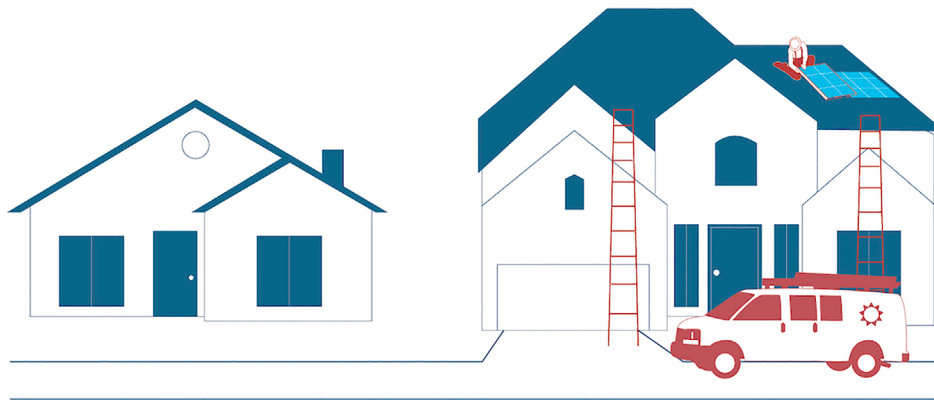


Article

Income-targeted marketing as a supply-side barrier to low-income solar adoption

Similar to in other industries, rooftop solar installers tend to target relatively high-income customers.

Lower access to installers and quotes is one reason why low-income households adopt rooftop solar less frequently than high-income households.



Income-targeted marketing poses challenges to efforts to accelerate a transition to more equitable rooftop solar adoption.

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Highlights

Rooftop solar installers
submit fewer quotes to
low-income households

Income-targeted
marketing could pose
barriers to equitable solar
adoption

Customers that receive
fewer quotes are less likely
to adopt solar

Policymakers could
design low-income solar
programs to address
supply-side barriers

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Article

Income-targeted marketing as a supply-side barrier to low-income solar adoption

Eric O'Shaughnessy,^{1,2,3,*} Galen Barbose,¹ Ryan Wiser,¹ and Sydney Forrester¹

SUMMARY

Low- and moderate-income (LMI) households remain less likely to adopt rooftop solar photovoltaics (PV) than higher-income households. A transient period of inequitable adoption is common among emerging technologies but stakeholders are calling for an accelerated transition to equitable rooftop PV adoption. To date, researchers have focused on demand-side drivers of PV adoption inequity, but supply-side factors could also play a role. Here, we use quote data to explore whether PV installers implement income-targeted marketing and the extent to which such strategies drive adoption inequity. We find that installers submit fewer quotes to households in low-income areas and those households that receive fewer quotes are less likely to adopt. The data suggest that income-targeted marketing explains about one-quarter of the difference in PV adoption rates between LMI and higher-income households. Policymakers could explore a broader suite of interventions to address demand- and supply-side drivers of PV adoption inequity.

INTRODUCTION

Rapidly falling prices have brought rooftop photovoltaics (PV) adoption into financial reach for more households (Borenstein, 2017). Despite these trends, low- and moderate-income (LMI) households remain significantly less likely to adopt PV than high-income households in the United States (Carley and Konisky, 2020). Inequitable PV adoption may be a transient feature of rooftop PV markets. Similar to the markets of most emerging technologies (Attanasio and Pistaferri, 2016), rooftop PV adoption is becoming more equitable over time as costs decline (Barbose et al., 2021). A growing community of policymakers and stakeholders are calling for an acceleration of the transition toward equitable rooftop PV as part of the emerging dialog on clean energy justice (Welton and Eisen, 2019). Rooftop PV adoption inequity violates several tenets of clean energy justice, including that the benefits of clean energy technologies should be distributed equitably (Sovacool and Dworkin, 2014). PV adoption inequity may also represent a missed opportunity for PV to mitigate the energy cost burdens borne by LMI households (Bednar and Reames, 2020; Brown et al., 2020). Further, PV adoption inequity could decelerate PV deployment, given that LMI buildings account for around 43% of PV-viable rooftop space (Sigrin and Mooney, 2018). PV adoption inequity and its energy justice implications could—and arguably already have—prompt legal and regulatory actions that reduce the role of rooftop PV in deep decarbonization (Welton and Eisen, 2019).

Persistent PV adoption inequity has become the focus of a growing literature and an increasing number of policies. To date, researchers have focused on demand-side explanations for adoption inequity, such as cash constraints, lower rates of home ownership, building structural issues, and language barriers (Sunter et al., 2019; Lukanov and Krieger, 2019; Mueller and Ronen, 2015; Brown et al., 2020). Likewise, LMI PV policies have been designed to address demand-side barriers, such as LMI adoption subsidies and LMI carve-outs in community solar programs (Paulos, 2017).

Supply-side factors may also pose barriers to PV adoption inequity. Supply-side barriers could take the form of PV installers targeting high-income customers. Income-targeted marketing could prevent LMI households from interacting with installers, an important step toward PV adoption (Sigrin et al., 2017; Rai et al., 2016). Furthermore, income-targeted marketing could reduce competition for LMI households, possibly resulting in those households receiving higher quote prices (O'Shaughnessy and Margolis, 2018).

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Income-targeted marketing would not be unique to PV; such practices are common in other industries (Turow, 2006). Further, income-targeted marketing would not be difficult. Given that income is geographically segregated in the United States (Reardon and Bischoff, 2011), installers can target high-income customers by marketing in relatively high-income areas and avoiding low-income communities. Income-targeted marketing could be part of a rational, profit-maximizing installer business strategy. PV installers may tend to locate their businesses in relatively affluent areas with better access to skilled labor (Chin, 2020) and high-income early adopters. Further, PV installers may perceive—rightly or wrongly—that LMI customers are more difficult to acquire. Finally, just as adoption inequity in general may be transient, income-targeted marketing would not necessarily be a permanent feature of rooftop PV markets.

Income-targeted marketing, even if it is an expected supply-side feature of rooftop PV markets, would pose barriers to an accelerated transition to equitable rooftop PV adoption. Yet no study to our knowledge has directly explored these potential supply-side barriers. This knowledge gap is problematic given that the policy implications of supply-driven PV adoption inequity would differ from the implications of demand-driven inequity. Similar to justice policy initiatives in other areas—such as access to healthy foods in inner cities (Bodor et al., 2010; Giang et al., 2008)—addressing both supply- and demand-side barriers could drive more holistic and effective measures to accelerate a transition toward more equitable PV adoption. We fill this research gap by analyzing PV installer marketing behavior on an online quote platform. Our primary research question is whether installers exhibit income-targeted marketing by submitting fewer quotes to customers in LMI areas. The data provide clear evidence of income-targeted marketing. We then analyze the effects of income-targeted marketing on LMI adoption and explore hypotheses to explain the phenomenon. We conclude by summarizing and exploring three levels of barriers to PV adoption equity.

RESULTS

Quote and demographic data

Most PV market research uses data on installed PV systems (O'Shaughnessy et al., 2019). Installed system data show that PV systems are underrepresented in LMI areas (Barbose et al., 2020). However, using installed system data, it is not possible to isolate supply- from demand-side drivers of inequitable adoption patterns: are installers less likely to pursue LMI customers, or are LMI households less likely to pursue installers? In this study, we isolate supply-side patterns using PV quote data, including quotes for installed systems, as well as rejected offers. Quote data allow us to isolate installer marketing patterns by exploring differences in the number of quotes submitted to different customers. We obtained quote data from EnergySage (see Method details in STAR Methods). Our final cleaned data set comprises data on 192,970 customers in 36 states and Washington, DC. Those customers received a total of 663,740 quotes from 2017 to 2020 on the platform, of which 10,951 quotes were accepted, representing roughly 1% of the U.S. residential PV market over that time period (Davis et al., 2020). Note that our data set is a randomly selected, representative sample of EnergySage's population of users and quotes over this time frame.

Installers do not know the income levels of prospective customers before they decide whether to submit quotes on the platform. Installers can only infer customer income based on the home's location, size, and household electricity use. As a proxy for installer perceptions of customer income, we construct Census tract-level variables from U.S. Census data (see Method details in STAR Methods). Throughout our study, we use the term LMI tract to refer to tracts whose median incomes are less than 80% of their respective states' median incomes. We test for income-targeted marketing by evaluating differences in the number of quotes submitted to customers in LMI tracts.

While we focus on potential supply-side drivers of PV adoption inequity, the quote data provide evidence that demand-side drivers begin before quotes are submitted. About 34% of customers live in tracts with median incomes less than the tract-level population-weighted median income. Put another way, the data suggest that below-median-income tracts are underrepresented in the data by about 16 percentage points. While some of this difference may reflect barriers specific to the use of quote platforms (e.g., internet access), the underrepresentation of LMI areas in the quote data suggest that LMI households are less likely to pursue PV quotes than higher-income households. We return to this point in a later discussion.

Extrapolation

Before proceeding to the results, it is important to note that quote platforms represent a small share of the U.S. rooftop PV market, on the order of 5% of sales (Mond, 2017). Further, installer behavior on quote

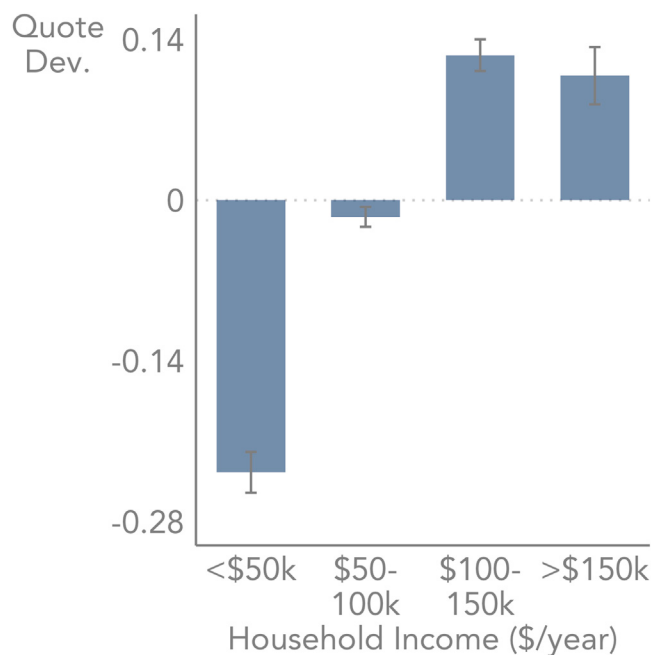


Figure 1. Differences in numbers of quotes received by household income bin

Quote deviation = average difference between the number of quotes received and the customer's state-level average number of quotes received (to control for geographic variation in market activity). Error bars depict 95% confidence intervals.

platforms does not necessarily reflect off-platform behavior off platforms. Installers may have less information about quote platform customers than they could have acquired off the platform (e.g., through door-to-door marketing). Further, given that prospective PV customers tend to obtain more quotes on platforms, installers may face a more competitive bidding environment on quote platforms. Notwithstanding these differences, we argue on-platform installer behavior provides evidence of comparable off-platform behavior for two reasons. First, the installers on the platform are a subsample of the broader population of off-platform installers—not a distinct group with distinct strategies. Installers must have at least three years of off-platform experience before bidding on the platform and most installers continuing marketing both on and off the platform. Second, the decision process of whether to submit quotes to specific customers is not fundamentally dissimilar on or off the platform. In both cases, installers must invest time and effort to analyze customer electricity use and home structural characteristics then compile relevant information for the quote (e.g., price, system size, inverter type). Profit-maximizing installers should—both on and off the platform—optimize their quote behavior by submitting quotes when the expected benefit at least offsets the marginal cost of quote preparation. Hence, while the magnitudes of the results of this study may not necessarily extrapolate to the broader PV market, the results should qualitatively describe off-platform installer behavior.

Correlations between quote submissions and area incomes

Customers in LMI areas receive significantly fewer quotes, on average, than customers in high-income areas (Figure 1). Customers in LMI tracts received about 3.1 quotes, on average, compared with 3.5 quotes in non-LMI tracts ($t = 28.3$, note that all t test results are based on two-sided tests, and all results are statistically significant at $p < 0.01$). Customers in LMI tracts were about 1.3 times more likely to receive only a single quote than customers in non-LMI tracts ($t = 19.7$) (Figure 2). Conversely, customers in non-LMI tracts were about 1.3 times more likely to receive 7 quotes (the maximum) than customers in LMI tracts ($t = 10.7$).

One explanation for differences in the number of quotes received is that different numbers of installers actively market in different areas. When a customer requests a quote on the platform, that request generates notifications that are sent to installers that operate in the customer's area. On average, a quote request generates 16 installer notifications. The number of installer notifications partly determines the number of

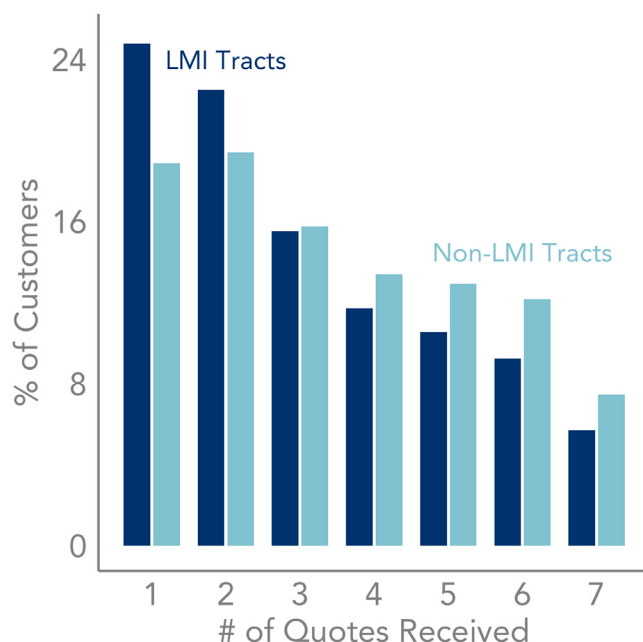


Figure 2. Distributions of quotes received for customers in LMI and non-LMI tracts

This figure illustrates these distributions for the entire data sample. Similar patterns of distributions—higher frequency of relatively few quotes in LMI tracts and higher frequency of more quotes in non-LMI tracts—are also apparent at the state level.

quotes received: a customer receives 0.09 more quotes, on average, for each additional notified installer ($t = 254.9$). Requests in LMI tracts generate fewer installer notifications, on average, than in non-LMI tracts. In California, for instance, requests in non-LMI tracts generate an average of 26.1 notifications, compared with 24.9 notifications in LMI tracts ($t = 7.4$). As a result, customers in LMI tracts may receive fewer quotes because their requests generate fewer installer notifications. This outcome may reflect the fact that installers tend to site their businesses in relatively affluent areas (see Potential Drivers of Income-Targeted Marketing).

Some of the correlation between installer quote decisions and income level could also reflect spurious correlation with other demographic factors, particularly race. Quote counts exhibit a nuanced correlation with racial characteristics. The data suggest that installers submit more quotes in communities with moderate levels of racial diversity (e.g., 10-50% non-white minority) than in less diverse areas (e.g., <10% non-white minority). However, installers tend to submit fewer quotes in majority-minority areas than in predominantly white areas (Figure 3). The case of American Indian populations is particularly stark, although it should be noted that those estimates are based on small sample sizes as evidenced by the large error bars in Figure 3.

Multivariate analysis

We isolate differences in installer marketing behavior in LMI tracts through a multivariate regression model (see Quantification and statistical analysis in STAR Methods). The customer-level dependent variable is the number of quotes received. The explanatory variable of interest is a dummy variable for customers in LMI tracts. We use an LMI tract dummy variable to produce a coefficient that directly reflects differences in installer quote behavior in LMI areas. The coefficient represents the average difference in the number of quotes received by households in LMI tracts, controlling for other factors. We present model results with tract median income rather than the LMI tract dummy variable in Table S1. The models include several control variables (Table 1), as well as state-year fixed effects. See STAR Methods for a discussion of the rationale for the control variables.

We present results for models with and without controls in Table 2. Model (1), which excludes all controls except the fixed effects, suggests that customers in LMI tracts receive 0.34 (10%) fewer quotes, on average,

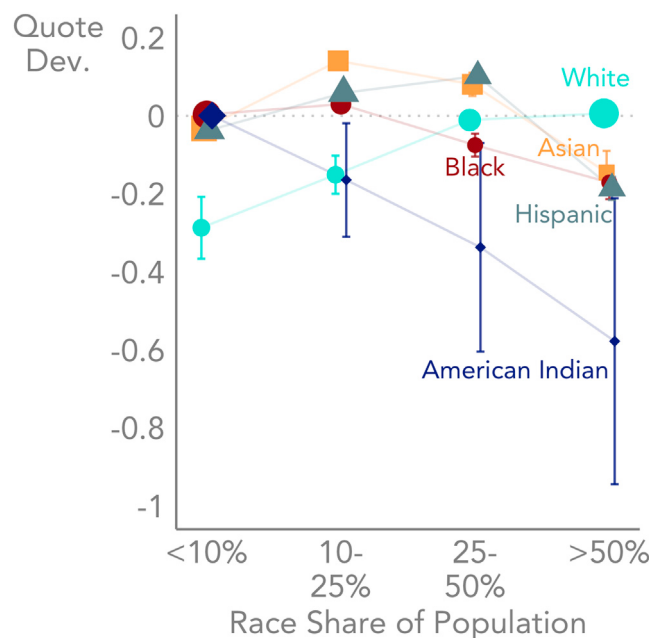


Figure 3. Differences in number of quotes received based on share of population self-identifying as specific races

Quote deviation = average difference between the number of quotes received and the customer's state-level average number of quotes received. Error bars depict 95% confidence intervals. Marker sizes correspond to each bin's share of observations for that race grouping.

than customers in other tracts. Model (2) suggests that customers in LMI tracts receive 0.27 (8%) fewer quotes, on average, when controlling for other factors. Finally, model (3) suggests that customers in LMI tracts receive 0.20 (6%) fewer quotes, on average, when controlling for the number of installers notified about quote requests. We present results with and without controls to illustrate that at least some observed differences in installer behavior may be attributable to other confounding factors. At the same time, these other factors are partially determined by income. For instance, low-income levels generally reduce electricity use, such that the electricity use variable absorbs some of the effect attributable to the LMI tract variable. Hence, while model (1) may over-estimate the degree to which quote behavior is biased based strictly on income, model (1) may provide a more valid measure of the magnitude of the barrier to LMI adoption. These results are robust to multiple model variations, including alternative income variable specifications (see [Table S1](#)), alternative control variables ([Table S2](#)), alternative model specifications ([Table S3](#)), and alternative geographic level (Census block group) for the LMI tract dummy ([Table S4](#)).

The control variables yield additional insights into installer marketing behavior. The interaction term with the area income delta variable (see [Quantification and statistical analysis in STAR Methods](#)) suggests that each \$10,000 increase in the incomes of surrounding tracts drives an additional 0.03–0.05 quotes to customers in LMI tracts. In words, this result indicates that LMI tract proximity to higher-income tracts can mitigate the impacts of income-targeted marketing, although the effect is small in magnitude. Conversely, the result suggests that geographic isolation of LMI communities could exacerbate income-targeted marketing. The model yields the expected results that installers submit more quotes to customers with higher electricity use (though the coefficients are statistically insignificant), in areas with newer homes (both in terms of home age based on Census data and roof age as reported by customers), and in areas with higher cumulative PV penetration. These three results could exacerbate income-targeted marketing, given that LMI households tend to use less electricity, live in areas with older homes, and live in areas with less cumulative PV penetration.

The results of the minority control variables suggest that quotes first increase then decrease with higher levels of racial diversity. These results should be interpreted with caution. Other confounding factors—such as urban density—could explain some of the apparent differences in quote levels based on racial composition. Nonetheless, the results suggest that minority households face steeper barriers to PV adoption than white households, both because minority households tend to live in low-income areas

Table 1. Variable definitions and summary statistics

Variable	Description (units)	Mean (SD)
Dependent		
Quotes	Number of quotes received per customer (#/customer)	3.44 (1.9)
Income		
LMI tract	Dummy variable for whether customer's tract-level median income is less than 80% of state median income (binary)	0.12 (0.32)
Area income delta	The difference between a customer's tract median income and the mean median income of the six closest tracts (x\$10,000)	−0.84 (2.2)
Controls		
Notified installers	Number of installers that were notified about the customer's request	16.16 (11.0)
Electricity use	Customer's reported annual electricity usage (MWh/year)	16.11 (10.2)
Home age	Median home age in tract (years)	33.31 (16.1)
Minority	Proportion of households in tract self-identifying as not only white (proportion [0:1]). We include a squared term to account for the potentially non-linear relationship (see Supplementary Note 1)	0.23 (0.2)
Householder age	Median householder age (years)	41.5 (7.2)
PV per capita	PV systems installed per household	0.04 (0.06)
Factor variable^a	Description	Response distribution
Roof age	Estimated roof age as reported by customers with two options: less than 20 years and more than 20 years	No response: 27%
		<20 years: 58%
		>20 years: 15%
Ownership preferences	Whether the customer prefers to outright own the system, secure a loan, or finance the system through a lease or power purchase agreement	No response: 28%
		All: 19%
		Own: 21%
		Loan: 30%
Other quotes	Whether the customer received quotes outside the quote platform	Finance: 3%
		No response: 37%
		Yes: 15%
		No: 48%

^aFactor variables based on responses provided by customers at time of requesting quotes, the omitted category are blank responses (i.e., the customer did not provide a value for the field).

and because certain demographic factors (e.g., cultural/language barriers) may exacerbate existing barriers.

Finally, the customer-reported variables provide further insights into installer marketing behavior. First, the ownership preferences variable suggests that installers submit significantly fewer quotes to customers that prefer to finance systems through leases or power purchase agreements. This result was expected, given that relatively few installers offer leases and power purchase agreements (O'Shaughnessy, 2018). This result is also significant from an equity perspective: LMI households are more likely to procure PV through leases and power purchase agreements than high-income households (O'Shaughnessy et al., 2021). Second, the results suggest that installers submit more quotes to customers that had already received other quotes off the platform. One interpretation of this result is that installers perceive customers with off-platform quotes

Table 2. Tobit model results (state-clustered, misspecification robust standard errors in parentheses)

Variable	(1) No controls	(2) Controls (except notified installers)	(3) Controls with notified installers
LMI tract	−0.34 ^a (0.04)	−0.27 ^a (0.05)	−0.20 ^a (0.04)
Area income delta		0.001 (0.01)	−0.0005 (0.005)
Interaction: LMI x delta		0.05 ^a (0.01)	0.03 ^a (0.02)
Notified installers			0.14 ^a (0.02)
Electricity use		0.01 (0.01)	0.003 (0.005)
Home age		−0.01 ^a (0.002)	−0.01 ^a (0.001)
Minority		1.48 ^a (0.42)	1.07 ^a (0.33)
Minority ²		−1.60 ^a (0.39)	−1.17 ^a (0.30)
Householder age		−0.002 (0.003)	−0.003 (0.002)
PV per capita		3.05 ^a (0.47)	2.18 ^a (0.38)
Roof age: <20 years		−0.06 (0.04)	−0.04 (0.03)
Roof age: >20 years		−0.10 ^a (0.03)	−0.09 ^a (0.02)
Ownership preference: All		0.002 (0.01)	0.01 (0.01)
Ownership preference: Own system		0.03 (0.03)	0.06 ^a (0.02)
Ownership preference: Loan		0.04 ^a (0.02)	0.03 ^a (0.02)
Ownership preference: Finance		−0.57 ^a (0.12)	−0.52 ^a (0.10)
Other quotes: Yes		0.10 ^a (0.02)	0.08 ^a (0.02)
Other quotes: No		−0.01 (0.01)	−0.004 (0.01)
State-year FE	X	X	X
Pseudo R ^{2b}	0.14	0.15	0.18

Values for Tobit models cannot be directly compared to more familiar R².

Values associated with ordinary least squares regression. For context, the R².

Value of model (3) specified as OLS is 0.52. See [Table S3](#).

^ap < 0.05.

^bThe pseudo R².

as more committed to PV adoption and more likely to close deals. Although this hypothesis of installer perceptions is speculative, the quote data suggest that such a perception would be accurate: installers that reported having received off-platform quotes are about 70% more likely to close a deal than customers that did not ($t = 19.8$).

Effects of income-targeted marketing on PV deployment

Income-targeted marketing could reduce LMI PV adoption rates by forcing LMI households to decide to adopt based on fewer quotes. Receiving fewer quotes could be detrimental to PV adoption for at least two reasons. First, customer-installer interactions are important information-gathering exercises ([Rai et al., 2016](#); [Sigrin et al., 2017](#); [Wolske, 2020](#)), such that customers with fewer such interactions may feel less informed and prepared to adopt. Second, receiving few quotes equates to fewer installers competing against one another, which leads to higher quote prices for customers that receive few quotes ([O'Shaughnessy and Margolis, 2018](#)).

The data support the hypothesis that the number of quotes received affects adoption decisions. Customers that receive few quotes are less likely to close a deal on the platform than customers that receive many quotes ([Figure 4](#)). Customers that received fewer than 4 quotes were about 3 times less likely to close a deal than customers that received more quotes, on average ($t = 53.8$). Income-targeted marketing could therefore reduce LMI adoption by reducing the probability that LMI households close deals. To test this hypothesis more directly, we modeled customer close rates as a function of income level and the number of quotes received (see [Quantification and statistical analysis in STAR Methods](#)). When excluding the quotes variable, the model suggests that customers in LMI tracts are about 36% less likely to close deals

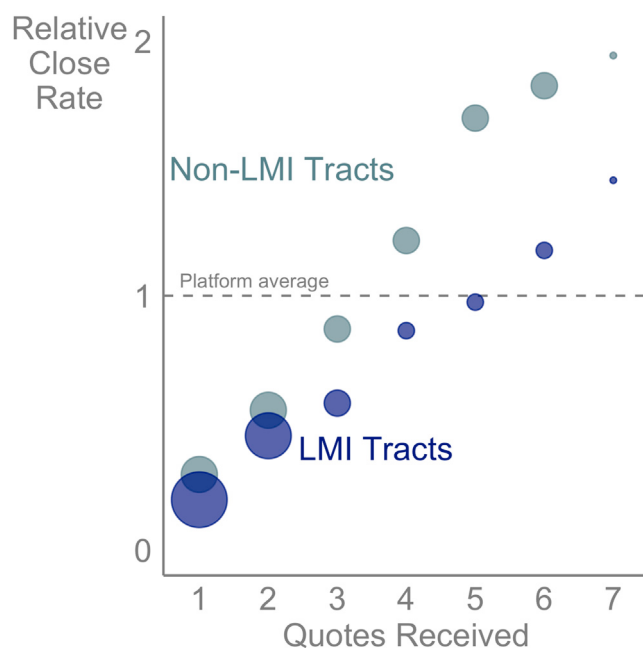


Figure 4. Customer close rates by number of quotes received in LMI and non-LMI tracts

Point sizes correspond to the share of customers receiving each number of quotes. The relative close rate is a normalized unitless metric to protect proprietary data.

than customers in non-LMI tracts (Table 3). The difference falls to 29% when controlling for the number of quotes received. The data suggest that each additional quote received increases the probability of closing by about 23%. The Tobit models suggest that customers in LMI tracts receive around 0.20–0.34 fewer quotes. Combining these two results, the data suggest income-targeted marketing reduces close rates in LMI tracts by around 6–8%, consistent with the difference in the two coefficients in Table 3. As a first order approximation, these results suggest that income-targeted marketing can explain around one-quarter of the difference in LMI customer close rates on the platform. While the magnitude of that approximation may not perfectly extrapolate off the platform (see Extrapolation), one can infer that off-platform income-targeted marketing would have similar impacts on off-platform PV deployment.

Potential drivers of income-targeted marketing

In the introduction, we posited two potential drivers of income-targeted PV marketing: (1) installers tend to locate their business in affluent areas; and (2) installers perceive that LMI customers are more difficult to acquire. The literature suggests that the second driver can be broken down into three installer perceptions: (a) installers may perceive that LMI customers equate to lower profit margins; (b) installers may perceive that LMI customers are less likely to close deals; and (c) installers may perceive that LMI customers are more likely to cancel contracts. These hypothetical drivers have varying degrees of support from the literature and from this study (Table 4).

The multivariate model suggests that business siting decisions play a minor role in income-targeted marketing. As shown in models (2) and (3) in Table 2, the income-targeting effect only falls from 0.27 fewer quotes in LMI tracts to 0.24 fewer quotes when controlling for the number of installer notifications. These results suggest that installer business siting decisions account for around 10% of the measured income bias in installer marketing patterns—although the magnitude of this result may not extrapolate to off-platform marketing behavior. Hence, the data suggest that other factors drive installers to avoid marketing in LMI areas. These potential drivers of income-targeted marketing are a suggested area for further research.

DISCUSSION

Our results suggest that both demand- and supply-side factors pose barriers to PV adoption equity. To move toward a more holistic understanding of these barriers, we develop a framework with demand- and supply-side

Table 3. Modeled impacts on close probabilities

Variable	(5) No control for quotes	(6) Control for quotes
LMI tract	−0.36 ^a (5.5)	−0.29 ^a (4.7)
Number of quotes		0.23 ^a (13.1)

To protect proprietary data on close rates, all coefficients are expressed in percentage terms, and t-statistics rather than standard errors are provided in parentheses.

^ap < 0.05.

barriers at three levels, as summarized in [Table 5](#): (1) barriers to LMI households pursuing PV adoption in the first place; (2) barriers to installers pursuing LMI customers; and (3) barriers preventing LMI customers from closing deals. A potential area for future research is the interaction between these levels. Demand-side barriers in levels 1 and 3 may affect installer perceptions and exacerbate barriers in level 2. Conversely, supply-side barriers in level 2 may affect LMI household perceptions and exacerbate barriers in levels 1 and 3. That is, if LMI households are exposed to less PV marketing in their neighborhoods, the underexposure could create a perception that rooftop PV adoption is not a viable option.

LMI solar policy, to date, has generally focused on addressing demand-side barriers in levels 1 and 3. Such policies include financial subsidies and LMI carve-outs in community solar programs. These programs have no direct measures to address the supply-side barriers in level 2. For instance, LMI PV incentive programs in California and Connecticut distributed incentives via a single installer. The results of our study should motivate more holistic approaches to PV adoption equity. Policymakers may consider measures to directly

Table 4. Potential drivers of income-targeted marketing

Potential driver	Evidence from literature	Evidence from this study
Installers locate their businesses in affluent areas	Businesses in other industries tend to site in affluent areas with better access to skilled labor (Chin, 2020).	Quote requests in LMI areas generate fewer installer notifications. Further, installer business location data (see Method details in STAR Methods) show that about 74% of installers in California have a headquarters in a zip code with a median income above the median of all zip code medians in the state (Figure 5). That is, above-median zip codes are overrepresented by about 24 percentage points.
Installers perceive that LMI customers equate to lower margins	PV price data show that installed PV prices positively correlate with area income levels (Gillingham et al., 2016), though higher prices do not necessarily equate to higher margins. Further, LMI households may require more “convincing” to adopt given their riskier financial situations (Wolske, 2020). From an installer’s perspective, that convincing equates to higher marketing costs and lower margins, all else equal.	The prices of accepted quotes do not differ significantly across area income levels. However, even if installed prices are the same across income levels, LMI customers may equate to lower margins if LMI customers are costlier to acquire.
Installers perceive that LMI customers are less likely to close deals	Not previously explored, to our knowledge	Customers in LMI tracts are about 30% less likely to close deals than other customers when controlling for the number of quotes received. Further research could explore whether these differential close rates affect installer perceptions.
Installers perceive that LMI customers are more likely to cancel	PV incentive data from California data suggests that cancellation rates are higher in low-income areas (Liao, 2020).	Not explored.

Table 5. Three levels of barriers to LMI solar adoption

Barrier level	Evidence	Potential drivers
LMI households are less likely to pursue PV adoption in the first place	Below-median-income tracts are about 16 points underrepresented on the quote platform	Demand-side barriers (e.g., cash constraints, home ownership) may discourage LMI customers from exploring PV. It is also possible that technological literacy and internet access pose specific barriers to use of quote platforms.
Installers are less likely to pursue LMI customers	Customers in LMI tracts receive around 10% fewer quotes, on average, than customers in non-LMI tracts	Installers site their businesses in relatively affluent areas; installers may perceive that LMI customers equate to lower margins, that LMI customers are less likely to close deals, and that LMI customers are more likely to cancel contracts.
LMI customers are less likely to close	Customers in LMI tracts are about 30% less likely to close deals than customers in non-LMI tracts, when controlling for the number of quotes received	Due to demand-side factors, LMI customers may pursue adoption less aggressively than other customers. Conversely, installers may pursue LMI customers less aggressively than they pursue other customers.

address barriers to LMI adoption at multiple levels: barriers to LMI households pursuing PV; barriers to installers marketing to LMI households; and barriers to LMI households closing deals.

Holistic policymaking to address demand- and supply-side barriers to equity has parallels in other fields. For instance, over the past several decades researchers and policymakers have increasingly recognized the problem of inadequate access to healthy foods in LMI neighborhoods. In the United States, this problem has been largely attributed to supply-side decisions: large grocery stores stocked with healthy foods tend to site in affluent areas, while small convenience markets with relatively low-quality foods tend to site in LMI areas (Giang et al., 2008). Through a series of state and local interventions, policymakers responded by providing supply-side incentives to induce business owners to site health-oriented grocery stores in LMI areas and to promote healthier foods in existing convenience stores (Giang et al., 2008; Bodor et al., 2010). These programs have shaped supply-side behavior and improved LMI access to healthy foods (Giang et al., 2008; Bodor et al., 2010).

Policymakers could similarly factor supply-side barriers into the design of policies to increase LMI access to PV. Our results suggest three specific areas for potential supply-side interventions. First, we find evidence that installers tend to site their businesses in relatively affluent areas. Future research could explore the extent to which business siting patterns constrain installer marketing behavior. Insofar as installer preferences to site headquarters in affluent areas shift installer marketing focus away from LMI neighborhoods, interventions to encourage installer business siting in LMI neighborhoods could mitigate income-targeted marketing. Policymakers could offer subsidies or non-financial incentives for installers to locate their headquarters in LMI communities. Second, we find evidence that LMI customers are less likely to close deals, in part because these customers tend to receive fewer quotes. Policymakers could explore supply-side measures to address low LMI customer close rates. For instance, policymakers could offer financial or non-financial incentives to installers based on submitted quotes rather than installed systems. Quote-based incentives could encourage installers to submit quotes to customers they may, rightly or wrongly, perceive to be less likely to close. Our results suggest that driving more quotes toward LMI households would increase LMI close and adoption rates. Further, policymakers could fund programs to train installers to understand the unique needs of LMI customers and how to help these customers navigate the PV adoption process. Third, the data suggest that installers submit fewer quotes to customers that prefer to finance systems through leases or power purchase agreements, financing arrangements that are known to increase LMI adoption. Policymakers could explore programs such as green banks that help even small-scale installers to obtain financing for LMI customers, potentially mitigating installer hesitance to submit quotes to customers that require financing. Future work can explore policy measures to address other potential drivers of income-targeted marketing, such as perceptions that LMI customers equate to lower profit

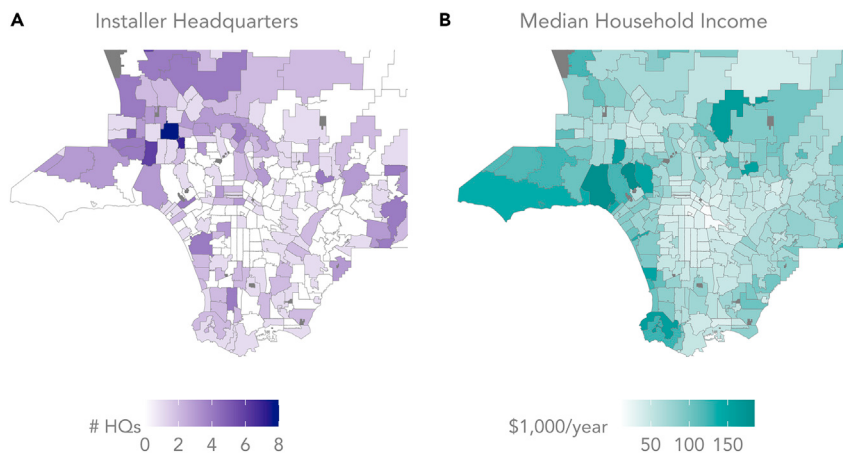


Figure 5. Correlation between installer business siting patterns and household income levels in southern Los Angeles County, California

(A and B) This figure visually compares the number of installer headquarters by zip code (A) to zip code median income levels (B). Many installers have headquarters in the relatively affluent areas of western Los Angeles, while relatively few installers have headquarters in the lower-income areas in the center of the county.

margins or are more likely to cancel. By factoring supply-side barriers into LMI PV policy design, policy-makers could implement programs that more effectively accelerate the transition toward equitable rooftop PV adoption.

Limitations of the study

Our model design benefits from the design of the quote platform, which limits the information on which installers base their quote submission strategies. As we discuss in [STAR Methods](#), we control for most factors on which installers could base their decisions that also correlate with household income. However, we were unable to control for rooftop characteristics, namely rooftop size. Rooftop size should generally correlate with income levels and is thus a relevant omitted variable. The effects of this omitted variable are mitigated, to some extent, by our control for household electricity use, which should generally correlate with rooftop size. Further, of the two variables, electricity use is arguably the more relevant from an installer's perspective ([Moezzi et al., 2017](#)), given that electricity use constrains system size under U.S. net metering regulations.

Further, it is worth reiterating that our study is based on data from an online quote platform. As we argue in the Extrapolation section, we believe that the results of our study can be qualitatively extrapolated to the broader rooftop PV market, but the numerical results of our study may reflect specific nuances of installer marketing behavior on the quote platform.

STAR★METHODS

Detailed methods are provided in the online version of this paper and include the following:

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SUPPLEMENTAL INFORMATION

Supplemental information can be found online at <https://doi.org/10.1016/j.isci.2021.103137>.

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AUTHOR CONTRIBUTIONS

Conceptualization and data curation, E.O. and G.B.; methodology, investigation, writing – original draft, formal analysis, and visualization, E.O.; writing – review & editing, G.B., R.W., and S.F.; funding acquisition and supervision, G.B. and R.W.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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STAR★METHODS

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Deposited data		
Modified quote data	This paper	N/A
Installer headquarter data	This paper	N/A

RESOURCE AVAILABILITY

Lead contact

Further information and requests for resources should be directed to and will be fulfilled by Eric O'Shaughnessy (eoshaughnessy@lbl.gov).

Materials availability

This study did not generate new materials.

Data and code availability

All original data and code are available in this paper's supplementary information. Due to the proprietary nature of the close rates, only randomized versions of the close rate variable are provided. Descriptive analyses were implemented using R. Regression models were implemented using Stata. Any additional information required to reanalyze the data reported in this paper is available from the lead contact upon request.

METHOD DETAILS

Quote data

We obtained PV quote data from the quote platform EnergySage, an online quote platform connecting prospective PV adopters to a network of PV installers. EnergySage customers apply for quotes by providing basic information about the home. Installers are notified of new applications and see home locations and annual home energy use before deciding whether to submit quotes. EnergySage allows up to 7 installers to submit quotes to any given customer. The quote data included customer location down to the Census block level, estimated annual electricity use, and price per quote, among other variables. We dropped records where the customer's reported annual electricity use was less than zero or greater than 100 MWh as likely data entry errors.

Defining LMI tracts

Census tracts are the smallest geographic unit at which most Census variables are aggregated, and roughly correspond to an area encompassing several city blocks. We define an LMI tract as any tract with a median income below 80% of the respective states' median income. The 80% threshold is frequently used to determine eligibility for federal and state low-income assistance programs, including federal programs administered by the U.S. Department of Housing and Urban Development.

Installer business locations

We use data from [O'Shaughnessy and Margolis \(2020\)](#) to identify PV installer business locations. That study compiled business locations based on installer addresses reported to the California Contractor State License Board. We used zip codes in the database to calculate the number of PV installers with headquarters in each zip code.

QUANTIFICATION AND STATISTICAL ANALYSIS

Tobit model

The dependent variable of interest is the number of quotes submitted to each EnergySage customer. We use a Tobit model to account for the fact that the number of quotes submitted are censored from above at a maximum of seven quotes. Our model takes the form:

$$q_{i,t} = lmi_t\alpha + e_i\beta + Y_t\gamma + \varphi + SY + \varepsilon \quad (\text{Equation 1})$$

where $q_{i,t}$ is the number of quotes submitted to customer i in census tract t , lmi_t is a dummy variable indicating whether tract t is an LMI tract, e_i is customer i 's annual electricity use, Y_t is a vector of tract-level variables (Table 1), φ is a constant, and SY is a state-year fixed effect, where the year is based on the year when customer i first applied for quotes. The state component of the fixed effects should soak up state-level variation that affects installer marketing, such as the availability of state-level incentives. The year component of the fixed effects should soak up market-wide changes in installer quote behavior over time. We interacted state and year to account for the fact that state-level incentives changed throughout the study period.

As noted in the Introduction, income segregation should facilitate income-targeted marketing. To test this hypothesis, we develop an area income delta variable that represents the difference between a tract's income level and the surrounding area's income level. For LMI tracts, positive area income deltas represent LMI tracts surrounded by higher-income tracts, while low or negative deltas represent LMI tracts surrounded by other LMI tracts. By interacting this term with the LMI tract dummy we can test whether LMI tract proximity to or geographic isolation from high-income areas affects installer marketing behavior in LMI tracts. We constructed the area income delta variable using the *spdep* package in R (Bivand et al., 2013).

Our selection of control variables was based on the information that installers relied on when deciding whether to submit quotes to specific customers. Some of this information is provided by the customer: electricity use, roof age approximation, ownership preferences, and whether the customer had previously received PV quotes off the platform. Some customers also indicated preferences for site visits and different equipment types, but these preferences did not differ significantly in LMI and non-LMI areas and were therefore excluded. Other information can be approximated based on the home's location: home age, household demographics, householder age, and cumulative PV penetration in the area. The home age, percentage minority, and householder age variables are based on U.S. Census 5-year American Community Survey data. We derive PV penetration (systems/household) based on tract-level data from Yu et al. (2018).

In all cases, these controls are provided to control for potentially confounding correlations between household income, installer marketing, and other demographic factors. For instance, LMI households tend to use less electricity, and installers tend to target households with higher electricity use (Moezzi et al., 2017). In the case of ownership preferences, LMI households were more likely to prefer to finance systems through leases or power purchase agreements, which could affect installer decisions to submit quotes to those customers. Similarly, PV penetration (systems per household) is generally lower in LMI areas. In LMI areas with low PV penetration, households are not primed for PV adoption the same way as households in high-income areas that have interacted with and learned from other PV adopters (Wolske et al., 2020). As a result, low PV penetration levels in LMI areas can self-perpetuate (O'Shaughnessy et al., 2021). Installers may avoid areas with low PV penetration levels under the presumption that customers in those areas are harder to acquire given their lack of exposure to PV adopting peers. We constructed a median housing age variable based on the median year of construction reported to the U.S. Census. We drop records where the reported median construction year was prior to 1900 (likely data errors).

We include a control variable for PV penetration given that quote behavior and income levels are both expected to correlate with PV penetration. However, we acknowledge that this control is potentially endogenous. Previous research has shown that customers that receive more quotes tend to receive lower prices (O'Shaughnessy and Margolis, 2018), and several studies show that customer interactions with installers are key factors in driving adoption decisions (Rai et al., 2016; Sigrin et al., 2017; Wolske, 2020). As a result, the number of quotes submitted may exert a causal effect on PV penetration, creating simultaneous causation between the dependent variable and PV penetration. While we include the PV penetration control in our preferred specifications, we note that excluding the variable does not have a significant impact on the results (see Table S2).

Close rate model

To test the effects of income and quote behavior on customer close rates, we implement the following linear probability model:

$$c_{i,t} = \beta_0 + \beta_1 lmi_t + \beta_2 q_i + SY + \varepsilon \quad (\text{Equation 2})$$

where $c_{i,t}$ is a binary variable indicating whether customers i in tract t closed a deal, lmi_t is a dummy variable for whether tract t is an LMI tract, q_i is the number of quotes received by customer i , and SY is a state-year fixed effect. We converted the coefficients into percentage terms to protect proprietary information on close rates on the platform. We tested another model controlling for the other variables in the regression model described in [Equation \(1\)](#), but most of the controls were statistically insignificant and their inclusion did not substantively affect the coefficient on the variable of interest (LMI). See [Table S5](#) for the results of this model.