Title

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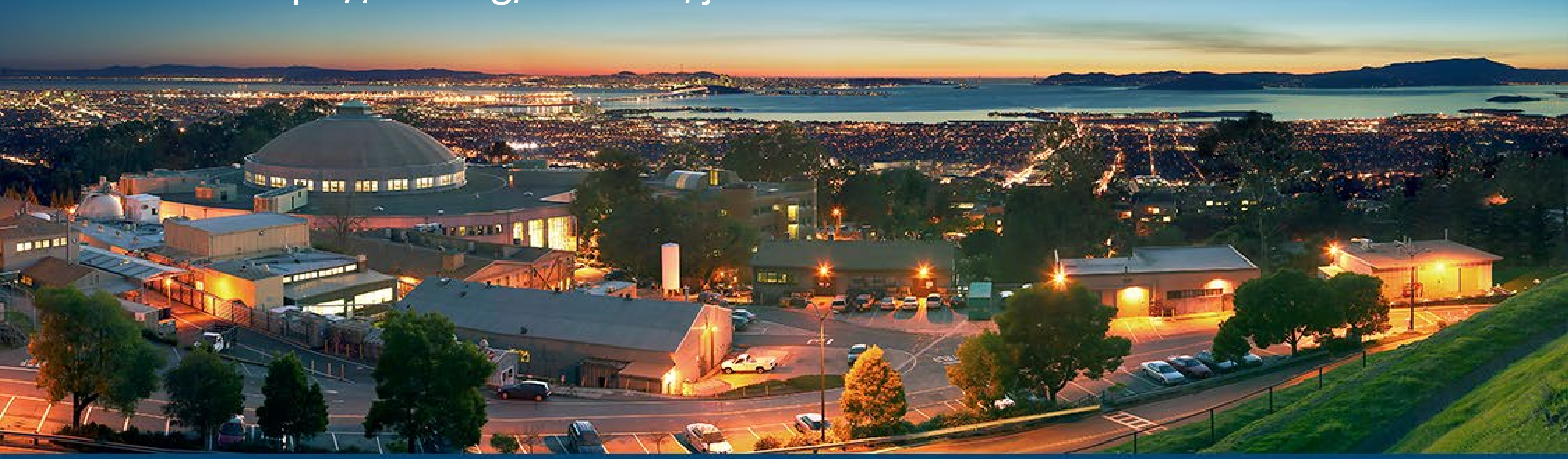

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Business siting patterns and inequitable rooftop solar adoption

Abstract

Entrepreneurs in certain industries tend to locate new businesses in relatively affluent areas. Business siting patterns can create retail "deserts" that reduce low-income household access to certain products. Some argue that retail deserts could explain inequitable consumption patterns, though such causal claims are often empirically weak. Here, we explore whether business siting patterns partly explain inequitable adoption of rooftop solar photovoltaics. We show that solar business formation drives an immediate and sustained increase in local solar adoption, including in low-income areas. However, solar business siting patterns have only weak impacts on solar adoption equity. The data show how solar businesses headquartered in low-income areas nonetheless install solar for relatively affluent customers. Customer-level adoption inequity partly offsets the potential equity gains of siting more businesses in low-income areas. We discuss how the emergent nature and unique business model of rooftop solar help explain these nuanced results.

1. Introduction

The question of where to locate new businesses is a key decision in many industries. Theoretical and empirical research have identified numerous drivers of business siting decisions, including cost constraints (e.g., fuel costs), proximity to competitors, proximity to customers, access to technical expertise, access to low-cost inputs (e.g., electricity), infrastructure, and proximity to universities (Hotelling 1929, Carlton 1983, Stahl 1987, Strauss-Kahn and Vives 2009, Florida and King 2018, Malizia and Motoyama 2019). A subset of this research explores the relationship between business siting patterns and local income levels. Entrepreneurs should theoretically prefer to open businesses in affluent areas with stronger local purchasing power and thus demand, all else equal (Waldfogel 2008, Meltzer and Schuetz 2012). The expected magnitude of income-correlated business siting depends on spatial constraints in product delivery (Waldfogel 2008). For instance, the location of a restaurant spatially constrains the restaurant's clients, whereas the location of a multinational software company may have little or no impact on the company's product distribution.

Empirical research has shown that income-correlated business siting can create low-income areas that lack access to specific products, often referred to as product "deserts" (Alwitt and Donley 1997, Powell, Slater et al. 2007, Meltzer and Schuetz 2012, Schuetz, Kolko et al. 2012, Chin 2020). While most research has explored food deserts, Schuetz et al. (2012) find deserts for a variety of in-store retail products, including pharmacies, laundry, department stores, and home furnishing stores. Retail deserts, some argue, could partly explain inequitable consumption patterns. In the case of food, for instance, low-income households generally consume less nutritious foods than high-income households (Allcott, Diamond et al. 2019). Following this reasoning, policymakers could mitigate inequitable consumption and its social costs (e.g., public health issues stemming from poor diets) by incentivizing business formation in low-income areas. This logic has underpinned subsidies in the United States to support grocers in low-income neighborhoods (The Food Trust 2019). The causal link between business siting patterns and consumption is, however, often tenuous (Wright, Donley et al. 2016). Business formation in low-income areas may have relatively weak impacts on low-income household consumption patterns, suggesting that interventions to shift business siting patterns may be ineffective (Allcott, Diamond et al. 2019).

We add to this research by exploring links between business siting patterns, product access, and adoption in rooftop solar photovoltaic (PV) installation. Rooftop PV installation shares two fundamental traits cited to promote policy interventions for product deserts: rooftop PV installers appear to prefer to locate businesses in relatively affluent areas (O'Shaughnessy, Barbose et al. 2021) and PV is inequitably adopted with respect to income (Barbose, Forrester et al. 2022). The question posed here is whether a causal link exists such that PV business siting patterns partly explain inequitable adoption.

Rooftop PV installation provides an interesting case study for three reasons. First, the rooftop PV business model is fundamentally distinct from retail businesses with in-store purchases. PV installation relies largely on active marketing efforts (e.g., door-to-door) and customer referrals. Second, unlike the already widely diffused products studied in retail desert research, rooftop PV is an emerging product. The U.S. rooftop PV market is growing by around 20% per year, reaching a cumulative adoption level of around 3.2 million households in 2021, or about 2% of U.S. households (Davis, White et al. 2022). The relationships between business siting, product access, and consumption may be distinct in the case of an emerging product from established products. Third, by using rooftop PV as a case study, we benefit from rich data sets documenting the headquarters of over 600 businesses and records for over 1 million systems installed in California. These rich data allow us to explore causal claims for the impacts of business siting on PV adoption patterns. The data suggest that installer business siting patterns create something akin to rooftop solar deserts. Unlike previous work on retail deserts, we find relatively clear evidence that business formation increases PV deployment. Consistent with previous findings, we find a much weaker link between PV business siting and inequitable adoption patterns.

2. Materials & Methods

We use three data sources to develop zip code-level estimates for PV business siting, adoption, and demographic characteristics in California. First, we identify PV installer headquarter locations using data published by the California Contractors State License Board. The contractor license data cover all licensed contractors in California, with California composing about 33% of the U.S. rooftop market (Davis, White et al. 2022). Second, we use rooftop PV adoption data from the Lawrence Berkeley National Laboratory's Tracking the Sun (TTS) data set (Barbose, Darghouth et al. 2021). TTS includes system-level PV data for over 2 million systems installed in the United States. We use an augmented version of TTS that includes household-level income estimates modeled by Experian. See O'Shaughnessy et al. (2021) for further information on the Experian income estimates. We use the TTS data to develop zip code-level estimates for PV deployment in California. Our California sub-sample comprises 1,039,220 systems installed in 1,581 zip codes from 1998-2020. Through direct and fuzzy matching we identified 646 rooftop PV installers in the contractor license data that could be uniquely matched to installers in TTS, representing about 27% of all installers in California with at least 10 systems installed. Third, we use U.S. Census American Community Survey data for zip code-level estimates of population (number of households) and median household income. For simplicity, we use the term low- and moderate-income (LMI) zip code to refer to zip codes in the bottom half of the zip code median income distribution. Similarly, we use the term LMI-headquartered installer to refer to installers with headquarters in LMI zip codes.

Previous research establishes the two premises for our research question: 1) that PV installers tend to headquarter in relatively affluent areas, and 2) that PV is inequitably adopted with respect to income. Our objective is to explore a causal link between these two conclusions, that is, whether income-correlated PV business siting partly explains inequitable PV adoption. Any impact would be partial and additional to other drivers of PV adoption inequity already identified in the literature, including structural income inequality and various demand-side barriers to low-income adoption (Lukanov and Krieger 2019, Sunter, Castellanos et al. 2019, O'Shaughnessy, Barbose et al. 2021, Reames 2021). We implement several approaches to explore this research question.

First, we implement a panel data regression to test the impacts of installer business siting patterns on PV deployment. The panel data are defined at the zip code (z) and quarter (q) levels. Our study sample comprises observations in 1,581 zip codes over the 44 quarters running from 2010-2020, yielding a balanced panel data set of 69,564 observations. The dependent variable is the cumulative number of PV systems installed in a zip code by a given quarter, denoted i_{zq} We also include results in terms of PV systems installed per household to account for different populations across zip codes. The independent variable of interest is the cumulative number of PV headquarters in a zip code by quarter, denoted hq_{zq}. To define the second, for each installer we identify the quarter in which that installer installed their first system according to the TTS data. We use the first installation quarter as a proxy for when the installer began marketing. According to this definition, 483 of the 646 installers in the contractor license data formed their businesses during the study period (2010-2020). We take first differences on both variables ($\Delta i_{zq} = i_{zq} - i_{zq-1}, \Delta hq_{zq} = hq_{zq} - hq_{zq-1}$) to identify the impact of PV business formation on deployment. First-differencing addresses the fact that installer business siting decisions and PV deployment are likely simultaneously caused. However, as we note in the Discussion, first differences exclude the potentially distinct impacts of existing businesses on PV deployment. We include county-quarter (CQ_{zq}) fixed effects to control for broader spatial and temporal trends, and we include seasonal fixed effects (S_{zq}) to control for seasonal PV deployment patterns. Our preferred specification is:

$$\Delta i_{zq} = \beta \Delta hq_{zq} + CQ_{zq} + S_q + \varepsilon \tag{1}$$

The model in Equation (1) captures the instantaneous effect of a change in the number of installer headquarters on the change in cumulative adoption. The instantaneous effect is a useful metric for establishing whether business siting patterns affect adoption rates but does not likely characterize the effect size accurately. Installer business siting may have long-term or lagged effects, particularly if an installer began operating close to the end of a quarter. We explore various sensitivities with lagged versions of the differenced headquarter variable:

$$\Delta i_{zq} = \beta_0 \Delta hq_{zq} + \beta_1 \Delta hq_{zq-1} + \cdots + \beta_4 \Delta hq_{zq-4} + CQ_{zq} + S_q + \varepsilon \tag{2}$$

The models described in Equations (1) and (2) are designed to measure the impacts of business siting decisions on PV deployment. We explore the impacts of business siting on LMI deployment, specifically, in two ways. First, we test models with separate variables for headquarters located in LMI and non-LMI zip codes:

$$\Delta i_{zq} = \gamma_1 \Delta \text{lmi}hq_{zq} + \gamma_2 \Delta \text{nonlmi}hq_{zq} + CQ_{zq} + S_q + \varepsilon \tag{3}$$

Where $\Delta\text{lmi}hq_{zq}$ and $\Delta\text{nonlmi}hq_{zq}$ are first differences of the number of headquarters in LMI and non-LMI zip codes, respectively. We implement this model for the full data sample as well as a subsample limited to LMI adopters, defined as customers with modeled incomes less than 120% of their area median income. For the subsample, our basic objective is to test whether $\gamma_1 > \gamma_2$, which would provide evidence that business formation in LMI zip codes drives LMI adoption more strongly than business formation in non-LMI zip codes.

Second, we test whether changes in installer business siting patterns directly affect the distribution of PV with respect to income. New LMI-headquartered businesses could increase adoption equity by shifting the balance of deployment from affluent to lower-income areas. One way to test this effect is by measuring changes in the average income levels of adopters. This effect would not be perceived at the zip code level given that a new business located in zip code z would not necessarily change the average income levels of adopters in z. Rather, this effect would be perceived by shifts in deployment over broader areas from relatively affluent zip codes to lower-income zip codes. We construct a county-level panel data set that allows us to test whether LMI-headquartered business formation drives this shift and reduces the average income level of PV adopters at the county level. The county-level panel data comprise data on 55 counties over 44 quarters, yielding a balanced panel data set of 2,420 observations. Again, we use first differences to control for spurious spatial variation:

$$\Delta inc_{cq} = \alpha_1 \Delta \text{lmi}hq_{cq} + \alpha_2 \Delta \text{nonlmi}hq_{cq} + SQ_{cq} + S_q + \varepsilon \tag{4}$$

Where Δinc_{cq} is the first difference of the cumulative average income in county c in quarter q, and SQ_{cq} is a state-quarter fixed effect.

Two limitations are worth noting. First, given that many installer business names are vague or redundant, we were not able to universally match all California PV installers to a record in the contractor license data. We worked with a limited sub-sample of installers, though we have no reason to believe this sub-sample is not representative of the broader installer base. Second, we use business addresses as reported on contractor licenses as a proxy for installer headquarter locations. As we shall demonstrate, this approach was effective in that most installers conduct most of their business close to these proxy headquarters. However, some PV installers are relatively large companies that operate throughout the state of California or throughout the country. In these cases, the business location may have little expected impact on the installer's marketing patterns.

4. Results

Before proceeding to the regression results, we use our data sets to demonstrate that PV installation meets some of the requisite conditions of product deserts. Namely, an industry can form product deserts if 1) businesses disproportionately site in high-income areas and 2) product delivery is spatially constrained. In terms of condition 1, installer headquarters are disproportionately sited in relatively high-income areas (Figure 1). Among zip codes with at least 100 households, there are 5.4 installer headquarters per 100,000 households in zip codes with median incomes above $80,000/year, on average, compared to 3.3 headquarters per 100,000 households in other zip codes (t=2.2). In terms of condition 2, most installers install most of their systems less than 50 kilometers from their headquarters (Figure 2), suggesting that PV installation is constrained, likely by transportation costs. At the same time, some PV systems are installed hundreds of kilometers from an installer's headquarters. Some of these cases likely reflect large-scale installers that operate many local branches or contract with local installers to conduct business far from their headquarters.

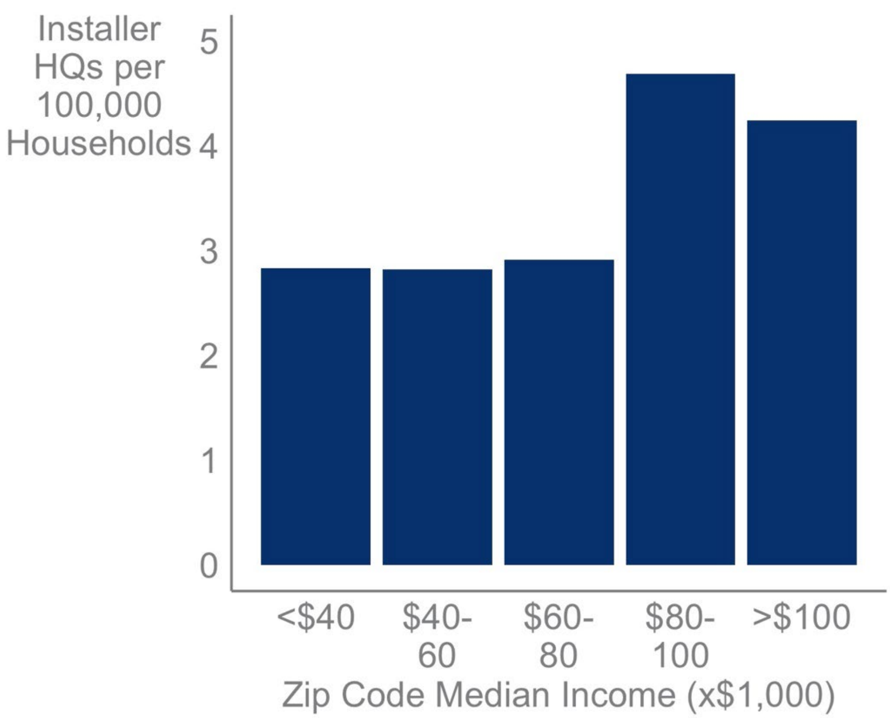

Figure 1. Installers tend to have headquarters (HQ) in relatively high-income zip codes. The plot shows the number of installer headquarters per 100,000 households at different zip code median income levels.

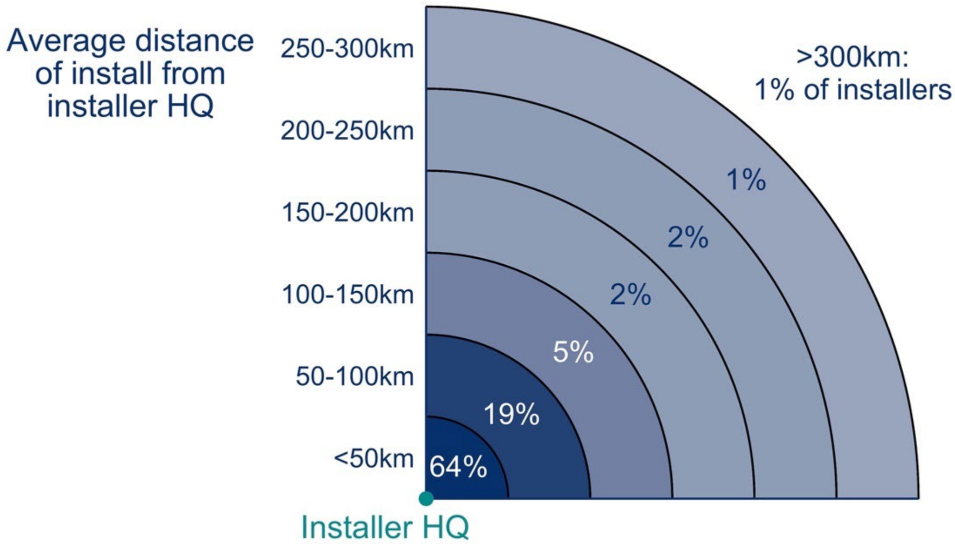

Figure 2. Most installers do most of their business close to their headquarters. This plot shows the distribution of average distances from installer headquarters (HQ) to their installations. Distances are based on the zip-code centroid coordinates of installer headquarters and their installed systems.

Table 1 presents the results of the panel data regressions. Model (1) presents the basic model described in Equation (1), while Model (2) presents results with lagged values for the change in installer headquarters described in Equation (2). Models (3)-(4) present the same models but with the dependent variable in terms of change in installs per 1,000 households. Recall that the models are in first differences. Results can be interpreted as a change in PV deployment resulting from the opening of a new business in a zip code. Looking first at Models (1) and (3), the results suggest that an additional installer headquarter is associated with an increase of about 17 installs in the same quarter, or about 0.5 installs per 1,000 households. All the lagged variables suggest similar effects from lagged changes in the number of headquarters. That is, the models suggest that business formation continues to increase PV adoption in subsequent quarters.

Table 1. Regression Results - Equations 1-2

	(1) **Y=Δi**	**(2)** **Y=Δi**	**(3)** **Y=Δi/1,000HH x100**	**(4)** **Y=Δi/1,000HH x100**
Δhq	16.82*	17.26*	0.49*	0.5*
	(3.45)	(3.58)	(0.15)	(0.16)
Δhq, 1st lag		16.55*		0.45*
		(3.31)		(0.19)
Δhq, 2nd lag		15.81*		0.37*
		(3.03)		(0.15)

Δhq, 3rd lag		16.46*		0.42*
		(2.87)		(0.15)
Δhq, 4th lag		17.8*		0.56*
		(3.05)		(0.16)
R^2	0.22	0.22	0.09	0.08

* $p<0.05$

We now turn to exploring how business siting patterns affect LMI PV adoption, specifically. Table 2 presents the results of the model described in Equation (3), with Model (5) applied to the full data sample and Model (6) limited to LMI adopters. The results of Model (5) show that an additional installer headquarter in a non-LMI zip code has a greater impact on adoption than an additional headquarter in an LMI zip code. This result was expected, given that PV markets tend to be larger in and around non-LMI zip codes. Model (6) limits the data to a sub-sample of LMI customers. Model (6) suggests that PV business formation has roughly equal impacts on LMI adoption regardless of whether the business is in an LMI zip code, though the impact is slightly larger for LMI-headquartered businesses.

Table 2. Regression Results – Equation 3

	(5) **Y=Δi**	**(6)** **Y=ΔLMI**
ΔLMI hq	9.49*	4.97*
	(2.95)	(1.18)
Δnon-LMI hq	18.33*	4.14*
	(2.38)	(0.78)
R^2	0.24	0.22

* $p<0.05$

The results in Tables 1 and 2 are based on pooled regressions, meaning that business formation in early years has the same impacts on the coefficients as business formation in later years. The pooled models provide a useful snapshot of the overall impact of business formation on PV deployment but ignore potential trends in that impact as the PV market grew over the study period. One possibility is that the impacts of new business formation are diminishing given that new business compete for business with a growing number of existing businesses. However, the data suggest that the effects of growing demand outweighed the diminishing effects from competition during the study period. Figure 3 depicts how the estimated impacts of business formation on deployment generally grew throughout the study period, including the impacts of business formation in LMI areas on LMI adoption (LMI HQs, LMI installs).

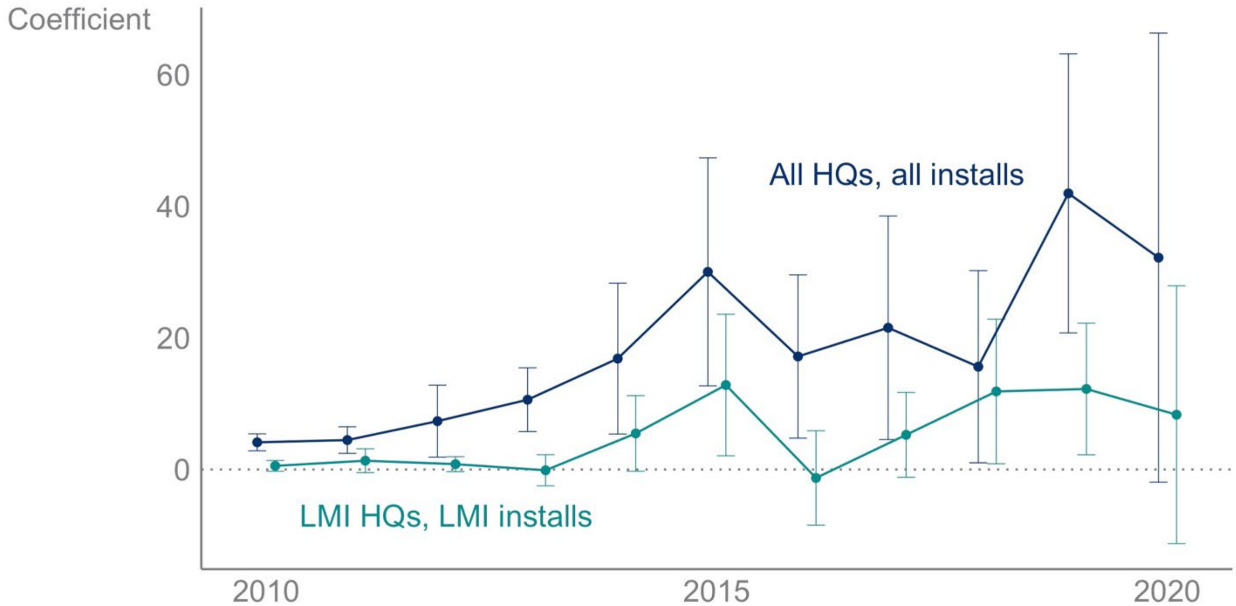

Figure 3. The impacts of business formation on PV deployment have grown with the PV market. Figure depicts coefficients from Table 1 Model (1) (All HQs, all installs) and Table 2 Model (6) (LMI HQs, LMI installs) when limiting the data to specific years. Bars represent 95% confidence intervals.

Finally, Table 3 provides the results of the model described in Equation (4), with and without lagged variables. The coefficients can be interpreted as changes in the first difference of the average income of customers in a county given a change in the number of LMI or non-LMI headquarters. Without lags, neither variable is statistically significant, though the relatively stronger negative sign on the LMI HQ variable is consistent with the hypothesis that LMI-headquartered installers tend to reduce overall income levels. With lags, all the lags for LMI HQ are negative and the first lag is statistically significant. Overall, these results suggest that opening installer businesses in LMI zip codes has a weak and delayed impact on PV adoption equity.

Table 3. Regression Results – Equation 4

	(7) **Y=Δincome**	**(8)** **Y=Δincome**
ΔLMI hq	-0.05	-0.11
	(0.08)	(0.06)
ΔLMI hq, 1st lag		-0.12*
		(0.04)
ΔLMI hq, 2nd lag		-0.1
		(0.05)
ΔLMI hq, 3rd lag		-0.04
		(0.12)
ΔLMI hq, 4th lag		0.02

		(0.05)
Δnon-LMI hq	-0.005	0.03
	(0.03)	(0.03)
Δnon-LMI hq, 1st lag		0.02
		(0.02)
Δnon-LMI hq, 2nd lag		-0.01
		(0.03)
Δnon-LMI hq, 3rd lag		-0.01
		(0.03)
Δnon-LMI hq, 4th lag		0.01
		(0.03)
R^2	0.05	0.04

The relatively weak effects estimated in Table 3 are somewhat surprising. If new LMI-headquartered installers increase adoption in LMI areas, as suggested by Table 2, then one should expect business formation in LMI areas to reduce PV adopter income levels. A closer look at the data provides a potential explanation for these weak results. For installers that conduct most of their business locally, the headquarter area income level correlates with customer income levels (Figure 4). However, as illustrated by the 45° line in Figure 4, this correlation is imperfect, meaning that customer income levels for LMI-headquartered installers are higher than one might expect. Excluding large-scale installers with more than 10,000 systems in the data, the customer-weighted average median income of LMI zip codes is about 49% ($50k) lower than non-LMI zip codes, yet customers served by LMI-headquartered installers only earn about 9% ($12k) less, on average, than other customers (t=27.1). Another way to view this is to compare relative incomes across installers, here defined as a customer's income as a percentage of the county median income. Unlike absolute incomes, installer relative income profiles inversely correlate with headquarter area income levels (Figure 5). Customers served by LMI-headquartered installers earn about 101% more ($65k) than their counties' median income, slightly larger than the 88% ($67k) difference for customers served by other installers (t=19.1). These results suggest that most installers—regardless of headquarter location—tend to install systems for relatively affluent customers. This customer-level adoption inequity substantially offsets the potential equity gains from forming new businesses in LMI areas. We explore this result further in the Discussion.

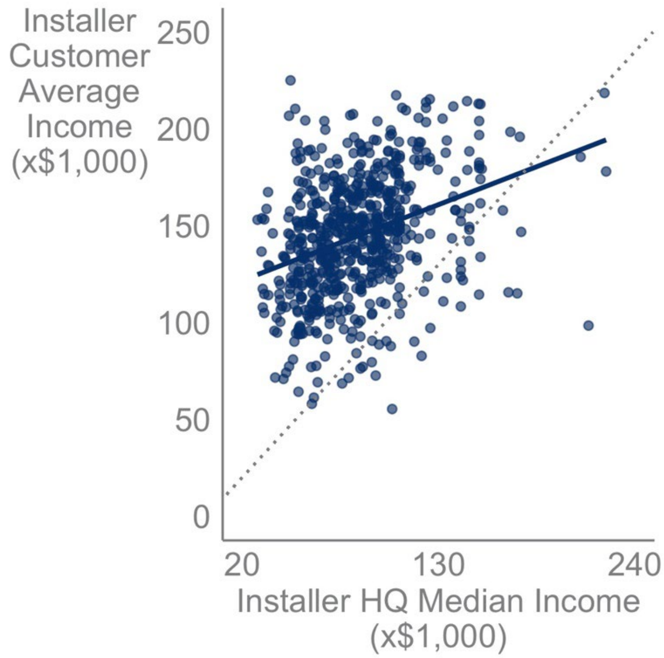

Figure 4. Installer headquarter demographics correlate with the demographic profiles of their customers. This plot depicts the correlation between average customer incomes and the median income levels of installer headquarter (HQ) locations. The 45° line illustrates the hypothetical point where customer income levels perfectly correlate with headquarter area income levels. That the true trend line crosses the 45° line suggests that customer income levels vary less substantially than do area income levels.

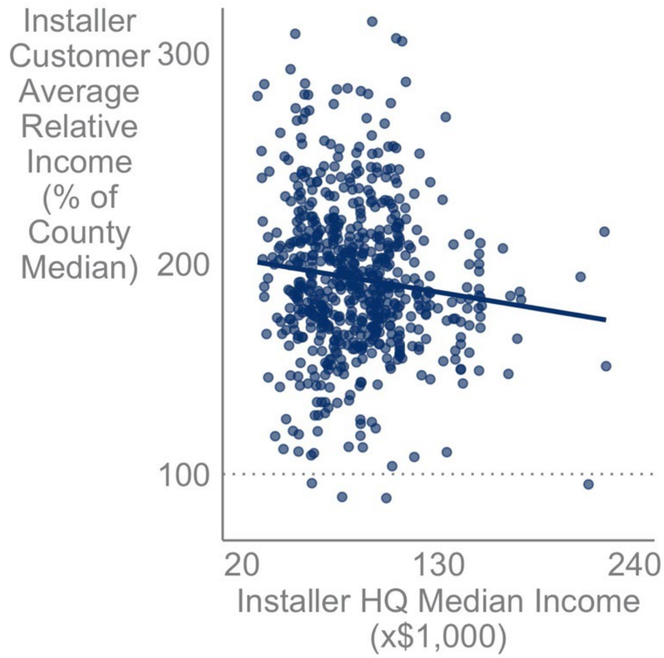

Figure 5. Most installers across all area income levels exhibit skews toward relatively affluent customers. This plot depicts the correlation between average customer relative incomes (% of county median) and the median income levels of installer headquarter (HQ) locations. The dotted line depicts the point at which customer income levels equal county median income levels (100% relative income).

5. Discussion

Unlike previous research exploring causal links between retail deserts and consumption patterns, we find relatively clear evidence that PV business formation directly affects PV adoption levels. One possibility is that business formation more directly affects consumption patterns for emerging products (e.g., rooftop solar) than established products (e.g., groceries). In the case of established products, Allcott et al. (2019) argue that business formation drives customers to substitute among existing options rather form new consumption patterns. For instance, a new local supermarket may allow a household to avoid trips to a more distant supermarket, but the opening of the supermarket may not affect household purchases from local convenience stores. Product substitution mitigates the impacts of business formation on consumption patterns for established, widely available products. The potential for substitution is far weaker in the case of rooftop PV. As already noted, though the rooftop PV market is growing rapidly only about 2% of U.S. households had adopted by the end of 2021 (Davis, White et al. 2022). Most U.S. households have thus never adopted rooftop PV and may have had limited if any exposure to PV installation businesses or marketing. PV business formation may prompt households in the local area to seriously consider adoption for the first time. Alternatively, PV business formation may generate more local competition, bringing PV installation prices within the budget ranges of more local households. Regardless of the exact mechanism, PV business formation could create genuinely new opportunities for consumption. Whether these results hold for other emerging products is a potential area for further research.

Despite the clear impacts of business formation on PV deployment, we find a nuanced relationship between business siting patterns and PV adoption equity. Our results suggest that business formation in LMI areas and non-LMI areas have similar impacts on LMI adoption levels (Table 2), and that business formation in LMI areas has relatively modest impacts on overall adoption equity (Table 3). The relatively weak impacts of business formation on LMI adoption could reflect demand-side factors like those cited by Allcott et al. (2019). However, we find this demand-side explanation unsatisfying in the case of rooftop PV. Unlike dietary choices, rooftop PV adoption is mostly a binary choice to adopt or not. Further, survey research suggests that LMI and non-LMI households share similar motivations in their desires to adopt rooftop PV (Wolske 2020).

We posit that the relatively weak impacts of PV business formation on adoption equity reflect supply- rather than demand-side constraints. Specifically, PV installers can shape their customer bases more effectively than retailers with in-store purchases. This capability is demonstrated by the fact that LMI-headquartered PV installers serve relatively affluent customers (see Figure 5). While we do not identify the cause of this result, previous work shows that many installers prioritize marketing to high-income customers (O'Shaughnessy, Barbose et al. 2021). Alternatively, these results could reflect the outcome of referrals and peer effects. Customer referrals are one of the most common customer acquisition strategies in PV installation (EnergySage 2022). Given that relatively affluent customers are more likely to adopt than LMI households due to budget constraints, all else equal, referrals are more likely to originate from high-income than LMI customers. Social science and social influence research suggest that high-income referrers are likely to refer other high-income households. Even without monetary incentives for referrals, high-income early adopters could influence other high-income neighbors to adopt through peer effects. In both cases, referrals and peer effects can create self-sustaining cycles of adoption among relatively affluent customers. Such cycles create paths of least resistance for LMI-headquartered installers, possibly mitigating the adoption equity impacts of PV business formation in LMI areas.

Our results yield mixed implications for public policy. Our results suggest that incentives for PV business formation in LMI areas could increase adoption in those areas, just not necessarily by LMI households. As a result, promoting PV business formation in LMI areas appears to be only one part of the puzzle. Completing the puzzle may require additional policy interventions designed to help LMI-headquartered installers to acquire LMI customers. One option could be to facilitate financing for LMI-headquartered installers, a measure that has proven effective at increasing LMI adoption in other contexts. However, measures such as facilitated finance could be broadly extended to any installer seeking to acquire LMI customers, regardless of their headquarter location. Our results thus largely corroborate the conclusions of Allcott et al. (2019), who conclude that subsidies for business formation in low-income areas may be an inefficient approach to resolving inequitable consumption patterns. This conclusion does not obviate the possibility that low-income business formation interventions could achieve other public policy objectives. For instance, business siting interventions could help achieve a broader set of energy justice policy objectives, such as ensuring an equitable distributions of jobs, local tax revenues, and economic development opportunities.

It is worth noting that we only analyze the impacts of business formation and overlook the potentially important role of existing PV businesses. Existing PV businesses may have acquired local knowledge or skills that help them more effectively market in unique local contexts. For instance, established PV businesses in linguistically diverse areas may be more likely to have employees that speak relevant languages than an entrepreneur opening a new business in the same area. Insofar as existing businesses hold specific local skills, our results may understate the equity benefits of local PV businesses. Future research could explore the impacts of having long-lived, established businesses in LMI areas on adoption equity.

Further, our analysis is limited to the near-term impacts of PV business formation. The lagged models suggest that PV business formation has persistent and potentially long-term deployment impacts. PV business formation could have long-term impacts on adoption equity that are overlooked in our study. For instance, early PV deployment in LMI areas can seed future LMI adoption by generating peer effects. In the context of our study, it is possible that new LMI-headquartered installers initially increase adoption in LMI areas among relatively affluent customers, but that these early adoptions drive longer-term deployment among LMI households. If so, our near-term models could understate the long-term impacts of business formation on adoption equity.

6. Conclusion

Business siting patterns can create product deserts in low-income areas. Some argue that product deserts could partly explain inequitable consumption patterns, though such causal claims are often empirically weak. Here, we explore the possibility that rooftop PV business siting patterns partly explain inequitable rooftop PV adoption. We find relatively clear evidence that PV business siting patterns directly shape PV adoption patterns. We posit that the direct impacts of PV business formation on deployment could stem from the emergent nature of rooftop PV. PV business formation creates opportunities for rooftop PV adoption that did not previously exist, in contrast to business formation for established products (e.g., groceries) that may simply drive substitution among existing products. Consistent with previous research on retail deserts, we find only weak evidence that PV business siting patterns explain inequitable PV adoption. While product desert research attributes these weak impacts to mitigating demand-side factors, we argue that supply-side factors explain weak impacts in the rooftop PV context. Rooftop PV installers can more effectively shape their customer bases than providers of in-store retail products. Through income-targeted marketing or passive approaches such as customer referrals, PV installers headquartered in low-income areas can favor relatively affluent customers. Customer-level adoption inequity partly offsets the potential equity benefits of interventions to promote PV business formation in low-income areas.

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