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

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Summary

- Demand for emerging technologies can be influenced by the adoption decisions of peers
- Peer influence has been well documented for rooftop solar
- We improve on existing peer influence models and evaluate peer influence across household income levels

Key findings:

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

Peer influence has a quantitatively weaker impact on low-income adoption rates, partly because influence does not address other barriers to low-income adoption.

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

Photo by Dennis Schroeder, NREL 45243

Background: What drives rooftop solar adoption?

- Most research focuses on personal incentives
- An alternative approach explores how social or “peer” influence drives rooftop solar adoption decisions
- Several solar peer influence mechanisms have been explored, such as interpersonal interactions, active persuasion, and visible cues

Photo by Joe DelNero, NREL 73221

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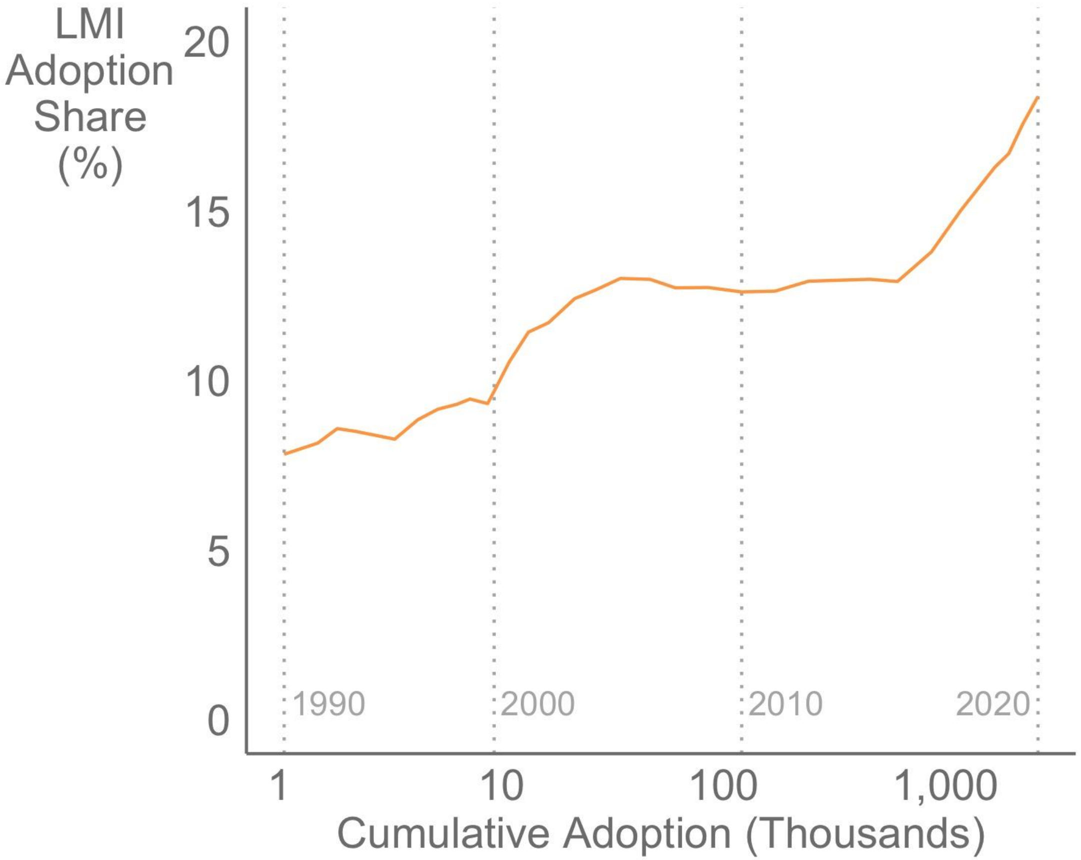
Background: Solar diffusion

- 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.

Research questions

- Does peer influence operate at all income levels?
- Could differences in peer influence partly explain differences in adoption rates across income levels?

Photo by Werner Slocum, NREL 66322

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
  - p is the price of a good
  - $Q_{\neq j,g}$ is the demand of *other* individuals in the group
  - X is a set of other relevant demand shifters.
- The impact of $Q_{\neq j,g}$ on $Q_{j,g}$ is known as a *peer effect*

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:

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

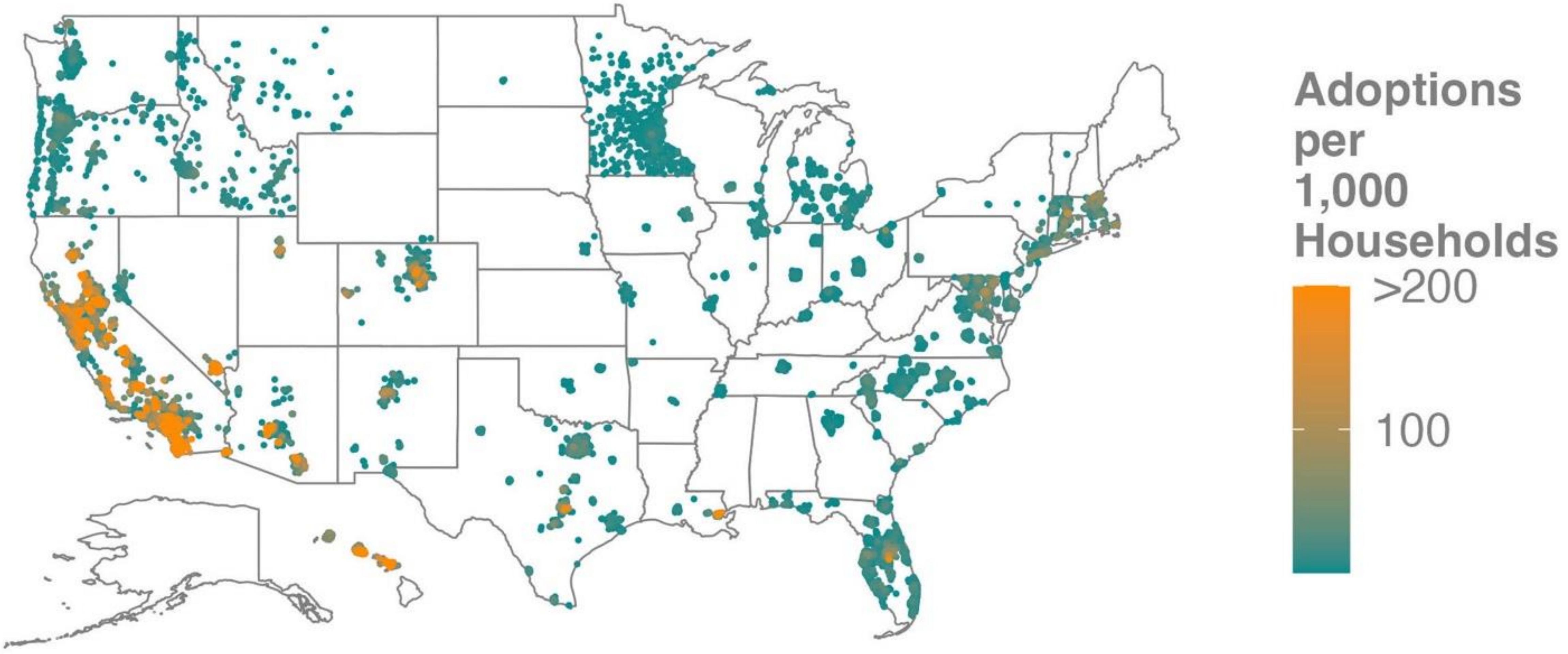
- Where a_{gt} is an adoption in group g at time t, b_{gt} is the cumulative installed base, and X is a set of relevant control variables
- Under certain verifiable conditions, β provides a robust estimate of peer effects

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

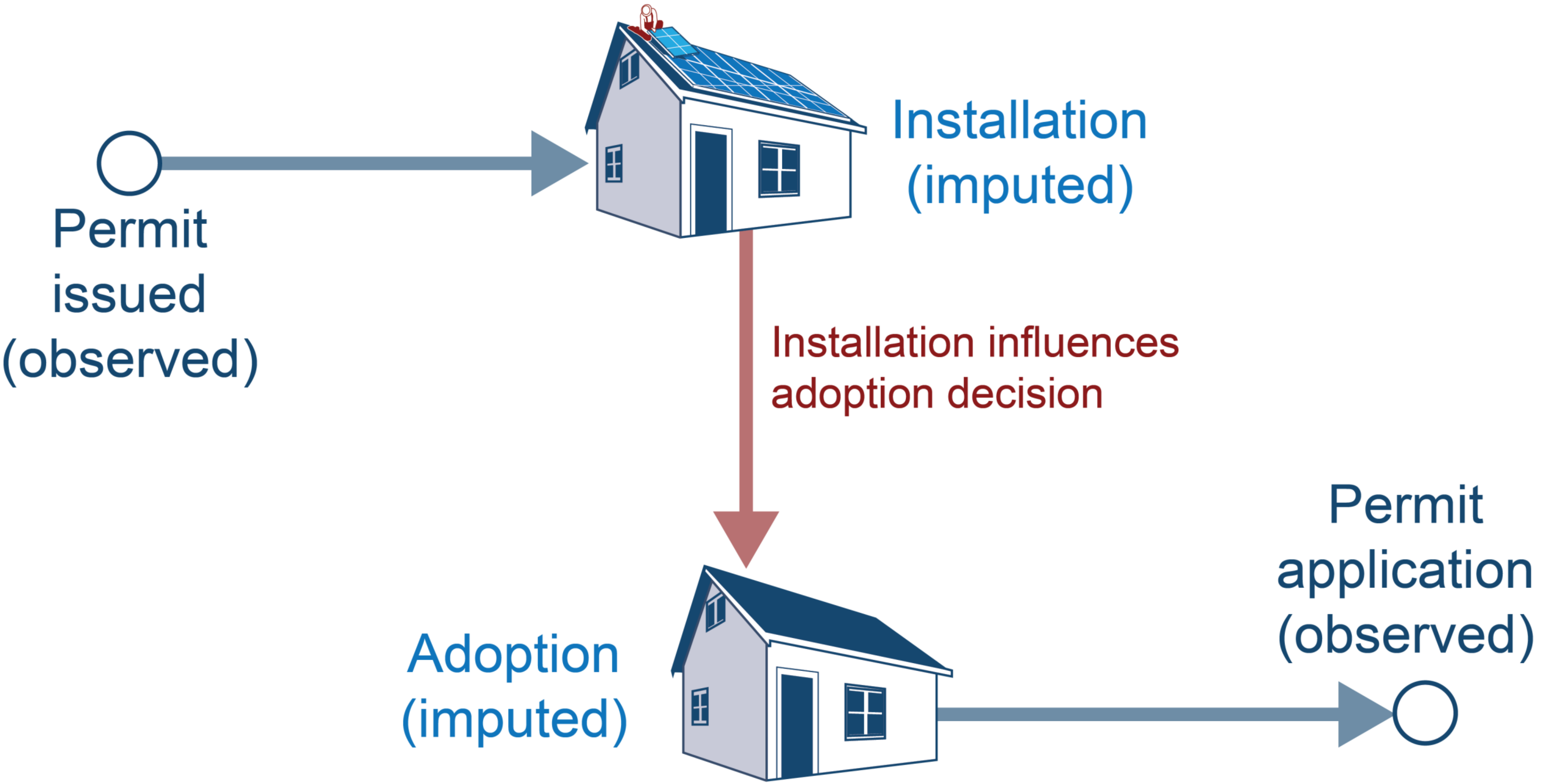
Data

- 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

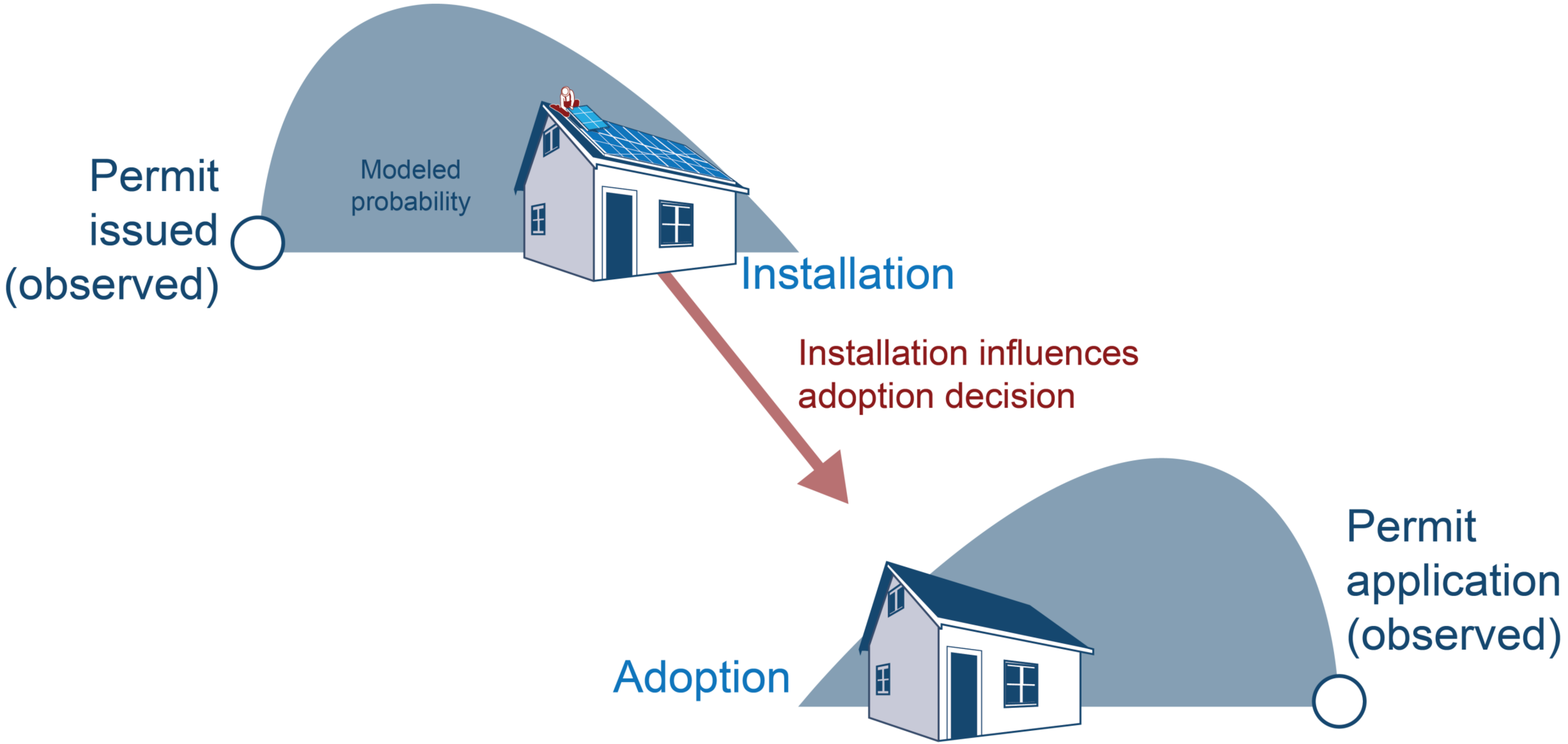
Study sample



Approach #1: Discrete (imputed) dates



Approach #2: Continuous probabilities



Empirical models

- Fixed-effects regression of adoption on the installed base, as measured in discrete dates, first-differenced discrete dates, or continuous probabilities
- To test peer influence across income levels, we subset the data into LMI households (earning less than 100% of area median income) and non-LMI households, and test variations of adoption decisions as functions of the installed base for different subsets of income levels

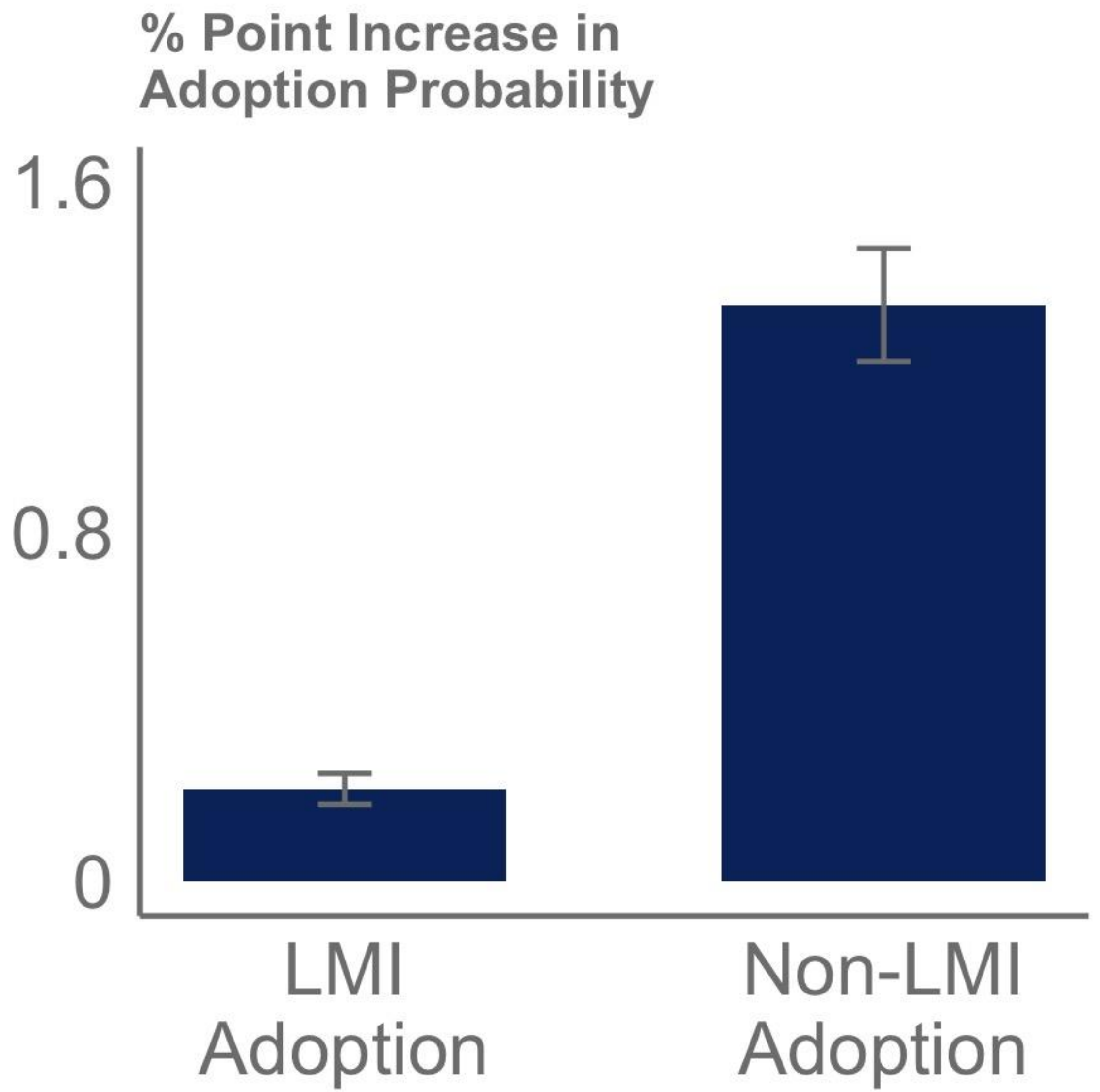
Results

Peer effects for all households

- The discrete date model suggests that an installation on a given day increases the probability of adoption by around **1.8 percentage points**
- The continuous probability model suggests that every two installations drive roughly one peer-influenced adoption

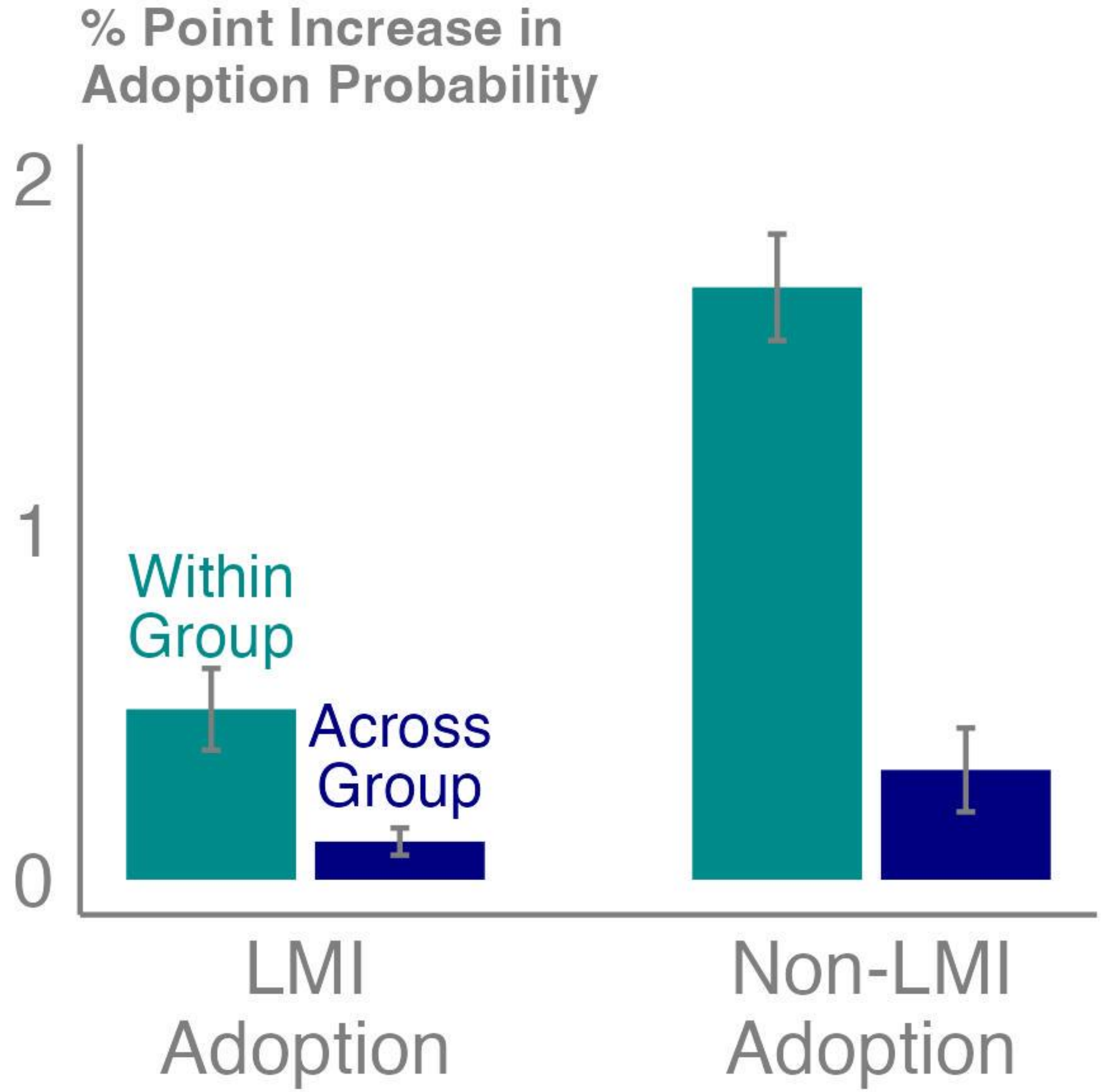
Peer effects across income levels

Peer effects are significantly smaller among LMI households



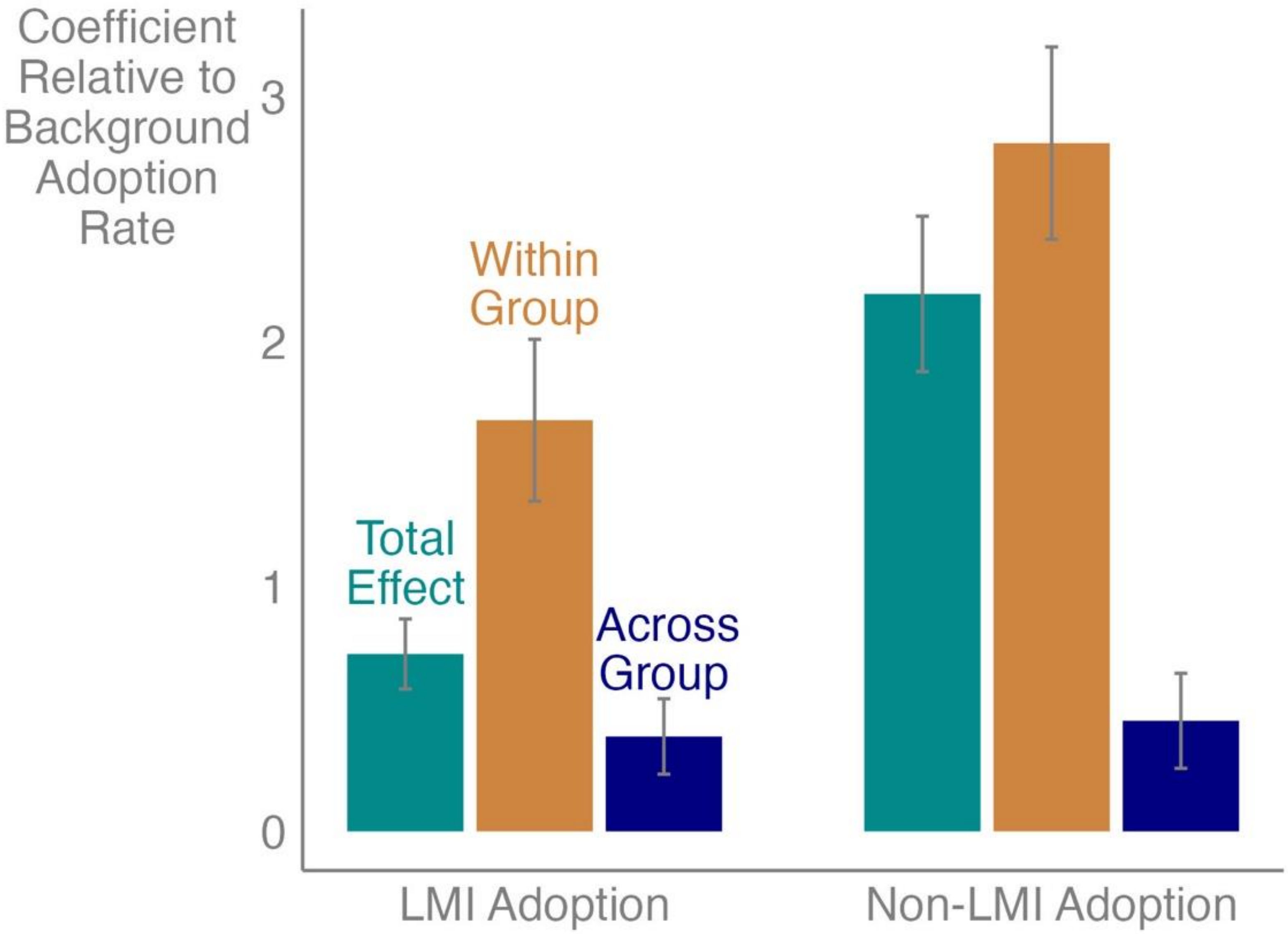
Peer effects within and across income groups

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

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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
- Peer influence is a relevant demand shifter for future economic analysis

Acknowledgments

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Questions?

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Supplementary Slides

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

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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

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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*	-0.02	2.99*	1.87*	0.23*	0.15*
	(0.01)	(0.02)	(0.30)	(0.41)	(0.01)	(0.007)
	[0.02]	[-0.004]	[0.5]	[0.3]		
Non-LMI installed base	-0.005*	0.12*	0.69*	11.64*	0.06*	0.48*
	(0.002)	(0.01)	(0.14)	(0.83)	(0.003)	(0.01)
	[-0.001]	[0.02]	[0.1]	[2.1]		
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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