Inequities are not inherent to rooftop solar. Indeed, rooftop solar could mitigate existing energy inequities, such as by reducing the energy cost burdens of LMI households (Bednar and Reames 2020). However, LMI households have been and remain significantly less likely to adopt rooftop PV than high-income households in the United States (Yu *et al* 2018, Lukanov and Krieger 2019, Barbose *et al* 2021b, O'Shaughnessy *et al* 2021b). Those historical adoption inequities are driven largely by structural inequalities, especially income inequality and geographic income segregation (O'Shaughnessy 2021). Income inequality provides the conditions for solar adoption inequity as some high-income households are more capable of adopting PV at current prices than LMI households. The literature has identified several income-driven differences in solar access, including LMI household cash constraints, lower rates of home ownership, building structural issues,

language barriers (Mueller and Ronen 2015, Lukanov and Krieger 2019, Sunter *et al* 2019, Brown *et al* 2020), and lower rooftop solar hosting potential in LMI neighborhoods (Reames 2021). The ‘split-incentives’ of energy efficiency, well documented in the literature (Bird and Hernández 2012, Gillingham *et al* 2012), are also present for solar (Bird and Hernández 2012, Inskip *et al* 2015), driving to less solar adoption among renters, who are disproportionately lower income (JCHSHU 2020). Income inequality can also lead installers to target high-income households, especially if income is geographically segregated such that installers can concentrate marketing efforts in high-income neighborhoods (O’Shaughnessy *et al* 2021a). Adoption inequity in the U.S., specifically, can also be attributed to federal and state tax credits for PV adoption that are less accessible to LMI households (Borenstein and Davis 2016). Solar inequity transcends income alone; rooftop solar adoption patterns are stratified by other demographic factors as well (Lukanov and Krieger 2019, Sunter *et al* 2019). Inequitable solar adoption will solidify and exacerbate broader social inequities. While a more equal distribution of the private benefits of solar among income groups will not reduce cost shifts, it will make them less regressive (Borenstein *et al* 2021). Realizing solar’s full market potential—and the associated climate, economic development, and employment benefits—will require adoption of solar at all income levels (Sigrin and Mooney 2018) as well as public and political support, which would be hindered by a perception of continued solar inequity (Eisen and Welton 2019). Adoption inequity is not a unique or necessarily permanent feature of rooftop PV (O’Shaughnessy 2021). Many emerging technologies go through a transient phase of high costs and inequitable adoption (Attanasio and Pistaferri 2016), and rooftop PV is on a trajectory to become more equitable over time as costs decline (Borenstein 2017, Barbose *et al* 2021b).

Previous work has explored rooftop solar adoption inequity at the state or national level (Barbose *et al* 2021b) and how policies and business models influence adoption inequity (O’Shaughnessy *et al* 2021b). In this paper, we build on this research by exploring how socioeconomic and market factors affect adoption inequity at a local (census tract) level. Our tract-level analysis allows us to demonstrate that PV adoption inequity does not only stem from regional PV deployment patterns. Rather, we show that PV adoption inequity persists down to the level of income differences between neighbors, though some tracts show more inequity than others. Our primary objective is to analyze these local differences and identify those conditions that yield more equitable adoption. In doing so, we aim to inform policy discussions on how to accelerate the transition to more equitable solar adoption. The analysis is based on a solar adopter income dataset unique in both its large sample size, as well as its reliance

on modeled, household-level PV adopter incomes, instead of US census data. The dataset’s size and resolution enable us to make statements that are both broadly applicable to the US context while focusing on local solar adoption equity patterns, which are distinct from national patterns.

The paper is organized as follows. The first section includes a description of the data and variable construction for both the descriptive and regression analysis. The initial set of results are from the descriptive analysis to understand national and state adopter income trends as well as to explore determinants of solar inequity. The second set of results focuses on the regression model to understand the various drivers of local inequity. The final section presents high level conclusions and interpretations of our results.

## 2. Data and methods

In this article, we focus on incomes of residential rooftop solar adopters in the US from 2010 through 2019. All data sources and key variables are defined and summarized in table 1. Our final data sample comprises records on 1.9 million systems, representing about 82% of all PV adopters in the US over the study period (84% for 2019 adopters). We used the household-level dataset to construct a census tract-level dataset (census tracts are geographic units representing several city blocks). The tract-level dataset comprises 12 561 tracts.

The modeled household level income estimates are a central element to this analysis; we perform several key operations on those data. We validated modeled household-level income data by establishing correlation between modeled incomes and zip-code level incomes and found that the income model consistently estimated lower household incomes for adopters that received LMI incentives (see O’Shaughnessy *et al* (2021b) for more details).

We analyze the impacts of various demographic and PV market factors on PV adopter income trends through the following tract-level linear regression model:

$$b = D\beta_D + M\beta_M + S + \varepsilon$$

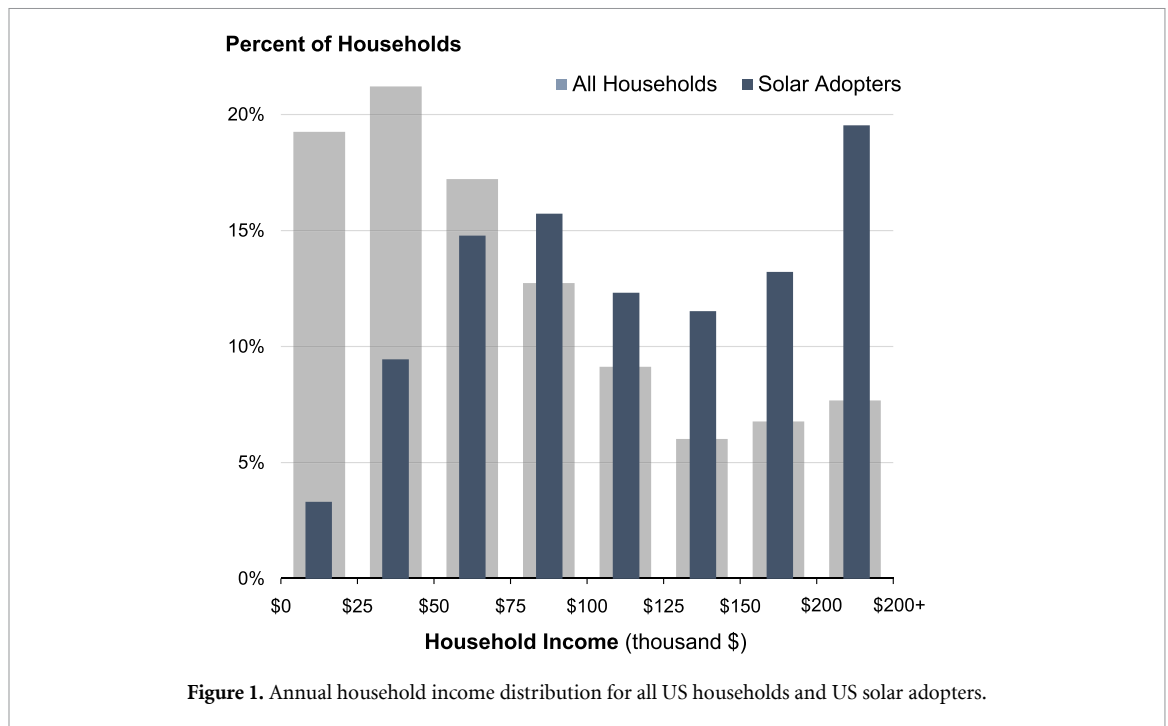
where  $b$  is the median tract-level income bias of PV adopters, defined as the difference between the median solar adopter income and the median income of *all* households in the tract,  $D$  is a vector of demographic variables,  $M$  is a vector of PV market variables, and  $S$  is a state fixed effect. The bias metric represents how PV adopter incomes differ from the incomes of other households at the US census tract level. The regression coefficients can be interpreted as the impacts of the independent variables on how PV adopter incomes differ from the incomes

Table 1. Data sources and descriptions.

Dataset	Description	Data type	Data source
Tracking the Sun (TTS)	Household-level rooftop solar adoption data, see detailed description in Barbose <i>et al</i> (2021a)	Solar PV addresses and system attributes	Most TTS variables are described in detail in Barbose and Darghouth (2019). Relevant variables for this analysis include household addresses, installer names, the percentage of systems in the tract that are customer-owned versus leased, the median installation price in the tract (in 2019 US\$ W <sup>-1</sup> ), and the median nameplate capacity in the tract (in kWDC).
Building permit data	TTS data are augmented with municipal permitting data from two building permit data aggregators: Ohm Analytics and BuildZoom.	Solar PV addresses	Household addresses where permitting data indicated the installation of a PV system.
Experian	Modeled household-level incomes (model is proprietary)	Household incomes for PV adopters	Modeled incomes appended to PV adoption records from TTS.
US Census American Community Survey	General population demographics data at the county and tract levels	Population-level demographic attributes	Median household income, population, race, education, owner occupancy rates, income inequality (GINI coefficient), urban score
Council for Community and Economic Research	County-level cost-of-living index, described in detail in Council for Community and Economic Research (C2ER) (2017)	Cost-of-living index	Independent variable used in regression analysis

of their neighbors (i.e. other households living in the vicinity in the same tract). Put simply, positive coefficients indicate that PV adopters living in tracts with higher values of that variable tend to earn more than their neighbors, all else equal. The demographic variables include the tract median income, a county-level cost-of-living (COL) index, the GINI coefficient (a measure of income inequality), the percentage of households that self-identify as Black or Asian, the percentage of households with more than a high school education, the percentage of households that own the homes where they reside (owner occupancy), and the percentage of the tract classified as urban. The PV market variables include the average installed system price, the average system size (kW), the percentage of customers that lease rather than own their PV systems (where the term ‘leasing’ comprises any form of third-party ownership, including power purchase agreements), the percentage of systems installed by LMI installers (defined as installers that install more than half of their systems in tracts below 80% of state median income), and the percentage of systems installed by small-scale installers (defined as installers with fewer than 1000 installs in the study period). We provide more detailed information on the construction of these variables. We use county-clustered, robust standard errors.

Before proceeding to the results, we note two limitations of our analysis. First, our analysis is based on geographically aggregated data. Though the analysis of geographically aggregated data is common in the social sciences (Clark and Avery 1976), one known weakness of such analysis is that the results are sensitive to the arbitrarily selected scale and shape of geographic areas (Nelson and Brewer 2017, Tidemann *et al* 2019). Aggregating at a higher geographic level, for instance, will increase standard errors on regression coefficients. However, assuming that the underlying data are spatially correlated, the value of regression coefficients for variables expressed in relative values are robust to changes in the scale and shape of aggregation (Geronimus and Bound 1998, Reynolds and Amrhein 1998, Pietrzak 2014). In our case, key variables are highly spatially correlated, particularly income (Reardon and Bischoff 2011), such that our arbitrary selection of census tracts as the unit of aggregation should not significantly affect the analysis. Second, previous research has shown that household income levels can affect PV market characteristics such as adoption rates (Yu *et al* 2018) and prices (Gillingham *et al* 2016). For this reason, we exclude adoption rates from the regression, given that this variable would be problematically endogenous. We chose to include other potentially endogenous



regressors, such as PV prices, but present regression results without any market variables as a robustness check.

### 3. Results

In this section, we first introduce some descriptive analyses to better understand some of the income trends of solar adopters, particularly as they relate to the broader population-at-large. We then investigate the drivers behind the observed solar adoption inequity.

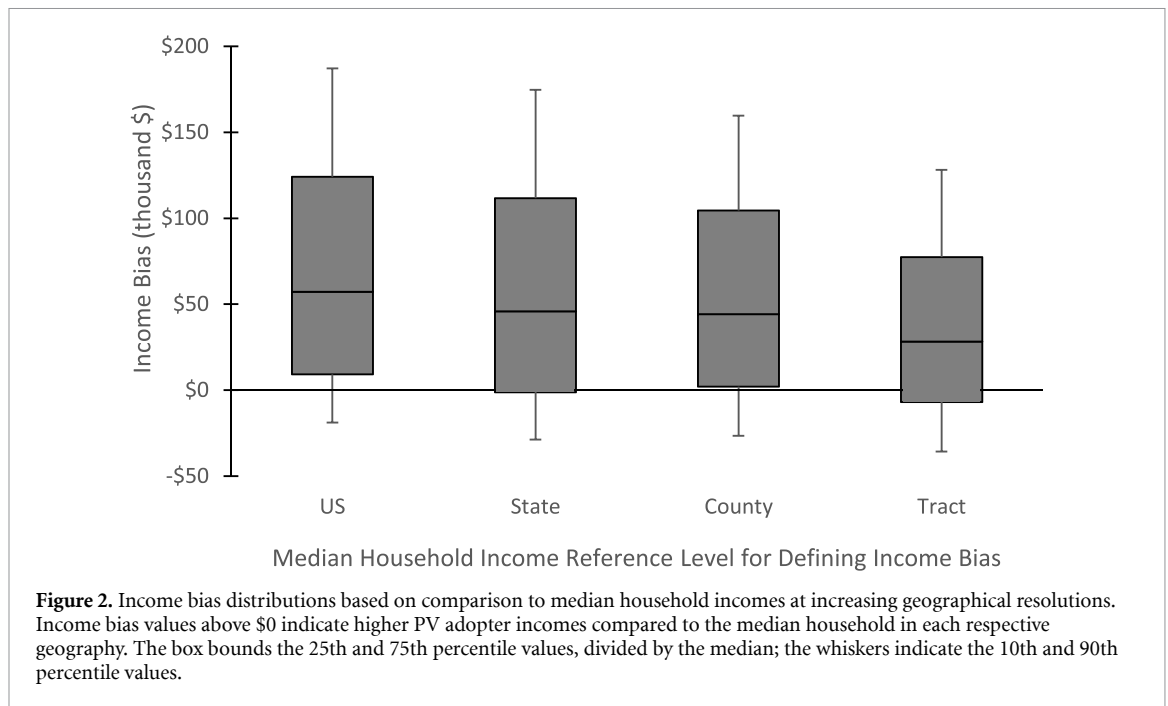
#### 3.1. PV adopter income trends: descriptive analysis

Figure 1 shows histograms of annual household incomes for all households (light bars) and for solar households only (dark bars). The figure illustrates two skews in the installer income distribution. First, the figure depicts income *inequality*: household income is unevenly distributed across adopters, with some adopters earning significantly more than others. Solar adopter income inequality is largely a reflection of underlying income inequality in the US, where incomes are highly unequal (Alvaredo *et al* 2013). Second, the figure depicts adoption *inequity*: high-income households are overrepresented among PV adopters relative to their shares of the total US population. The median annual income of all households is \$64k whereas the median income of all solar adopters is \$120k. The disparities in the distribution are most pronounced at the low and high ends of the income spectrum, as also reported in Barbose *et al* (2021b).

We quantify solar adoption inequity in terms of *income bias*. This is defined as the difference between solar adopter incomes and the median income of

all households within the broader population. That broader population can be specified at any geographic scale, which impacts the level of income bias. To illustrate, figure 2 shows the distribution of income bias across solar adopters using four geographical definitions for the population-at-large: US, state, county, and US census tract; in the remainder of this article, we will refer to these as ‘US income bias’, ‘state income bias’, ‘county income bias’, and ‘tract income bias’, respectively. As shown, income bias generally decreases as the reference income level for the broader population progresses to smaller geographical scales. PV adopters more closely resemble other households in the same tract, in terms of income, than they do the county, the state, or the US population. This pattern reflects income segregation; high- and low-income households tend to geographically cluster in distinct areas (Reardon and Bischoff 2011). Income segregation and the clustering of PV adoption in high-income tracts explain some of the income bias observed at a US level. Nevertheless, median tract income bias, though lower, it is still positive. This indicates that solar adopters tend to earn more than other households even at more granular geographies.

The income bias observed in figure 2 is largely determined by income bias distributions for states with larger PV markets—in particular, California, which represents over 50% of our solar adopter sample. The high household incomes of the general population in California, relative to the US population, contributes to the US income bias levels (left-most bar in figure 2). In addition to the high absolute income levels, California also has amongst the highest median US and tract income bias compared to other states, as shown in figure 3 (in panels



(a) and (b), respectively). Almost all states display positively skewed income bias, indicating solar adoption inequity, though for most states, this trend is less pronounced than in California. The following section dives into the drivers for the local inequity.

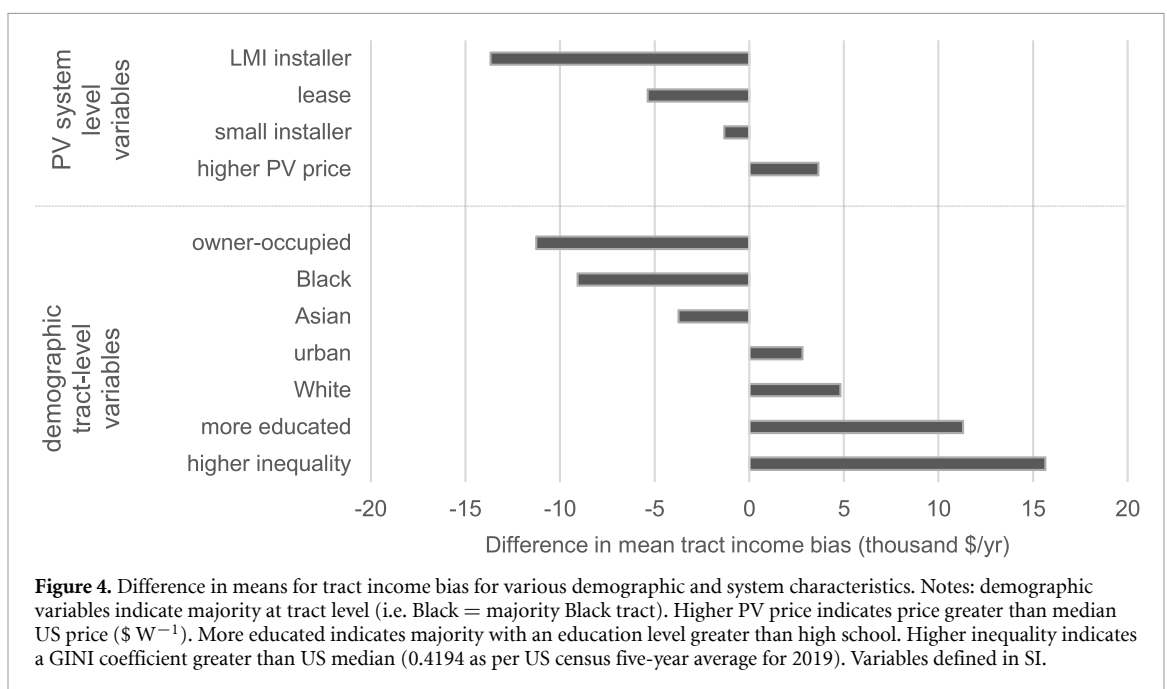
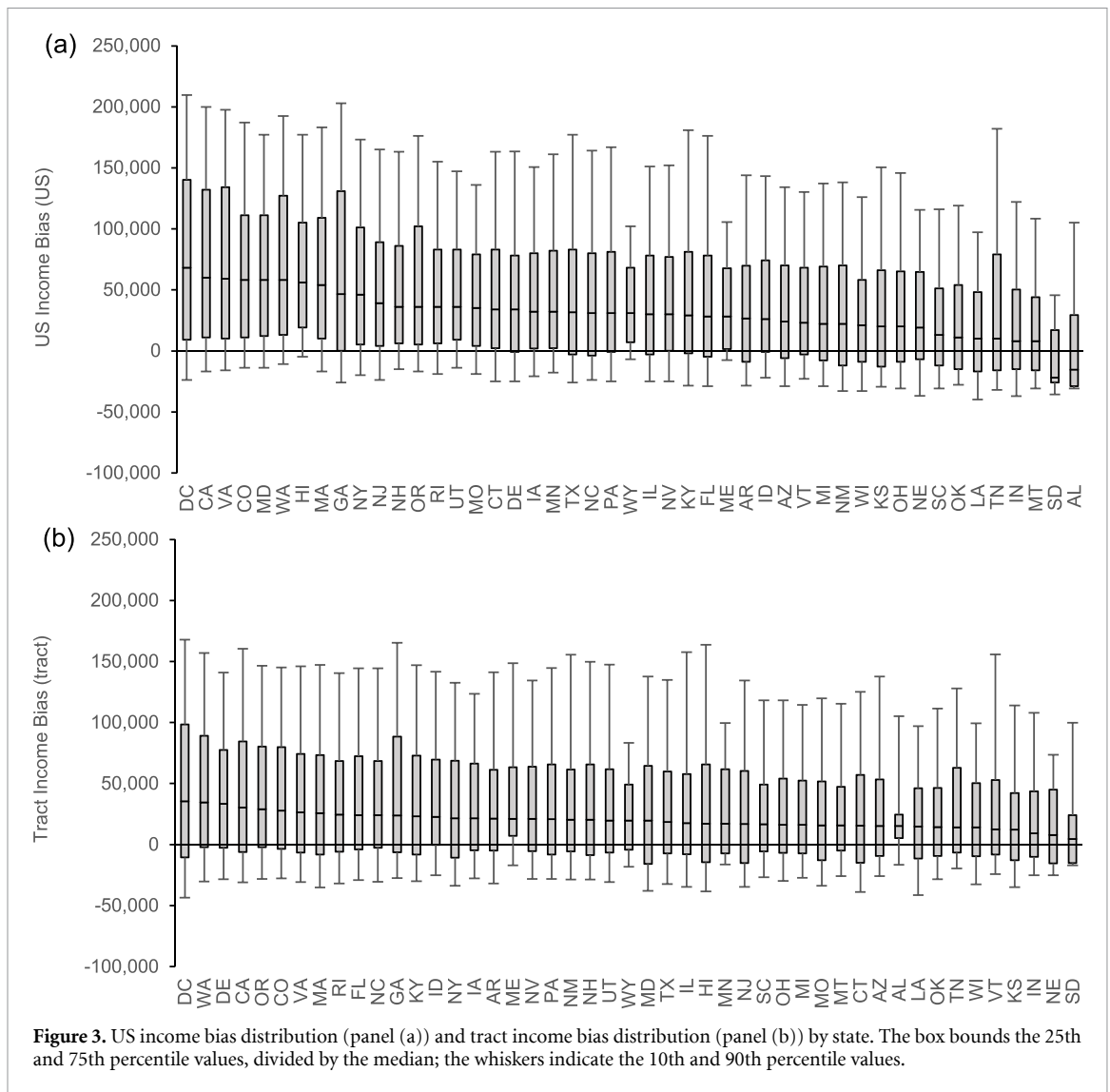
### 3.2. What drives solar adoption inequity at a local level?

To examine what demographic and solar market characteristics drive solar adoption inequity at a local level, we consider 11 variables that could explain differences in local income bias. These variables, described in section S1, include demographic characteristics of the solar adopters' tracts (education, race, urban/rural, income inequality) and characteristics related to the PV system (the system price, whether it is leased or owned, the size of the installer, and whether the installer focuses on LMI PV adopters). Note that we exclude some potential drivers of adoption inequity—such as federal or state tax credits—that do not meaningfully vary at a tract level. For each of these variables, we analyze differences in mean tract income bias between different values of each variable (e.g. the difference between the mean tract income bias in majority Black vs non-majority Black tracts). The tract income bias difference in means for each variable considered is shown in figure 4 (all statistically significant at the 0.05 level) and signifies whether there is more or less solar adoption inequity as a result of specific characteristics. For example, the difference in means is negative for majority Black tracts; although income bias is still positive in majority Black tracts, it is lower than in majority non-Black tracts (i.e. adoption is more equitable in majority Black tracts). A hypothesis for these results is offered in the following section, which

explores several regression models to better understand the drivers for tract income bias.

Table 2 presents the results of three variations of the regression model to evaluate the robustness of specific results: (a) our preferred specification with all variables described in section 2; (b) a model with only the demographic variables; and (c) a model with only the PV market variables. Recall that the dependent variable is adopter tract income bias, a proxy for solar inequity. To facilitate comparison across the variables, we standardized values for all variables such that each coefficient represents the change in PV adopter income bias from a one standard deviation change in the variable.

The regression includes three variables related to local income levels. First, the income coefficient suggests that tract income bias is higher in lower-income areas, all else equal. In relatively low-income areas, only a subset of relatively high-income households may be financially capable of adopting PV at current prices. As a result, in low-income areas, one would expect PV to flow to those high-income households, increasing tract income bias. Second, the model suggests that tract income bias is higher in areas with higher living costs. Similar to the case of income, this result suggests that PV adoption is less equitable when some households face cash constraints due to high living costs. Third, the GINI result shows that tract income bias is higher in areas with greater income inequality. This result illustrates how income inequality is a necessary—though not sufficient—condition for PV adoption inequity. Income inequality is clearly a necessary condition, in that tract income bias would always be zero if income were evenly distributed across households. However, *average* tract income bias would also be zero if PV systems were randomly





**Table 2.** Regression results dependent variable ( $Y$ ) = median adopter tract income bias; county-clustered, robust standard errors in parentheses.

	(a) All variables	(b) Demographic variables	(c) Market variables
Tract median income	−11.84 <sup>a</sup> (0.81)	−9.99 <sup>a</sup> (0.98)	—
COL index	9.41 <sup>a</sup> (1.49)	7.22 <sup>a</sup> (1.53)	—
GINI	7.86 <sup>a</sup> (0.57)	8.63 <sup>a</sup> (0.62)	—
%Black	−2.35 <sup>a</sup> (0.30)	−3.30 <sup>a</sup> (0.38)	—
%Asian	2.24 <sup>a</sup> (0.57)	2.15 <sup>a</sup> (0.52)	—
Education	16.54 <sup>a</sup> (1.71)	18.45 <sup>a</sup> (2.07)	—
Owner occupancy	−5.11 <sup>a</sup> (0.80)	−4.19 <sup>a</sup> (0.70)	—
Urban	3.86 <sup>a</sup> (0.51)	2.18 <sup>a</sup> (0.50)	—
PV price	−0.16 (0.10)	—	0.19 (0.40)
PV system size	7.00 <sup>a</sup> (0.69)	—	0.61 (1.17)
Leasing	−4.16 <sup>a</sup> (0.94)	—	−9.95 <sup>a</sup> (1.14)
LMI installer	−3.46 <sup>a</sup> (0.43)	—	−6.53 <sup>a</sup> (1.12)
Small installer	−1.31 <sup>a</sup> (0.63)	—	0.89 (1.18)
State FE	X	X	X
$N$	12 561	12 561	12 561
$R^2$	0.48	0.44	0.16

<sup>a</sup>  $p < 0.05$ .

distributed across households with different income levels. That is, income inequality only translates to PV adoption inequity if there are mechanisms that drive PV to high- instead of low-income households. As discussed in the section 1, such mechanisms exist on both the demand and supply side of PV markets. On the demand side, high-income households are more financially capable of adopting PV and may thus be more likely to adopt, all else equal. On the supply side, installers are more likely to target high-income households (O’Shaughnessy *et al* 2021a). In both cases, income inequality creates conditions that exacerbate these mechanisms and drive PV onto high-income rooftops.

The coefficients on the two race variables suggest that tract income bias is lower in areas with greater shares of Black households but higher in areas with larger Asian populations, all else equal. Both results lack straightforward explanations. One possibility is that tract median income is an imperfect control for differences in local income levels and that the result reflects spurious correlation between race and income. Another possibility is that the results reflect correlation with an omitted variable. For instance, due to racist housing practices, homes in areas with large Black populations

may be systematically different from homes in other areas in ways that affect adoption inequity. Still, the robustness of the results suggests that racial diversity has real impacts on adoption equity. We offer three hypotheses, which all present potential areas for further research. First, racial differences may correlate with differences in social structures with respect to income levels. For instance, areas with large Black populations may have stronger social ties between high- and low-income households, and those ties could act as conduits of social influence that drive LMI PV adoption across income levels. Second, the result may reflect differences in how income is geographically segregated. Due to racist housing practices, Black households of all income ranges were restricted to living in certain areas. Therefore, income tends to be less segregated within tracts with large Black populations (Reardon and Bischoff 2011, Intrator *et al* 2016). All else equal, income integration removes the structural cues that drive income-targeted marketing (O’Shaughnessy *et al* 2021a), such as clear geographic distinctions between high- and low-income neighborhoods, and will therefore improve adoption equity. Third, installers in communities with large Black populations may have, or may develop, specific skills that enable them

to market more effectively to a more diverse customer base both in terms of race and income. The data are consistent with this installer-led hypothesis. Only about 2% of installers generate more than 10% of their sales in areas that are more than 50% Black. Households served by those installers earn about  $\$7600 \text{ yr}^{-1}$  less, on average, than households served by other installers, controlling for median tract income ( $t = 10.0$ ). As a result, the presence of specific installers in areas with larger Black populations could explain some of the observed results.

The model suggests that tract income bias is higher in more educated areas. Like the result for whether a tract is majority Black, this result lacks a straightforward explanation. Again, the result may reflect correlation with an omitted variable. One possibility is that education levels correlate with differences in social structures. For instance, education levels are generally higher in areas surrounding college campuses. Such areas are often defined by a transient group of relatively low-income households, such as students and temporary researchers, that are less likely to make long-term home investments. In these areas, PV may naturally flow to a population of stable, relatively high-income earners. The relationships between these types of local social strata and PV adoption inequity are another area for further research.

The results indicate that income bias is lower in areas with higher owner-occupancy rates, but higher in more urban areas. We offer the following interpretation of these results. Homeowners are more likely to adopt PV and earn more, on average, than renters. As a result, in areas with low rates of owner occupancy, PV will naturally flow toward a small group of relatively high-income homeowners. Higher owner-occupancy rates break this mechanism, so that PV adoption is more equitable at a local level in areas with fewer renters. Similarly, in urban areas with a heterogeneous mix of single and multifamily housing, PV will tend to flow to a group of relatively high-income households, primarily single-family homeowners. We excluded variables for housing types due to collinearity with the owner-occupancy variable. Variables for solar suitability, including roof condition, age, and shading, were also excluded due to data constraints. The effects of housing patterns on PV adoption equity are an additional area for future research.

The regressions provide several insights into the relationships between market characteristics and PV adoption equity. First, the model suggests that differences in local PV prices are not associated with differences in adoption equity. This null result is surprising, indicating that high local PV prices do not significantly exacerbate adoption inequity as may be expected. However, it is worth reiterating that PV prices are potentially endogenous, that is, PV prices may not be truly independent given that PV adopter incomes have been shown to influence prices. Second,

the results suggest that tract income bias tends to be higher in areas with larger PV systems. We interpret this result to mean that areas with larger PV systems are areas with larger homes with more rooftop space to support more panels. Third, tract income bias is lower in areas with higher rates of PV leasing, consistent with previous findings showing that LMI households are more prone to leasing than higher-income households (O'Shaughnessy *et al* 2021b).

Finally, the results suggest that differences across installers influence PV adoption equity. Income bias is lower in areas served by LMI installers and, to a lesser extent, by smaller installers, though this result is not robust when excluding the demographic variables. One interpretation of these results is that certain installers have, or develop, skills that allow them to access a broader customer base in terms of income. The data provide some preliminary support for this hypothesis. For instance, LMI installers are more likely to install leased systems and less likely to install systems with premium features such as high-efficiency modules, DC optimizers, or battery storage (see section S2). Similarly, among small installers, leased systems are more frequently installed and premium features are less frequently installed in lower-income tracts. These differences may reflect ways that LMI and small installers cater to LMI customer needs. The hypothesis that installer skillsets and marketing tactics can influence adoption equity is a suggested area for future research.

#### 4. Conclusion and discussion

Rooftop PV has been and continues to be inequitably distributed with respect to income in the United States. PV adoption inequity is largely the outcome of structural inequalities that impact the adoption of most emerging technologies, especially income inequality and income segregation. Nonetheless, PV adoption inequity is not an inevitable outcome, and PV has been more equitably deployed in some areas than in others. In this paper, we analyzed the drivers of PV adoption inequity at a local level. Deconstructing the factors that explain difference in PV adopter incomes can assist policymakers in designing targeted interventions at a more local scale to facilitate more equitable PV adoption. Our results yield three key implications.

First, while solar adoption inequity is frequently attributed to high PV prices, the insignificant effects of prices in our regression model suggests that this attribution is not straightforward. Falling costs have made PV more financially accessible to LMI households, and most customers have access to financing options that require little or no money up front. Our regression model suggests that falling costs reduce the role of price in explaining PV adoption inequity. Instead, other structural barriers may play more

important roles. For instance, lower LMI home ownership rates may drive adoption inequity, as indicated by the significant coefficients on the urban and owner-occupancy variables in the regression. These results suggest that researchers should continue to explore the structural barriers to LMI adoption and validates the measures policymakers undertake to increase solar equity, including facilitating PV adoption for renters, in multifamily housing, and in urban areas (e.g. community solar, virtual net metering, targeted subsidy programs).

Second, we find several interesting results in terms of relationships between race, education, and PV adoption equity. Both the descriptive and regression results suggest that racial make-up and education levels may affect local PV adoption patterns. While the legacies of racist housing policies are likely to be implicated in these findings, we also posit that these effects may be connected to sociological factors, such as distinct social networks in communities with larger shares of non-white households that could affect how social influence translates to PV adoption. With further study, researchers may be able to identify ways to use local social networks to accelerate PV adoption equity.

Finally, our descriptive and regression model results suggest that PV adoption is more equitable in census tracts served by specific types of installers, particularly installers that operate at smaller scales and have experience working in LMI and racially diverse tracts. Although further research is required, these results suggest that some installers have or develop specific skills to more effectively reach LMI households. Future qualitative research could analyze the marketing practices of these installers and identify specific strategies that result in more equitable customer acquisition. Policymakers could explore supply-side interventions that diffuse these strategies to more installers. One such strategy is for installers to offer financing, particularly leasing. Consistent with previous research, our descriptive and regression results show that leasing is associated with more equitable adoption at a local level. However, leasing can be a challenging business model, particularly for small-scale installers. Policymakers could explore ways to facilitate leasing or other financing models for small-scale installers, such as through state green banks.

In conclusion, our results demonstrate that PV adoption patterns are not inherently inequitable. The degree to which PV adoption is equitable varies, and some of this variation can be explained by local demographic and PV market factors. PV is equitably distributed in different areas to different degrees, and some of these differences can be explained by local demographic and PV market factors. The drivers of these differences have implications on equity discussions about who benefits from solar and who bears the burden of cost shifts at the local level. Future

research and policy can explore ways to leverage these differences to accelerate the transition to equitable PV adoption.

## Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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