CleanEnergy States Alliance

# Peer Influence in Residential Solar Adoption:

## New Research from Berkeley Lab

March 6, 2024

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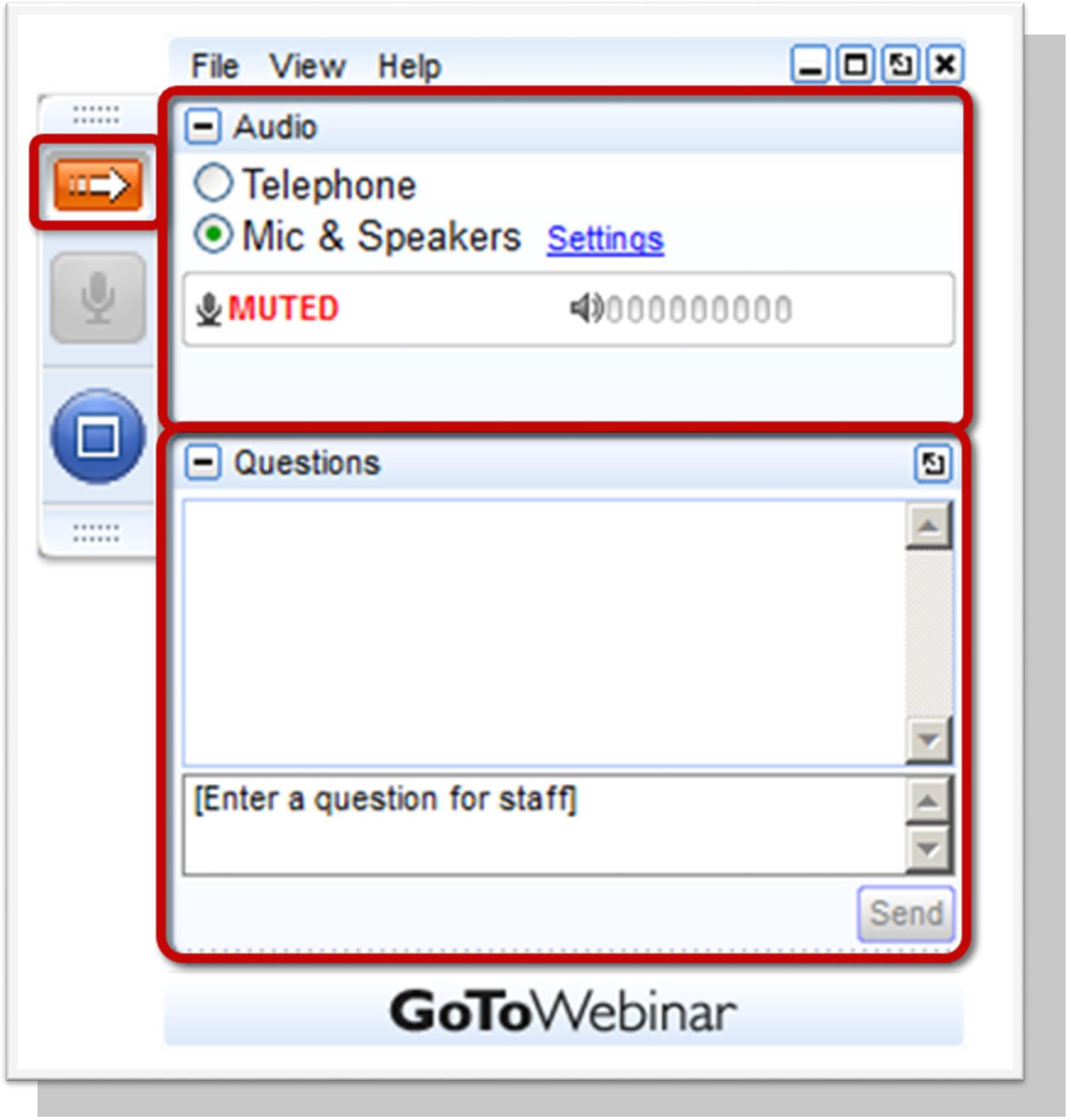


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# The role of peer influence in rooftop solar adoption inequity in the United States

November 2023

Eric O’Shaughnessy, Alexandra Grayson, Galen L. Barbose / Lawrence Berkeley National Laboratory

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The role of peer influence in rooftop solar adoption inequity in the United States

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ABSTRACT

Individual demand for emerging technologies can be influenced by the demand of other individuals within defined peer groups. These so-called peer effects have been demonstrated in emerging clean energy technologies such as rooftop solar. To date, peer effects have disproportionately driven solar adoption among relatively affluent households. Here, we use household-level income estimates of rooftop solar adopters to explore how peer effects drive adoption for low-income households. We find evidence of peer effects for both high- and low-income households and find that peer effects are generally stronger within than across income groups. Our results indicate that peer effects translate to adoption less frequently among low-income households. These results suggest that low-income peer effects are mitigated by barriers to low-income adoption. Heterogeneous peer influence is another demand shifter that explains the inequitable adoption of emerging technologies.

1. Introduction

Small-scale consumer technologies such as rooftop solar photovoltaics (PV) could play key roles in electric grid decarbonization and climate change mitigation (Dietz et al., 2009; O'Shaughnessy et al., 2022b). Rooftop PV deployment depends on the idiosyncratic adoption decisions of millions of individual households. Understanding the factors that shape rooftop PV demand and adoption has thus driven a growing body of research (Sintov and Schultz, 2015; Alipour et al., 2020; Schulte et al., 2022). Most of this work applies a rational actor model, modeling PV demand as a function of various incentives that drive adoption decisions. Another prominent adoption model is based on interpersonal influence within peer groups, or simply peer influence (Axsen and Kurani, 2012; Xiong et al., 2016; Wolske et al., 2020). Peer influence plays a prominent role in models of how technologies diffuse into society (Rogers, 2003; Van den Bulte and Stremersch, 2004). The literature has identified numerous potential mechanisms through which peers can influence technology diffusion, such as through sharing experience (i.e., learning) (Foster and Rosenzweig, 1995), reducing the uncertainty associated with new products (Van den Bulte and Stremersch, 2004), word-of-mouth communication, persuasion (Wolske et al., 2020), and visible adoption actions (e.g., PV systems installed on street-facing rooftops) (Bollinger et al., 2022). In practice, peer influence is identified through peer effect models estimating the impacts of peer demand on individual demand (Pratkanis, 2007; Graf-Vlachy et al., 2018). Several studies find evidence of peer effects in early rooftop PV adoption (Bollinger and Gillingham, 2012; Graziano and Gillingham, 2015; Moezzi et al., 2017; Palm, 2017; Mundaca and Samahita, 2020; Balta-Ozkan et al., 2021; Bollinger et al., 2022).

More recently, an emerging body of research explores the factors that explain heterogeneous rooftop PV adoption across income levels (Sunter et al., 2019; O'Shaughnessy et al., 2021). As is common for emerging technologies, low- and moderate-income (LMI) customers adopt rooftop PV less frequently than more affluent customers (Attanasio and Pistaferri, 2016; Forrester et al., 2022). Inequitable PV adoption could pose challenges to long-term deployment (Welton and Eisen, 2019), and policymakers are increasingly exploring ways to drive LMI adoption (Carley et al., 2021). LMI PV adoption research has largely focused on socioeconomic barriers that prevent LMI households from adopting clean energy technologies (Mueller and Ronen, 2015; Lukanov and Krieger, 2019; Brown et al., 2020). Some previous work posits a potential role for peer influence in LMI adoption (Wolske, 2020; Wolske et al., 2020), and potential differences in peer influence according to area income levels (Bollinger and Gillingham, 2012). No study, to our knowledge, quantifies peer influence on LMI adoption based on household-level income estimates.

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# Impacts of non-residential solar on residential adoption decisions

November 2023

Eric O'Shaughnessy, Alexandra Grayson, Galen L. Barbose, Isa Ferrall-Wolf, Deborah Sunter / Lawrence Berkeley National Laboratory

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## Impacts of non-residential solar on residential adoption decisions

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Household decisions to adopt rooftop solar photovoltaics are partly driven by social influence. Previous research on solar adoption influence has focused on influence among residential peers. Here, we expand the framework of solar adoption influence by exploring the influence of non-residential installations on residential adoption decisions. We use staggered differences-in-differences to estimate non-residential influence effects using a large data sample of residential adoptions. We also critically evaluate prevailing frameworks for solar adoption influence. We find that non-residential installations are associated with accelerated residential adoption rates, on the order of 0.4 additional residential adoptions per quarter per non-residential installation. We show that non-residential systems exert a continuous, long-term influence on residential adoption decisions. We explore separate results and influence mechanisms for solar installed on commercial buildings, government buildings, and houses of worship. The results suggest that non-residential solar adopters could serve as partners in policies to "seed" residential adoption in underserved communities.

KEYWORDS
solar, adoption, influence, behavior, peer effects

### 1 Introduction

More than 3 million households had adopted rooftop solar photovoltaics (PV) in the United States by the end of 2022 (Davis et al., 2022). Every rooftop PV system reflects the outcome of an idiosyncratic individual or household adoption decision. A growing literature has emerged to explore what explains rooftop PV adoption decisions, such as financial incentives, environmental motivations, and customer interest in novel technologies (Sintov and Schultz, 2015; Alipour et al., 2020; Schulte et al., 2022). Within that literature are several studies showing that individual rooftop PV adoption decisions are partly driven by the adoption decisions of other individuals (Bollinger and Gillingham, 2012; Graziano and Gillingham, 2015; Moezzi et al., 2017; Palm, 2017; Mundaca and Samahita, 2020; Balta-Ozkan et al., 2021; Bollinger et al., 2022). The impacts of previous adoptions on subsequent adoption decisions are evident in the physical clustering of PV systems and statistical associations between the timing of PV installations and adoption decisions (Bollinger and Gillingham, 2012).

The relationship between past and subsequent PV adoptions has been characterized as a form of social influence (Axsen and Kurani, 2012; Xiong et al., 2016; Baranzini et al., 2017; Wolske et al., 2020). The term "influence" has been used in PV adoption research in a broad sense. Rooftop PV adoption decisions may be directly affected by active social interactions, such as with neighbors who have already adopted (Sigrin et al., 2017). The literature also suggests a role for more passive influence mechanisms, such as an individual being primed

# Webinar Speakers

**Matt Ohloff**
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**Galen Barbose**
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# Thank You

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# Peer Influence in Residential Solar Adoption: New Research from the Berkeley Lab

Eric O'Shaughnessy and Galen Barbose

March 6, 2023

Clean Energy States Alliance Webinar Series

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# Summary

- Demand for emerging technologies can be influenced by the adoption decisions of peers
- We evaluate two new questions on the role of influence in solar adoption: 1) how does influence vary across income levels; and 2) does influence operate across different customer types?

## Key findings:

Peer influence affects household rooftop solar adoption decisions at all income levels.

Influence is stronger within income groups (e.g., low-income influence on low-income adoption decisions) than across income groups.

Solar installations on non-residential buildings influence residential adoption decisions, including commercial buildings, government buildings, schools, and houses of worship

Photo by Dennis Schroeder, NREL 45243

# More detailed information is available in the publications

Contents lists available at ScienceDirect

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Impacts of non-residential solar on residential adoption decisions

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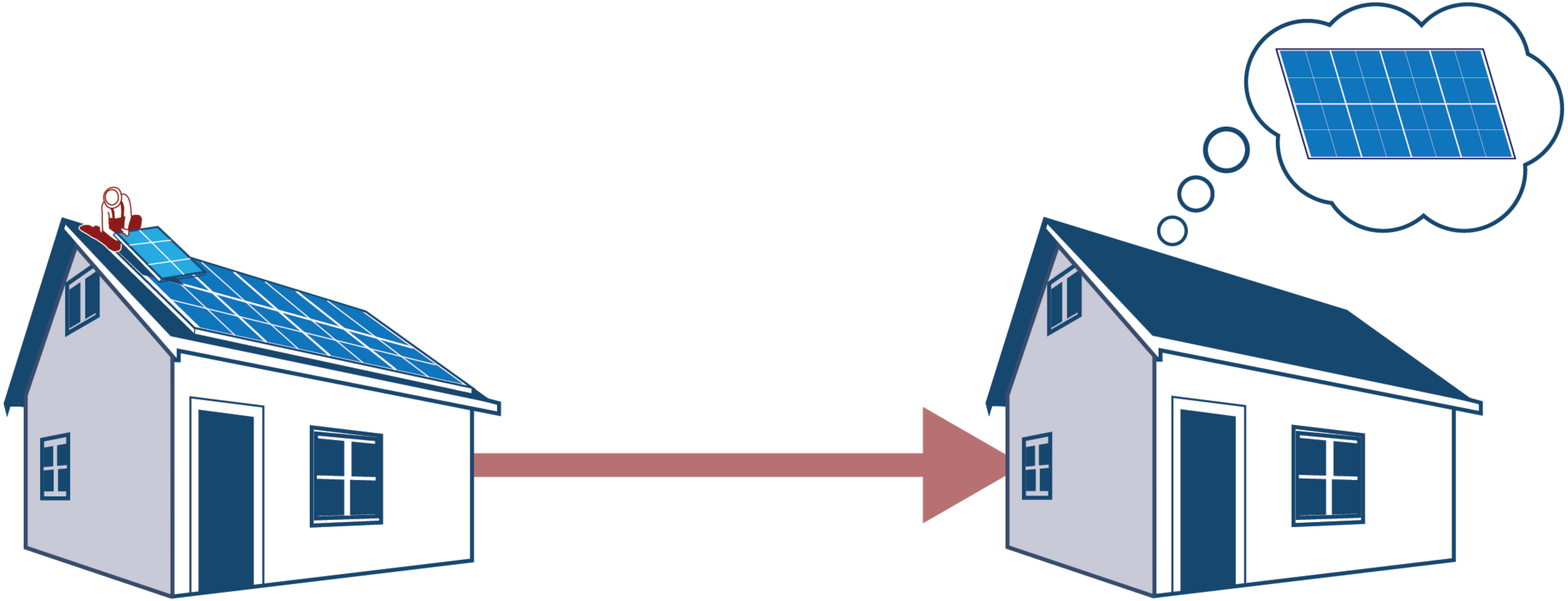
# What drives rooftop solar adoption?

Most research focuses on personal incentives using a rational actor model

# What drives rooftop solar adoption?



An alternative approach explores how social or “peer” influence drives rooftop solar adoption decisions

# Research questions

- **Study 1:** Does peer influence operate at all income levels, and could differences in peer influence partly explain differences in adoption rates across income levels?
- **Study 2:** Do non-residential installations influence residential adoption decisions?

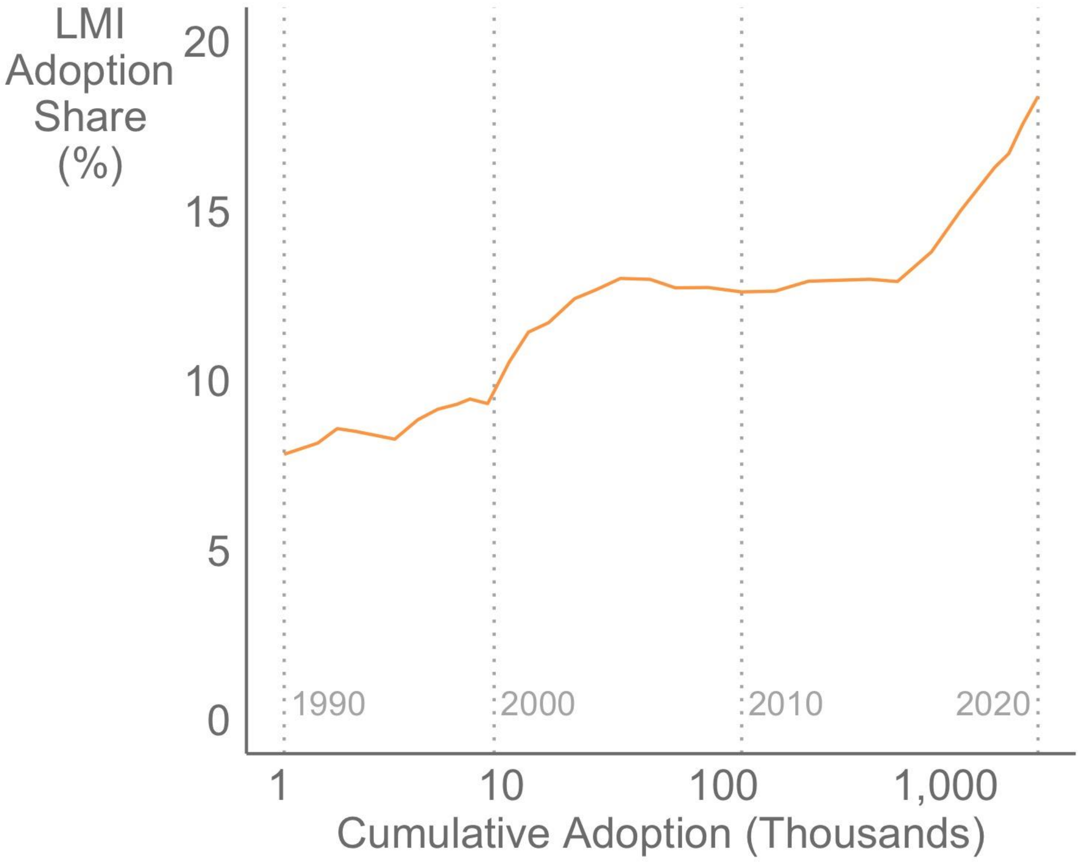
Photo by Werner Slocum, NREL 66322

# Study #1

Peer influence across household income levels

# Background: Solar diffusion

- Rooftop solar, like other emerging technologies, has become more equitable over time
- Still, to date, low- and moderate-income (LMI) households are underrepresented among rooftop solar adopters
- Peer influence has primarily driven adoption among relatively affluent households




**Share of rooftop solar adopters earning less than the U.S. national median income.**

Figure from O'Shaughnessy et al. 2023. *Environmental Research Letters* 18 024024.

# Peer effects modeling

- Peer influence can be modeled as a demand shifter:

$$Q_{j,g} = D(p, Q_{\neq j,g}, X)$$

- Where:
  - $Q_{j,g}$ is the demand of individual j in a peer group g
  - $Q_{\neq j,g}$ is the demand of *other* individuals in the group
- The impact of $Q_{\neq j,g}$ on $Q_{j,g}$ is known as a *peer effect*

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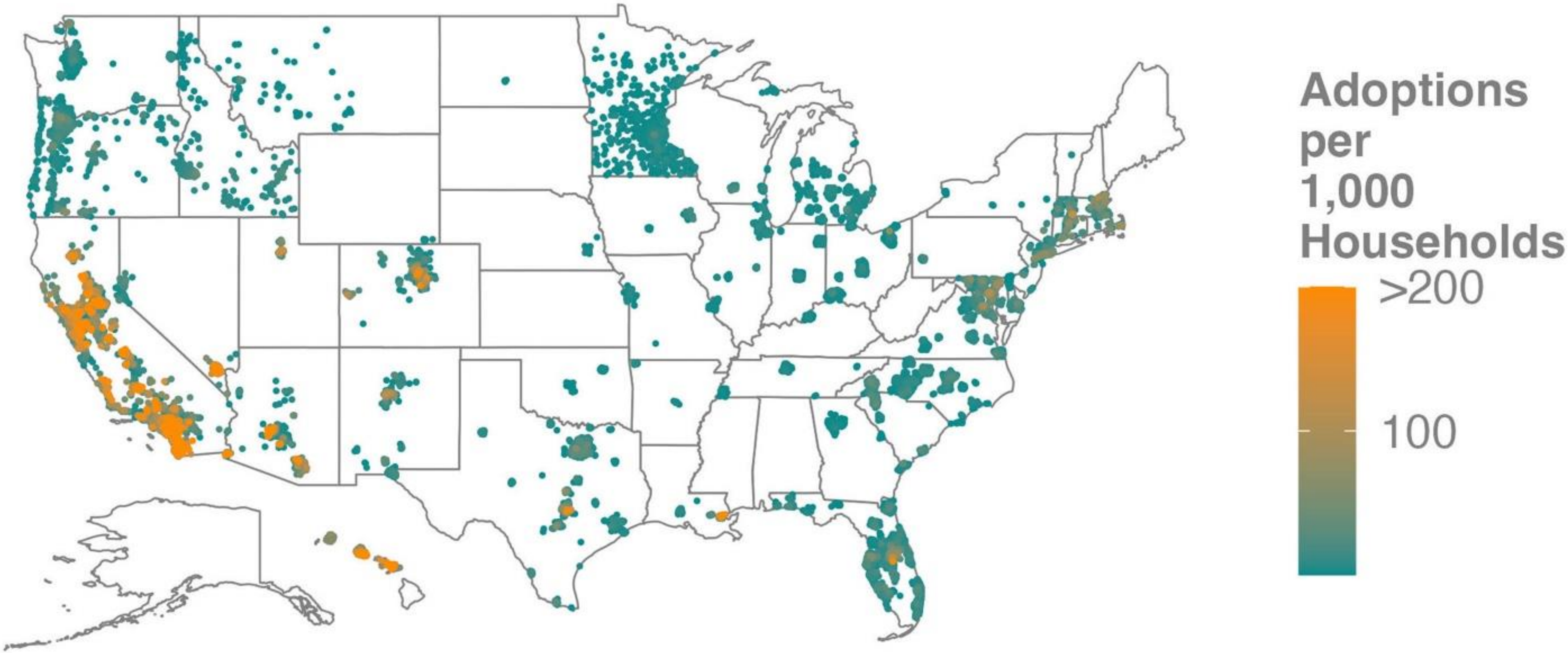
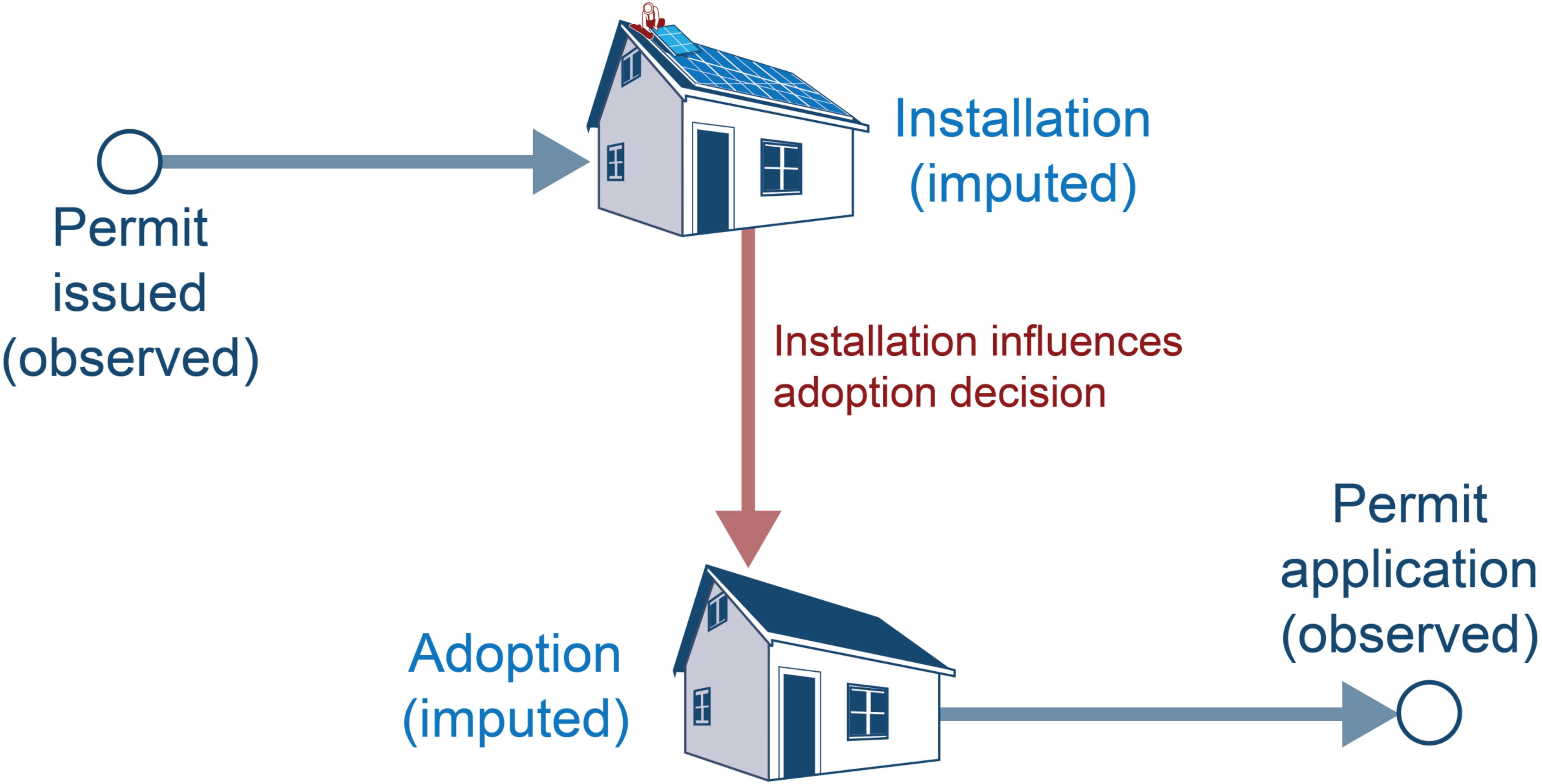
# Study sample

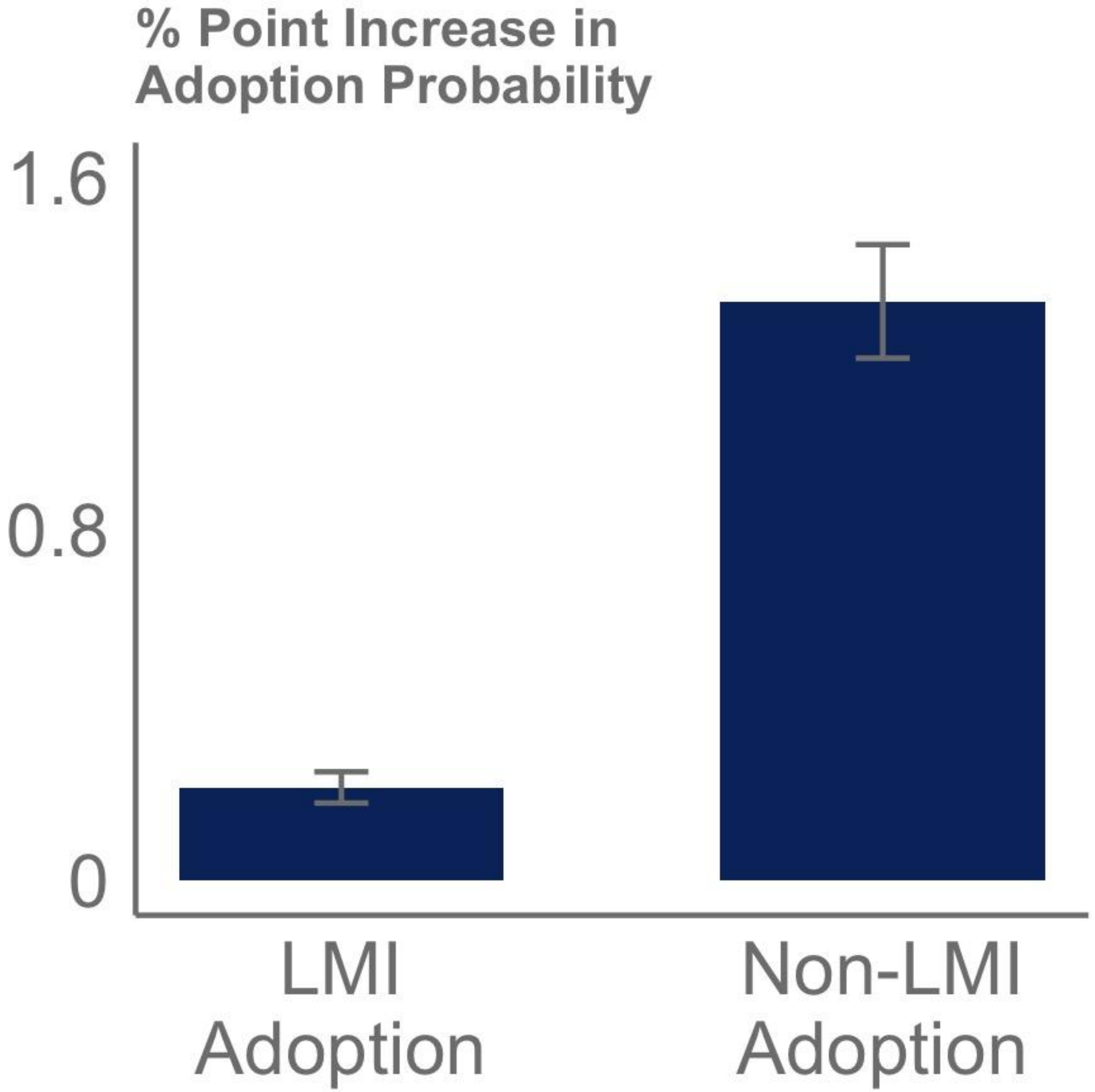


# Inferring adoption dates



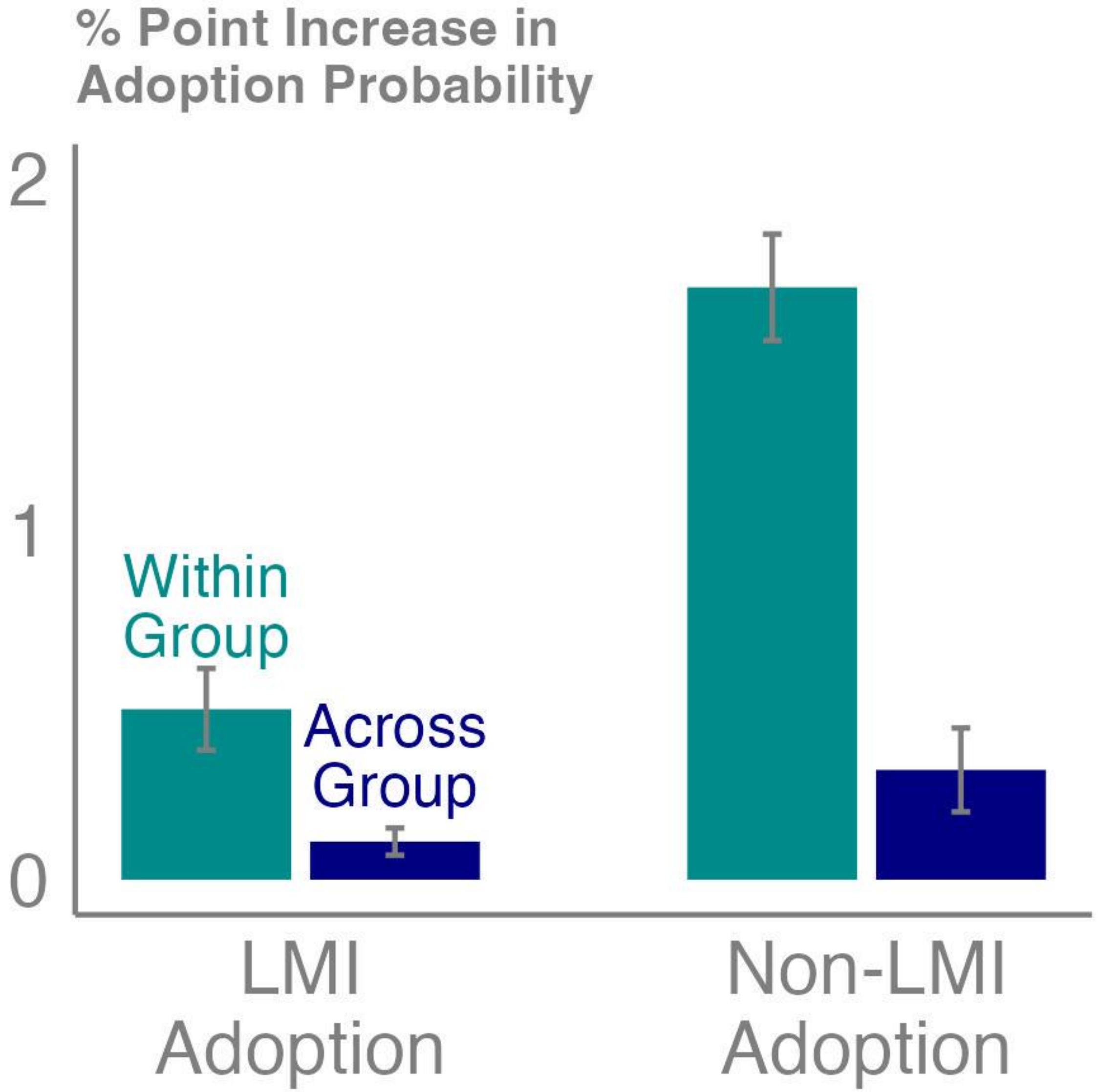
# Peer effects across income levels

- Results suggests that installations increase the probability of adoption by around 1.8 percentage points (all income levels)
- Peer effects are significantly smaller among LMI households (defined here as <100% area median income)



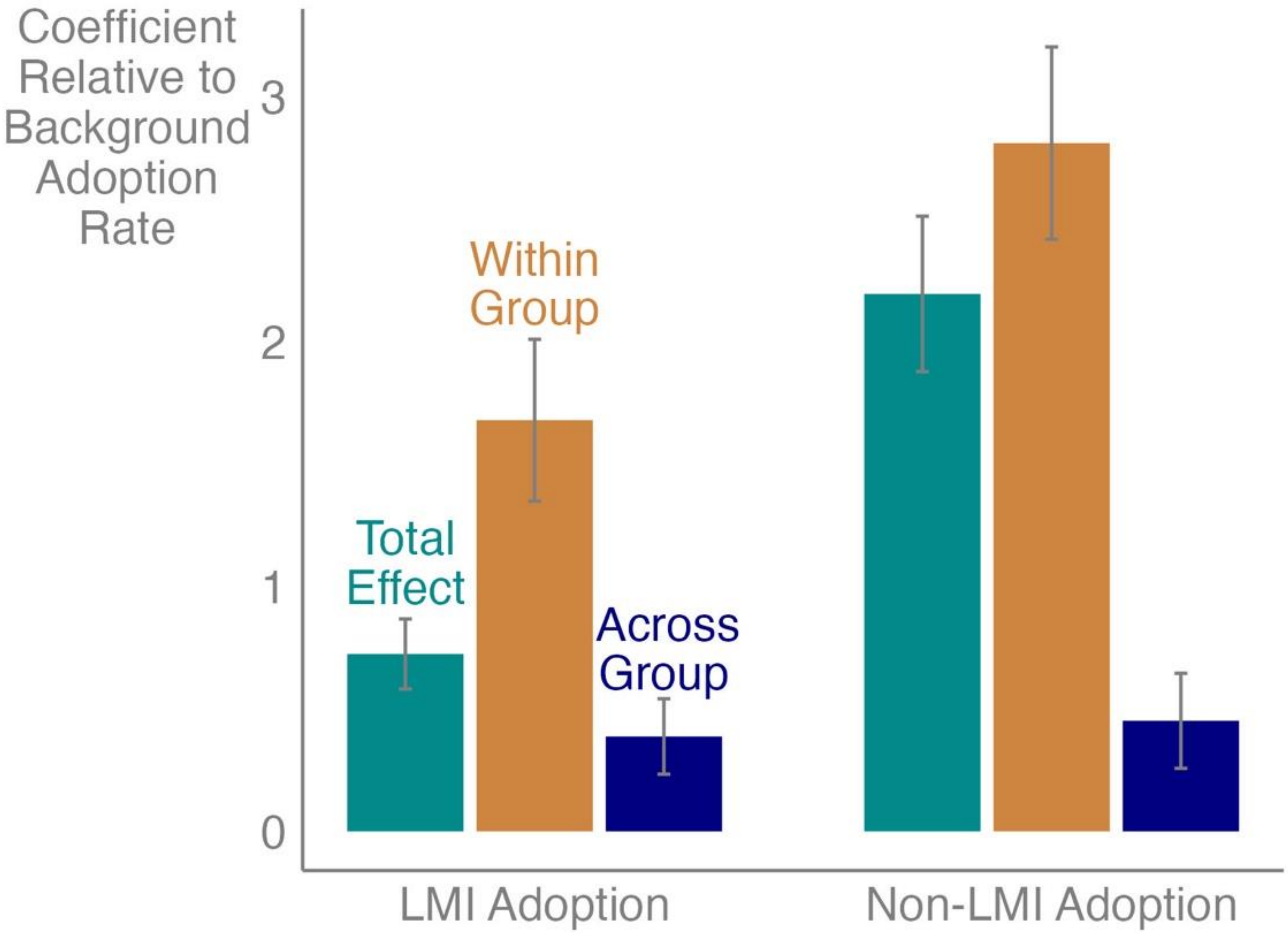
# Peer effects within and across income groups

Peer effects are stronger within income groups (e.g., LMI on LMI) than across income groups



# Peer effects relative to background adoption rates

- Weaker LMI peer effects partly reflect lower background adoption rates
- Controlling for differences in background adoption rates partly, but not fully, accounts for differences in peer effects



# What explains weaker LMI peer effects?

- Weaker LMI peer effects mean that peer influence is less likely to translate to LMI adoptions, not necessarily that influence is less important to LMI household decision-making
- Peer influence may prime LMI households to consider adoption, but influence alone does not address other barriers, such as budget constraints

# Why is peer influence stronger within income groups?

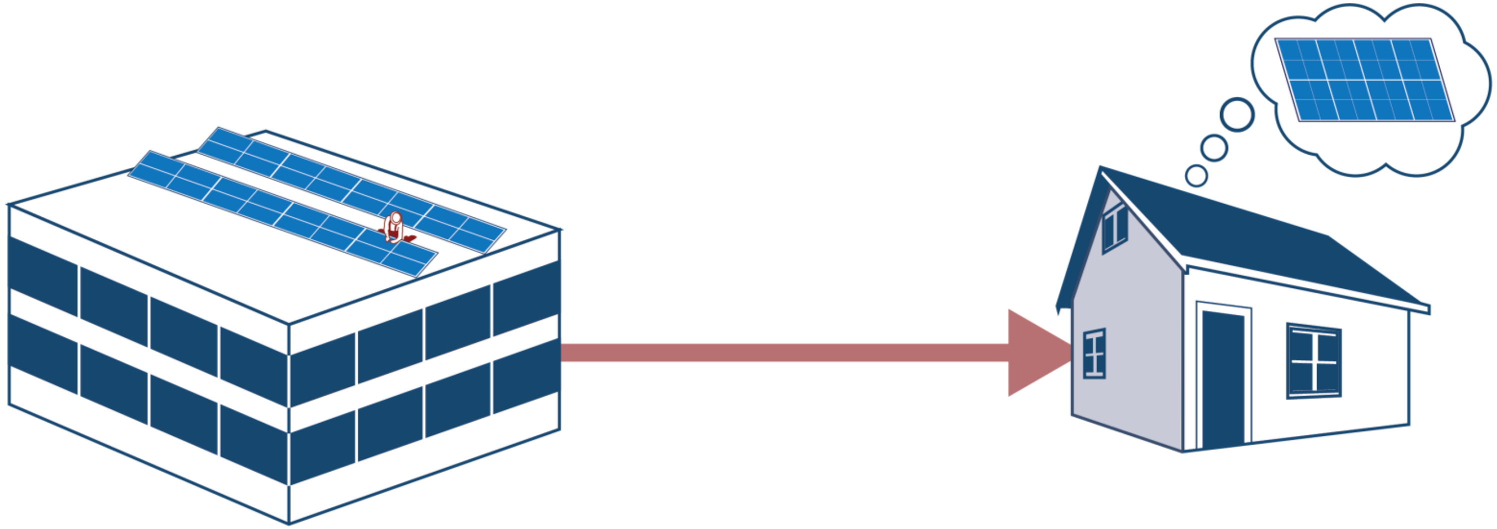
- The result that peer effects are stronger within income groups is consistent with theoretical and empirical work on influence: individuals are more strongly influenced by the actions of peers with whom they more closely identify
- LMI solar interventions could potentially leverage this fact, such as by "seeding" LMI adoption in low-income areas

# Study #2

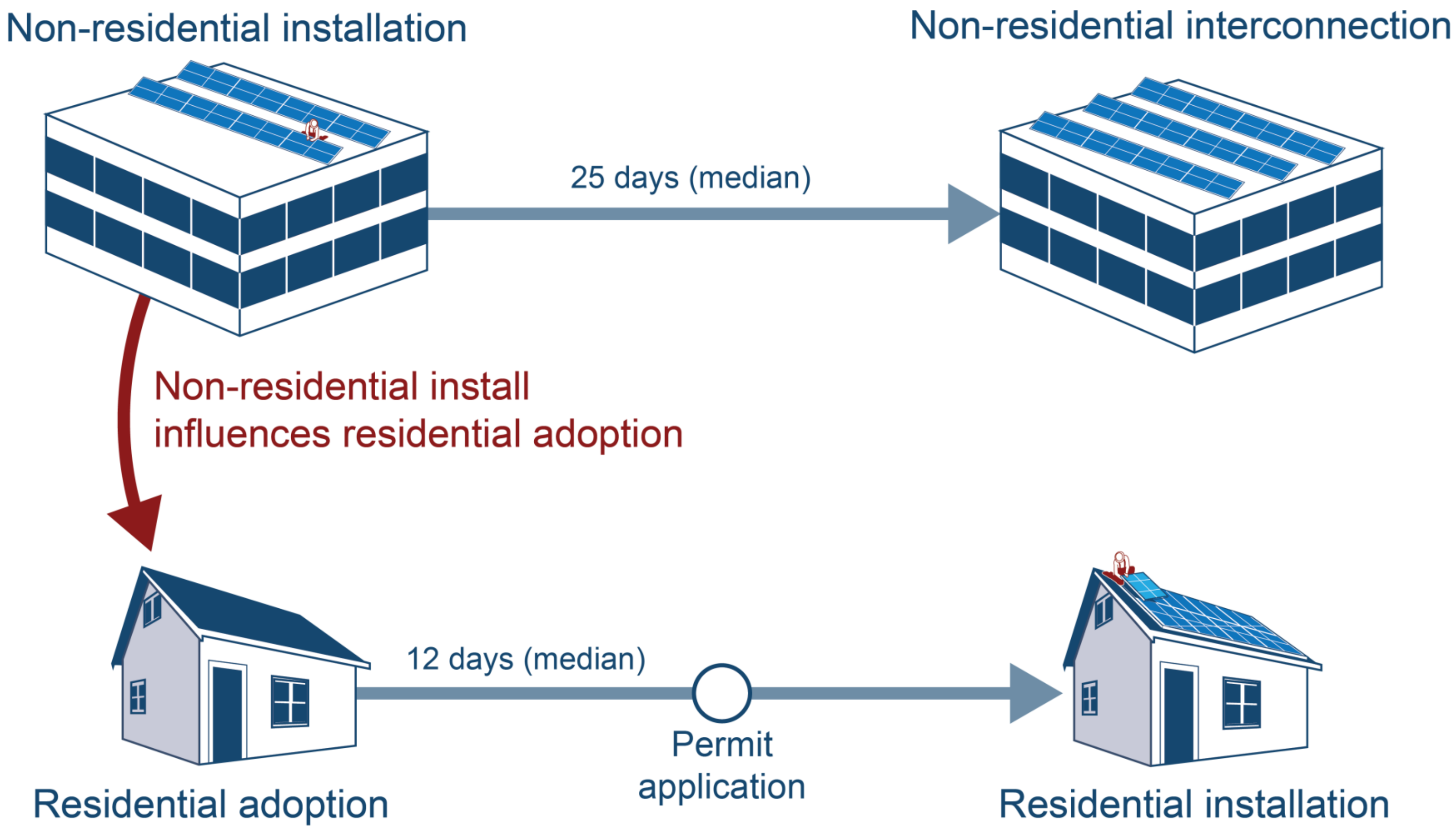
Social influence across customer types

# Background: Non-residential influence

- Rooftop or ground-mounted solar at non-residential sites could influence residential adoption decisions
- Influence could be passive (e.g., seeing panels) or active (e.g., interactions with customers, constituents, and congregations)

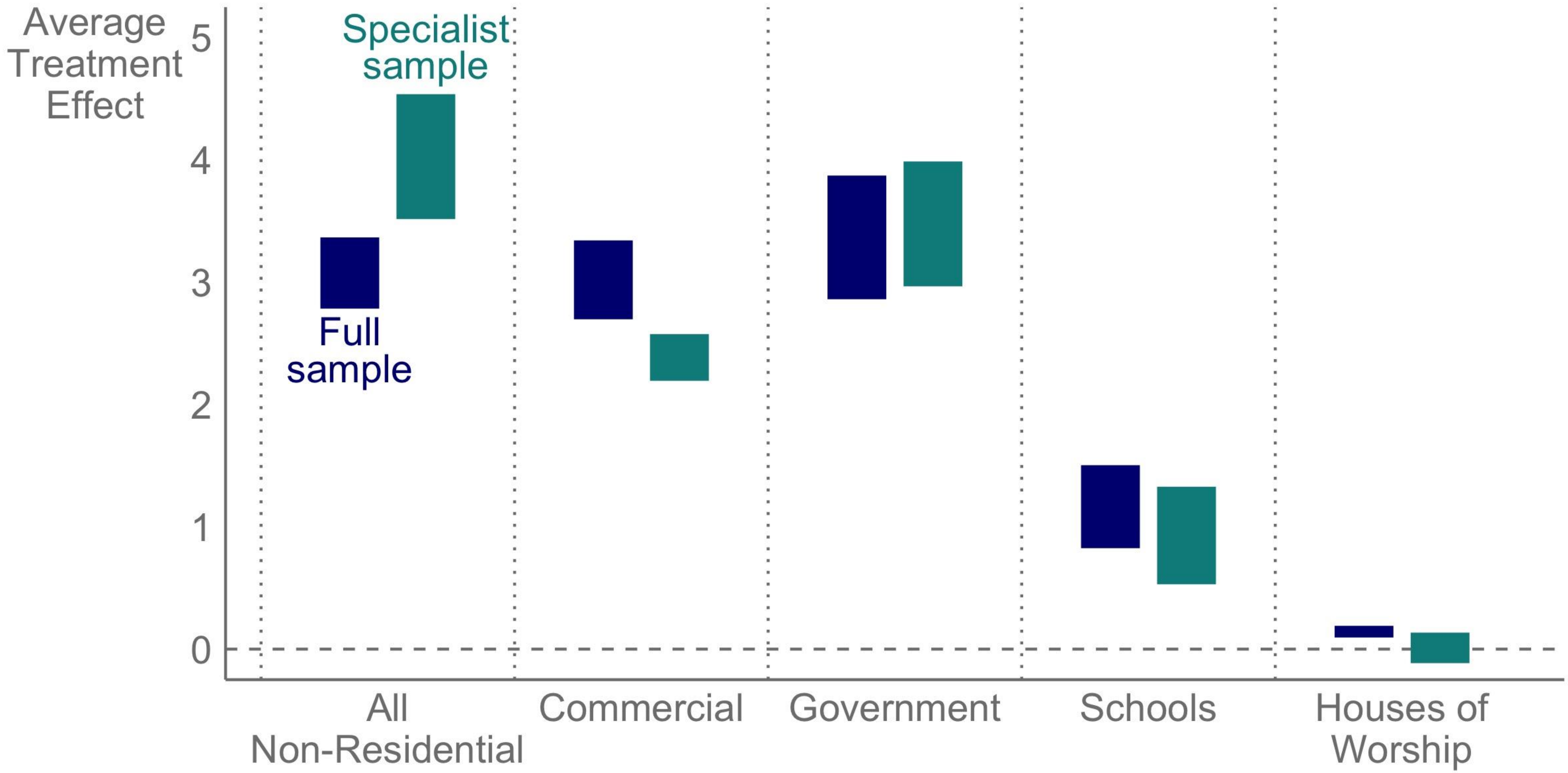


# Methods



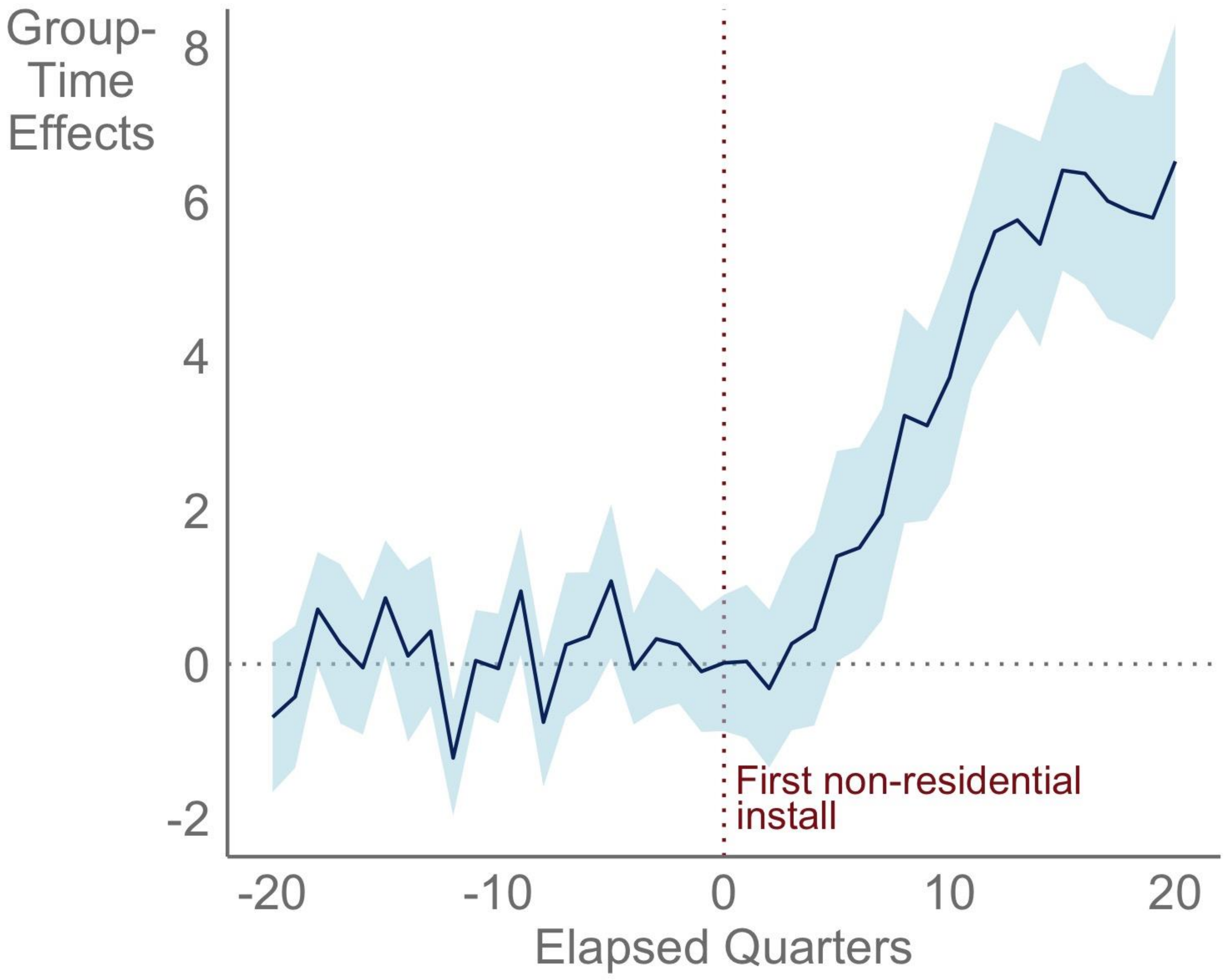
Non-residential installation
Non-residential interconnection
25 days (median)
Non-residential install
influences residential adoption
12 days (median)
Permit
application
Residential adoption
Residential installation

# Results: Evidence of influence across all building types

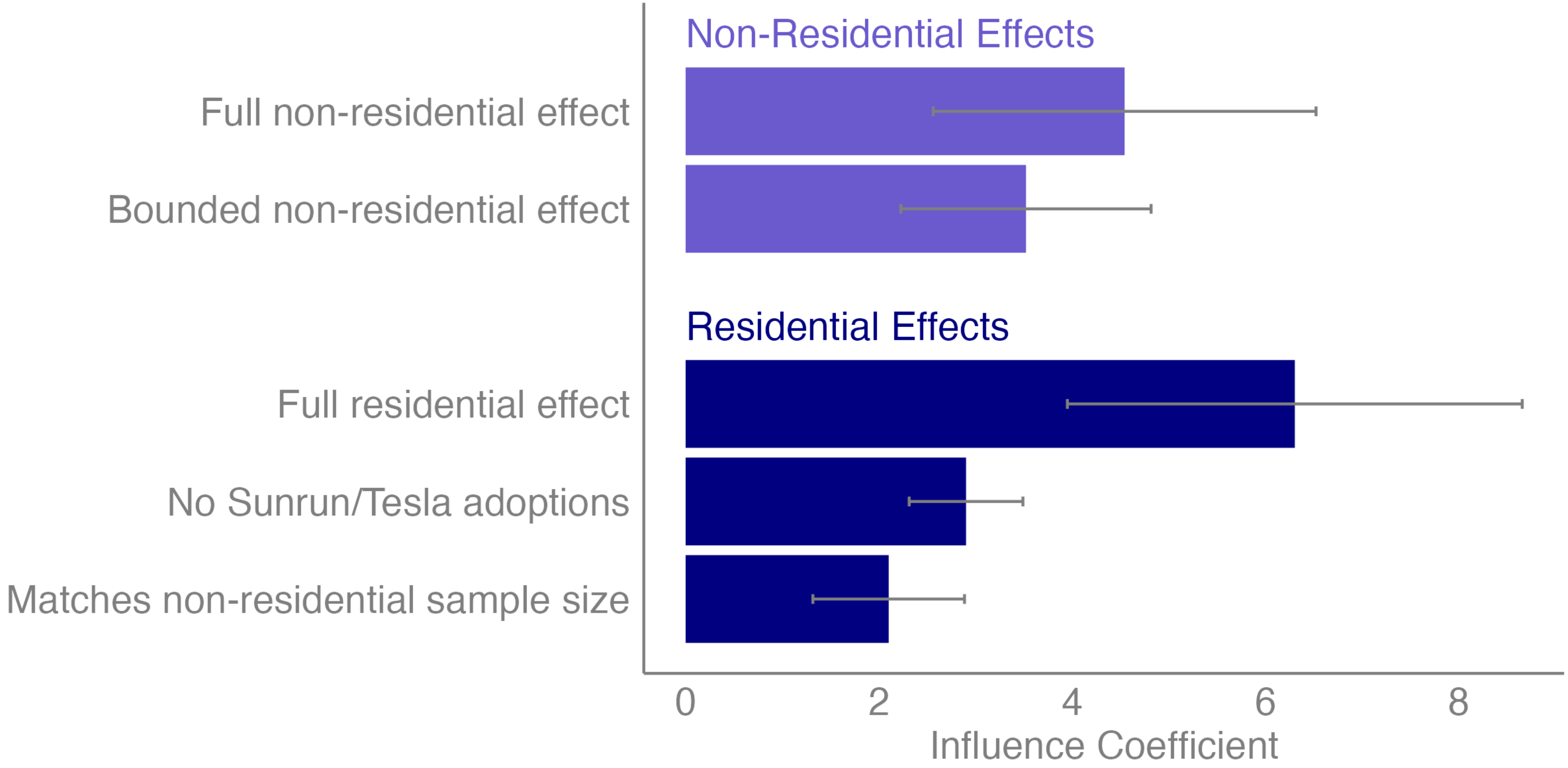


# Results: Sustained influence over time

- Results suggest that residential adoption rates increase in zip codes with non-residential installs
- That influence effect is persistent
- The sustained influence could reflect compounding influence over time: initially influenced adoptions go on to influence other adoptions



# Results: Non-residential influence effects comparable to residential effects



# Conclusions

# Conclusions

- Peer influence affects solar adoption decisions at all income levels
- Peer effects are weaker at lower income levels, though that does not necessarily mean that influence is less important
- Peer influence is stronger within than across income groups
- Social influence works across customer types: non-residential installations can affect residential adoption decisions

# Open questions

- What are the mechanisms of social influence in solar adoption?
- Could certain non-residential institutions more effectively influence residential adoption than other institutions?
- How can influence-driven adoption be leveraged and optimized?

# Acknowledgments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# Questions?

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# Supplementary Slides

# Study #1 Data

- Rooftop PV adopter data compiled by the Lawrence Berkeley Lab (provided by BuildZoom)
- The data set comprises 801,534 records on households that adopted rooftop PV from 2010-2020 which could be matched to **modeled household-level income estimates**
- Peer groups defined as Census tracts
- Our full data set comprises 82,867,232 tract-day observations

# Identification of peer effects

- Bollinger & Gillingham (B&G)* developed an approach for identifying peer effects in the context of rooftop PV adoption
- B&G show that PV peer effects can be identified through a fixed effects model regressing adoption decisions on the installed base:

$$a_{gt} = \alpha + \beta b_{gt} + X\gamma_{gt} + \epsilon_{gt}$$

- Under certain verifiable conditions, $\beta$ provides a robust estimate of peer effects



* Bollinger & Gillingham. 2012. *Marketing Science* 31(6):900-912.

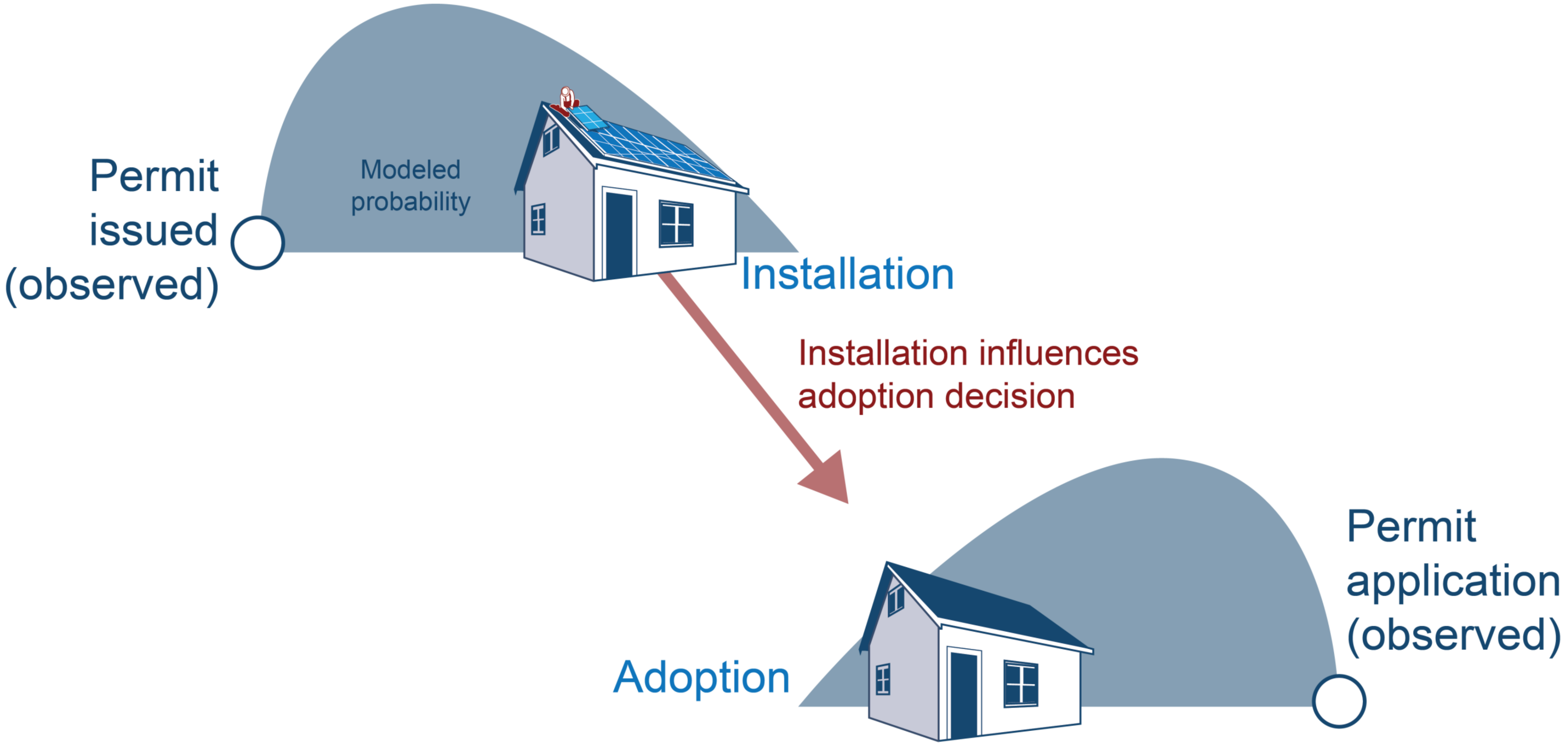
# In case you're curious…

- A system installed is the outcome of an adoption decision, and an installation date is just an adoption date plus some lag
- The B&G peer effects model regresses adoption on a lagged version of itself:

$$a_{gt} = \alpha + \beta a_{gt-l} + X\gamma_{gt} + \epsilon_{gt}$$

- Where *t-l* refers to the adoption decision date, and *l* represent the lag (in days between an adoption and an installation
- Serial autocorrelation is a concern in this model. As a result, B&G demonstrate that identification requires the assumption that the lag (l) exceeds the order of autocorrelation, in which case autocorrelation does not bias the peer effect estimator

# Approach #2: Continuous probabilities



# Summary Statistics

| Variable | Mean | SD. | Min | Max |
|---|---|---|---|---|
| Adoption rate (per household in $10^{-6}$) | 5.92 | 83.99 | 0 | 83,333.3 |
| LMI adoption rate ($10^{-6}$) | 1.78 | 43.97 | 0 | 82,987.6 |
| Non-LMI adoption rate ($10^{-6}$) | 4.14 | 68.21 | 0 | 68,376.1 |
| Installs | 0.01 | 0.13 | 0 | 113 |
| LMI installs | 0.003 | 0.06 | 0 | 112 |
| Non-LMI installs | 0.007 | 0.10 | 0 | 72 |

# Peer effects: Full sample

| | Discrete Date Base ($x10^{-6}$) | Discrete Date Deltas ($x10^{-6}$) | Continuous Probability |
|---|---|---|---|
| Installed base | 0.11* | 10.38* | 0.50* |
| | (0.01) | (0.72) | (0.01) |
| | [0.02] | [1.8] | |
| Tract FE | X | | X |
| Area-quarter FE | X | X | X |
| Year-month FE | X | X | X |
| Day-of-month FE | X | X | X |
| Day-of-week FE | X | X | X |
| N | 82,867,232 | 82,867,232 | 82,867,232 |
| Adjusted $R^2$ | 0.04 | 0.02 | 0.65 |

# Peer effects across income levels

| | Discrete Date Base (x10$^{-6}$) | | Discrete Date Deltas (x10$^{-6}$) | | Continuous Probability | |
|---|---|---|---|---|---|---|
| | Y=LMI | Y=Non-LMI | Y=LMI | Y=Non-LMI | Y=LMI | Y=Non-LMI |
| Installed base | 0.01* | 0.10* | 1.29* | 9.09* | 0.10* | 0.40* |
| | (0.001) | (0.006) | (0.13) | (0.67) | (0.004) | (0.01) |
| | [0.002] | [0.02] | [0.2] | [1.6] | | |
| Tract FE | X | X | | | X | X |
| Area-quarter-year FE | X | X | X | X | X | X |
| Year-month FE | X | X | X | X | X | X |
| Day-of-month FE | X | X | X | X | X | X |
| Day-of-week FE | X | X | X | X | X | X |
| Adjusted $R^2$ | 0.01 | 0.03 | 0.01 | 0.02 | 0.38 | 0.63 |
| N | 82,867,232 | 82,867,232 | 82,867,232 | 82,867,232 | 82,867,232 | 82,867,232 |

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# Peer effects across and within income groups

| | Discrete Date Base (x10$^{-6}$) | | Discrete Date Deltas (x10$^{-6}$) | | Continuous Probability | |
|---|---|---|---|---|---|---|
| | Y=LMI | Y=Non-LMI | Y=LMI | Y=Non-LMI | Y=LMI | Y=Non-LMI |
| LMI installed base | 0.10* (0.01) [0.02] | -0.02 (0.02) [-0.004] | 2.99* (0.30) [0.5] | 1.87* (0.41) [0.3] | 0.23* (0.01) | 0.15* (0.007) |
| Non-LMI installed base | -0.005* (0.002) [-0.001] | 0.12* (0.01) [0.02] | 0.69* (0.14) [0.1] | 11.64* (0.83) [2.1] | 0.06* (0.003) | 0.48* (0.01) |
| Tract FE | X | X | | | X | X |
| Area-quarter FE | X | X | X | X | X | X |
| Year-month FE | X | X | X | X | X | X |
| Day-of-month FE | X | X | X | X | X | X |
| Day-of-week FE | X | X | X | X | X | X |
| Adjusted $R^2$ | 0.01 | 0.03 | 0.008 | 0.02 | 0.39 | 0.63 |
| N | 82,867,232 | 82,867,232 | 82,867,232 | 82,867,232 | 82,867,232 | 82,867,232 |

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# Study #2 Data

- Non-residential systems
  - LBL's Tracking the Sun data set identifies 35,526 non-residential PV installations from 2010-2021, including systems installed on commercial buildings (N=23,975), government buildings (N=3,989), and schools (N=2,089)
  - We also identified systems installed on houses of worship based on data from Interfaith Power & Light and the Department of Homeland Security (N=1,329)
- Residential system data comes from BuildZoom (N=1,449,189)

# Study #2 Methods

- We use staggered difference-in-differences to measure temporal changes in residential adoption rates after non-residential system installations (see paper for complete description of Methods)
- We implement the analysis at the zip code-quarter level:
  - The "treatment" is a non-residential installation, the treatment group comprises zip codes with non-residential systems from 2010-2021
  - The "control" group comprises zip codes without non-residential systems from 2010-2021