

Valuing Solar Subsidies*

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January 15, 2025

Abstract

Individuals trade present for future consumption across a range of economic behaviors, and this tradeoff may differ across socioeconomic groups. To assess these tradeoffs, we estimate a dynamic model of residential solar adoption and system sizing in California using household-level data on solar irradiance, electricity consumption, and electricity rates that offer plausibly exogenous variation in the future benefits from adopting relative to upfront costs. We find implicit discount rates of 15.3%, 13.8%, and 10.0% for low-, medium-, and high-wealth households. Counterfactual simulations demonstrate opportunities to reduce the regressivity of solar adoption, increase policy cost-effectiveness, and improve welfare for low-wealth households.

Keywords: solar, discount rates, energy policy, distributional impacts, dynamic discrete choice models.

JEL Codes: L94, Q48, H23, D12

*The authors thank Erica Myers, Laura Grant, Soren Anderson, Ryan Kellogg, Steven Haider, Frank Verboven, and the seminar participants at IO+, AERE@ASSA2022, Clemson University, UC Davis, Stanford GSB, NBER EEE Spring Meeting, NBER Distributional Consequences of New Energy Technologies and Policies, and Marketing Dynamics for their valuable feedback. We also would like to thank an NBER Workshop on Distributional Consequences of Environmental Policies for support.

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1 Introduction

The rate at which individuals trade present consumption for future consumption is important across a range of economic behaviors, including savings, human capital formation, and investment in personal health. Understanding this tradeoff is critical for public policy, which often subjects individual actions and behaviors to incentives or restrictions to achieve long-run objectives that are deemed socially desirable. Laboratory experiments with hypothetical choices to examine intertemporal decision-making are numerous, but credible quasi-experimental estimates of discount rates revealed by market decisions are relatively rare (Hausman, 1979; Lawrence, 1991; Warner and Pleeter, 2001; Bollinger, 2015; de Groote and Verboven, 2019). Evidence on how discount rates vary across policy-relevant sub-populations is even scarcer. As noted by Barsky et al. (1997), econometric estimation of preference parameters, including time preferences, may be “particularly inadequate” when heterogeneity of preferences in the population is important, due to identification issues.

This study examines how consumers of different wealth groups trade off present for future consumption in a highly policy-relevant context: the adoption of rooftop solar photovoltaic (PV) systems. There has been substantial criticism of past solar policies by economists for primarily benefiting high-wealth households and shifting electricity system costs from relatively wealthy households who are more likely to adopt rooftop solar to relatively poor households who less likely to adopt (Borenstein and Davis, 2016, 2024). Net energy metering (NEM) is a very common policy that has been used at some point by 43 states in the United States. Under the standard NEM policy, solar adopters can export excess solar generation above consumption to the grid and receive credit for it in future months, thus earning compensation at the retail rate of electricity (usually up to the consumer’s total annual consumption). The value of this incentive to consumers critically depends on their discount rates, which may vary across wealth groups.¹ Upfront rebates and financing mechanisms for solar have been widely studied (Kirkpatrick and Bennear, 2014; Hughes and Podolefsky, 2015; Rogers and Sexton, 2015; Pless and van Benthem, 2016; Gillingham and Tsvetanov, 2017), but despite the prevalence of NEM policies, we are not aware of any previous research that has evaluated their effectiveness in spurring additional solar PV capacity across wealth levels as a result of differences in discounting, or their effect on consumer welfare. Much of the focus has instead been on spatial misallocation (Sexton et al., 2021; Colas and Saulnier, 2024).

¹Houde and Myers (2021) provide evidence that in the realm of household appliances, higher income consumers weight operating costs more than purchase price.

With more solar adoption by wealthier households (Forrester et al., 2023), adding solar can unintentionally shift the costs of supporting the grid from wealthier households to poorer households. This is relevant to policymakers for equity reasons and it also raises questions about the viability of traditional utility models as solar market share increases. If there is more distributed solar generation, then the fixed costs of the grid are spread across fewer non-solar customers, leading to higher electricity rates, and possibly inducing further grid defections that could yield a “utility death spiral” (Kind 2013). In response to these concerns, many states across the United States are currently reducing their compensation for excess solar electricity fed into the grid. For example, in 2023, California implemented “NEM 3.0,” which reduced compensation for excess solar electricity by about 75%, a drastic change in the long-term benefit of rooftop solar. The effects of such a policy could differ across the population if there is heterogeneity in intertemporal tradeoffs.

In this paper, we employ rich and unique micro-data on rooftop solar panel adoption, and on the expected returns from such adoption, to estimate heterogeneous ‘implicit’ discount rates by household wealth group. We refer to the estimated discount rates as ‘implicit’ because they are the rates that rationalize observed decisions. Adopting rooftop solar entails an upfront cost to install panels that generate future electricity cost savings. These savings depend on the system characteristics, sunlight, and the compensation rate for excess generation. Using proprietary Google Sunroof data for rooftop-specific expected electricity generation of optimal solar installations for every home in select California zip codes along climate borders, in conjunction with household utility bills, we calculate the value of the flow of benefits of both purchasing and leasing solar as a function of the implicit discount rate for the household. In this calculation, we account for the household’s observed electricity consumption and the optimal installation size for using an optimal sizing model. We combine these data with observed solar adoptions and household-specific demographic information to estimate our structural model.

In our study, implicit discount rates are identified from plausibly exogenous household-specific variation in future electricity bill savings from adopting solar due to differences in solar irradiance (as a function of rooftop characteristics, such as pitch, orientation, and shading from trees and structures), and from sizable differences in electricity rates across administratively-determined climate zones within the state. In previous work, econometric identification of discount rates often relies heavily on strong functional assumptions.² Some papers utilize arguably exogenous changes to the environment, such as the entry of a new

²For example, Hausman (1979) assume an exact lifetime for air conditioners, no deterioration over time, no differential in expected inflation rates of appliance prices and electricity, and constant utility over time for air conditioning.

choice option (Warner and Pleeter, 2001) or policy change (Bollinger, 2015; de Groote and Verboven, 2019). These approaches using time-series variation typically involve strong assumptions about agent expectations. In contrast, our approach identifies implicit discount rates from cross-sectional variation at the household level in the relative value of the upfront costs of installing solar and the long-term benefits, leaving us less dependent on assumptions about unobserved consumer expectations for identification.

Our estimation approach generally follows Arcidiacono and Miller (2011). However, our utility bill data is anonymized, so we cannot match each non-solar household to a specific utility bill. This leads to an econometric challenge akin to the challenge of incorporating micro-data into BLP estimation (Conlon and Gortmaker, 2023), due to the fact that household-level likelihoods are no longer independent within zip code.³ We overcome these challenges by integrating over the observed zip-code empirical distribution of household electricity consumption with replacement.

We find economically meaningful differences in implicit discount rates between low- and high-wealth homeowners: 15.3% versus 10.0%. This leads high-wealth households to value the same stream of benefits approximately 50% more than low-wealth households. This is an especially important finding because it means that low-wealth households value NEM incentives substantially less than high-wealth households. Based on our estimation results, we run several counterfactuals that change the solar policy while holding the rest of the electricity rate structure fixed.

In our first counterfactual, we find that if the NEM compensation is substantially reduced to the average avoided cost of solar generation in California, and half of the generated solar electricity is exported to the grid, solar adoption for both wealth groups would decrease by 14%. Yet the consumer surplus reduction would be almost five times higher for high wealth households, highlighting how much more high-wealth households value NEM benefits. Such a policy would also reduce environmental benefits, but would substantially decrease federal tax credit outlays and benefit electric utilities.

In a second counterfactual, we again replace NEM with a scheme that compensates excess solar generation at the avoided cost. But we take approximately half of the funding that would have been used for NEM payments and allocate that funding to upfront subsidies (split between a per-W and per-installation subsidy), such that the total installed capacity is roughly the same as under the baseline (in MW), but with a very different distribution of installations. In particular, low-wealth households would be much better off relative to

³To see why, consider that if one specific household is a high-consumption household, this would lower the probability that the other households in a zip code can also be a high-consumption household because the aggregation of all household consumption within a zip code must equal the observed empirical distribution.

high-wealth households. Under the counterfactual, high-wealth installations decrease by 3%, and low-wealth installations increase by 21% (overall installations increase by 7%, although they are smaller on average, leading to the same total installed MW). This leads to a 39% decrease in consumer surplus for high wealth households and a 10% increase for low wealth. We calculate the marginal benefit of public funds (Hahn et al., 2024) of the upfront subsidies in this counterfactual to be greater than one for low-wealth and medium-wealth households, but less than one for high-wealth households, indicating that the expenditure from upfront solar subsidies to wealthy households is greater than the value of the social willingness-to-pay of those subsidies. Subsidies to wealthy households of course also increase inequality concerns.

Our estimates provide credible evidence that individual implicit discount rates that are rationalized by solar adoption decisions exceed common market rates and that these vary by wealth in ways that have important implications for economists and policymakers. This finding of relatively high implicit discount rates accords with results in the ‘energy-efficiency paradox’ literature of undervaluation of future energy savings in energy efficiency purchases (Metcalf and Hassett, 1999; Allcott and Greenstone, 2012; Gerarden et al., 2017; Gillingham and Palmer, 2014; Gillingham and Myers, 2025). One policy takeaway from our counterfactual results is that it is possible to achieve welfare improvements from a reduction in NEM compensation and increase in upfront subsidies. Our results also highlight a structural inequity in existing solar policy. We show that standard NEM is a regressive policy and that a switch to upfront subsidies can also improve distributional equity.

2 Background

2.1 Solar Policy

The adoption of rooftop solar PV has benefited from billions of dollars of subsidies. The most prominent subsidies in the United States over the past two decades have been the many state-level upfront adoption rebates, such as the California Solar Initiative program, the federal investment tax credit (ITC), and NEM. Elsewhere in the world, popular policies include NEM and feed-in tariffs, in which solar adopters send electricity generated from solar to the grid and are compensated at a price that is usually above the retail electricity rate. Net-billing tariffs (NBT) refer to mechanisms in which excess solar generation above consumption that is exported to the grid is compensated at some predetermined rate that is usually below the retail electricity rate. Under NBT, consumers receive a ‘net bill’ each month and credits for more generation than consumption in each month cannot roll over, as they can under NEM. California’s new “NEM 3.0” is version of NBT, with some additional

elements. In recent years, most U.S. state rebate programs have been discontinued, but the federal ITC is still in place and NEM is still widely used across the country, despite some efforts to phase it out.

From a social welfare perspective, policies to encourage adoption of solar can be motivated by innovation market failures, such as learning-by-doing, or as a second-best approach to addressing uninternalized environmental externalities. One key distinction between the different types of solar subsidies is whether they are upfront adoption subsidies, such as tax credits or rebates, or flow subsidies, such as NEM and feed-in tariffs. Typically, a subsidy on the extensive (adoption) margin would sacrifice efficiency on the intensive (generation) margin, as there would be less incentive to improve the productivity of generation and undertake maintenance to ensure generation (Aldy et al., 2017). However, in the case of solar panels, there is very little that can be done to improve efficiency of already-installed rooftop systems and the systems rarely require routine maintenance.⁴ Therefore, the decision to adopt solar is made as a “set it and forget it” decision requiring only consideration of the up-front investment and the (constant) flow benefits for the next 20-25 years, which critically depend on the household implicit discount rate.

The existing literature on the cost-effectiveness of solar subsidies has generally found relatively high costs from upfront subsidies due to free-riders who would have installed solar anyway without the subsidies (Hughes and Podolefsky, 2015; Gillingham and Tsvetanov, 2014). However, it might still be possible to justify at least some rooftop solar subsidies on economic-efficiency grounds based on uninternalized social costs of greenhouse gas emissions (Rennert et al., 2022), uninternalized local air pollution emissions (Sexton et al., 2021), and learning-by-doing externalities (Bollinger and Gillingham, 2023). Yet without careful policy design, the distributional consequences may be perverse, especially in a state like California that has increasing block pricing for electricity, so that those who consume more (usually wealthier households) pay higher rates and thus benefit more from adding solar.

2.2 Implicit Discount Rates Across Wealth Groups

This paper focuses on estimating implicit discount rates across wealth groups because they are a crucial ingredient for comparing the welfare impacts of subsidy policies that have different time profiles of benefits. However, while implicit discount rates characterize the intertemporal tradeoff implied by actual decisions, they may capture more than just the pure rate of time preference of different groups. Risk aversion, the marginal propensity to consume,

⁴See for instance <https://www.energysage.com/solar/101/solar-panel-maintenance/>.

and differences in lending and borrowing costs can all also help explain the tradeoffs observed by economists either in the laboratory or in the field (Cohen et al., 2020).

Coller and Williams (1999) show that the consumer’s real rate of return should equal their discount rate only if it lies between their borrowing and lending costs, and thus differences in borrowing rates or binding credit constraints could lead to higher implicit discount rates for lower-wealth households than others (Allcott et al., 2015). We explore this in our setting by controlling for the household’s available lines of credit. Wealthier consumers may also have a greater ability to smooth consumption due to greater liquidity, which could also lead to observed intertemporal tradeoffs differing by wealth (Cubitt and Read, 2007). This may be less relevant in our setting, as the flow subsidies we are examining tend to be smooth over time.

Risk aversion may differ across wealth groups, which have very different levels of consumption. Cohen et al. (2020) show that in a simple two-period tradeoff, risk aversion scales down the actual discount rate from the estimated “implicit” discount rate rationalized by decisions. We allow for this by modeling heterogeneity in the marginal utility of income across wealth groups.

3 Data

In order to identify heterogeneity in implicit discount rates across wealth groups without strict distributional assumptions, it is essential to have rich household-level data on the main drivers of solar adoption. To this end, we assemble a detailed household-level data set on solar adoptions, home characteristics, and household characteristics covering the period 2014 to 2016. Our research design focuses on adjacent zip codes in California that face different electricity rates due to being categorized into different climate zones. We identify 28 zip codes in Pacific Gas & Electric (PG&E) territory that are entirely contained in a single climate zone and have an adjacent zip code in a different climate zone. Figure 1 illustrates the zip codes included in our study, all of which are in the greater San Francisco Bay Area of California.

3.1 Data sources

Our first data source contains address-level data on home characteristics from CoreLogic. We focus on all single-family detached owner-occupied non-mobile home residences that were built before 2014 in the 28 zip codes. The data include the year built, heated square footage, and number of stories. This provides the set of potentially adopting households.

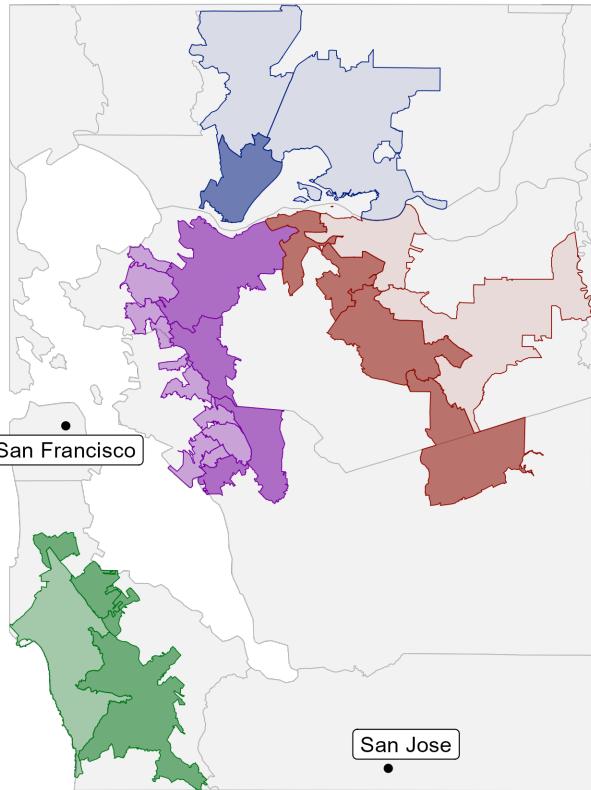


Figure 1: **Sample zip codes.** Zip codes in PG&E service territory that share a CEC climate zone boundary. Climate zones determine the electricity pricing scheme each zip code faces. Adjacent zip codes along a boundary face a different average value of offset electricity. Colors indicate particular climate zone boundaries, with the shading illustrating the side of the boundary the zip code is on.

Our second data source is publicly-available voter registration data from the California Secretary of State. For each address, we categorize households to be Democrat, Republican, or mixed.⁵ We merge in household characteristics data from InfoUSA, including the number of children, race, home-ownership status, the length of time at the residence, the number of open lines of credit, and the calculated wealth of the household, inclusive of equity in the home. If the address has more than one household, we use the data from the household that occupied the home for the plurality of our study period.

Our installation-level dataset of solar adopters is a restricted-access version of the Lawrence Berkeley National Laboratories “Tracking the Sun” (TTS) database which contains the address of the installation, application date, installation date, system size (in watts), and total system cost exclusive of subsidies and tax credits. Our study window is after the California Solar Initiative (CSI) subsidy period had ended. We match the solar adopter data to the data on potential adopters with a 96% success rate, and we remove any households that adopted prior to 2014. The final sample contains 7,244 solar adoptions during the study period out of a total of 183,667 potential adopting households. Finally, we bring in data on the amount of sun reaching each solar rooftop from Google Sunroof and data on household electricity consumption from PG&E. The next subsection will further explore these data. Further details about the data construction are in Appendix A.

Table 1 shows summary statistics for the homes and households in the sample by adopter status. The wealth variable includes the estimated value of the home. Solar adopters tend to be middle- and high-wealth, are more likely to have children, and have larger homes. Adopters are only slightly more likely to be all-Democratic in voter registration, and have shorter length of residence.

3.2 Solar Irradiance and Electricity Consumption

Some of the relationships we observe in the summary statistics may be capturing heterogeneity in the pecuniary value of adopting solar. To explicitly calculate the monetary benefit from adopting solar, we need to know how much solar electricity would be generated for any given installation on any given house. Thus, for every house in the base data, we leverage data on the ‘effective’ solar irradiance that reaches each rooftop. By definition, solar irradiance is the amount of sunlight that hits the surface of the earth and is a function of climate. It varies considerably across the United States and around the world, and even within states, e.g., across zip codes. Effective irradiance in our data also accounts for the obstruction of solar irradiance by surrounding structures and vegetation, as well as panel orientations and pitches

⁵We identify the household as registered Democrat if and only if both of the two longest-registered 2014 voters are registered Democrats or are registered with the Green Party.

Table 1: Sample Summary Statistics

	All		Adopters		Non-adopters	
	Mean	Std. dev	Mean	Std. dev	Mean	Std. dev
Variables (N=183,667 households)						
Wealth (\$1,000's)	2500.09	1017.81	2624.27	909.25	2494.99	1021.70
1(Low wealth bin)	0.33	0.47	0.24	0.43	0.34	0.47
1(Medium wealth bin)	0.33	0.47	0.42	0.49	0.33	0.47
1(High wealth bin)	0.33	0.47	0.34	0.47	0.33	0.47
Lines of credit (count)	0.67	1.41	0.75	1.53	0.66	1.40
1(Children present)	0.32	0.47	0.41	0.49	0.31	0.46
Length of residence (years)	15.56	12.26	13.42	10.65	15.65	12.31
Square Footage (1,000 sq.ft.)	1.79	0.75	2.16	0.81	1.77	0.75
1(Single story)	0.32	0.47	0.45	0.50	0.32	0.47
1(Dem voter registration)	0.43	0.49	0.45	0.50	0.43	0.49
1(Possible non-owner)	0.18	0.39	0.06	0.24	0.19	0.39
Adopted System Size (N=7,244)						
System Size (kW)			5.29	2.36		
Low-Wealth Adopter Sys. Size (kW)			4.91	2.23		
Med-Wealth Adopter Sys. Size (kW)			5.51	2.34		
High-Wealth Adopter Sys. Size (kW)			5.29	2.45		

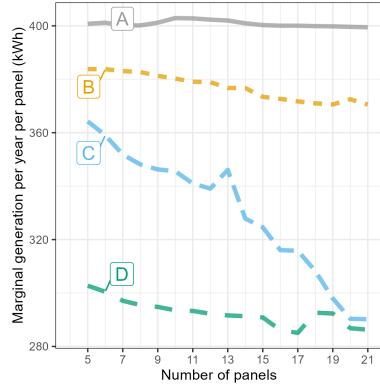
that may fail to capture all irradiance due to rooftop characteristics. Effective irradiance provides micro-level variation in the electricity generation of a unit of solar capacity, namely from household to household within neighborhoods. Moreover, for a given home, effective irradiance varies across the rooftop, with some portions of the rooftop receiving more sunlight than others.

Figure 2 shows an example of the effective irradiance of four homes and what it means for solar generation. Panel (a) shows Google Sunroof imagery of the homes which is modeled by Google based on satellite imagery. Panel (b) shows how expected solar generation declines with more panels due to reduced irradiance.⁶ Google Sunroof predicts electricity bill savings from adopting solar for each rooftop based on the irradiance profile, electricity rate, and the optimal size as a function of household electricity consumption and utility rate. Homes located in deep shade or with a roof profile that does not angle southward need more panels to generate a given amount of electricity, increasing the cost per kWh to that household. This and the utility rate borders provide our two main sources of identifying variation.

⁶While the expected solar generation is downward sloping with the number of solar panels, the relationship is not necessarily monotonic. Following standard installation practice, each roof segment, or partition of a roof with a common pitch and azimuth, is filled before an additional segment is used. Thus, small non-monotonicities can occur when the first panel on a subsequent segment is installed. When non-monotonicities imply multiple equimarginal crossings, we select the smaller number of panels.



(a) Google Project Sunroof display



(b) Solar generation profiles

Figure 2: **Solar generation profiles** for four selected rooftops on a single block in Solano County, California. Panel (a) shows the Google Sunroof imagery, while panel (b) shows the marginal generation for each household per panel on the vertical axis and the number of panels on the horizontal axis. Contrast dashed green (house D), which exhibits low irradiance (300 kWh/yr) for the first panel and a slow decline up to 15 panels followed by a leveling off, with gray (house A), which exhibits strong irradiance for the first 20 panels (400 kWh/yr). Dashed blue (house C) shows high initial irradiance (365 kWh/yr) but a rapid decline corresponding to the multifaceted roof line.

The value of adopting solar depends on household electricity consumption in our setting for two reasons. First, there is minimal compensation for generation above the household's annual consumption.⁷ Second, there is an increasing tiered electricity rate structure, so the marginal value of generation to the consumer is greater if it reduces a high-consuming household's electricity imports from the grid. Because of the importance of this rate structure, we obtain data on annual electricity consumption for all customers who reside in any of the 28 zip codes PG&E border zip codes in our sample. The timing of solar adoption in the administrative data enable us to match solar adopters with their energy consumption data. For non-adopting households, we only know their zip code. Further details about the consumption data are in Appendix A, as is information about PG&E electricity rates.

We can calculate the marginal leveled cost per kilowatt-hour (kWh) for solar generation by discounting the monetary value of the flow of generation over time.⁸ This marginal cost per kWh is increasing with more solar panels due to the declining marginal generation with

⁷Compensation for excess generation through Net Surplus Compensation (NSC) was set by the California Public Utilities Commission (CPUC) at roughly two to three cents per kWh, far below the marginal leveled cost of solar for any household in our sample. Thus, we treat NSC as negligible.

⁸The leveled cost is a measure computed as the present discounted value of lifetime costs divided by lifetime production. We use the default rate of 4% employed by Google Sunroof, which reflects the defaults commonly used by solar installers when recommending system size. We also convert from DC generation to usable AC electricity.

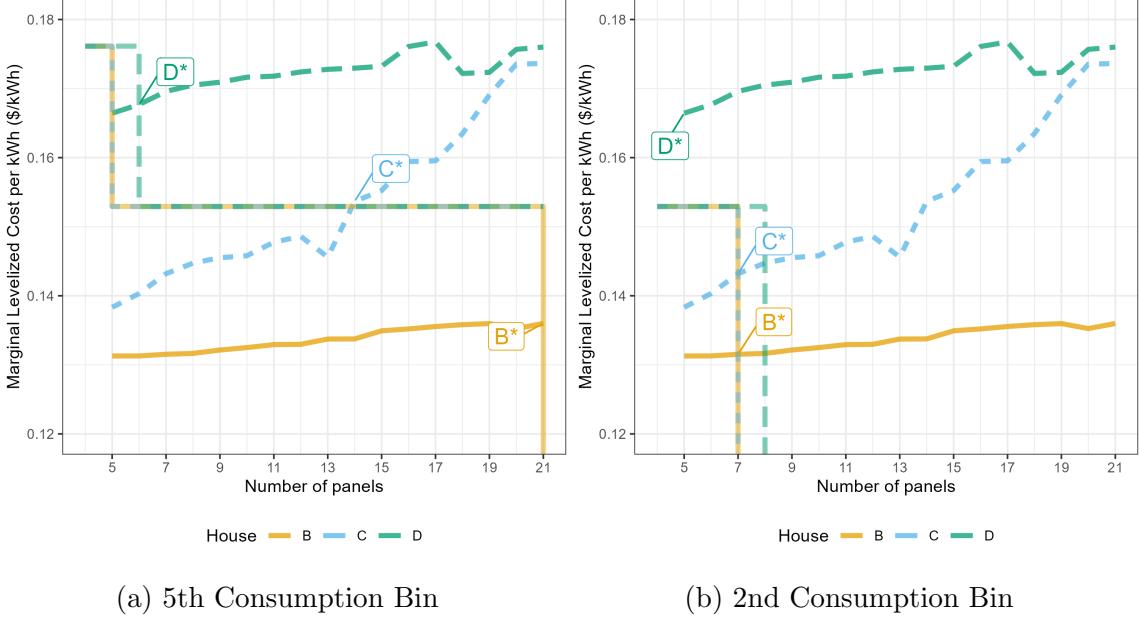


Figure 3: Optimal System Sizes for Two Example Consumption Levels. Figure shows the marginal per-kWh price of solar generation for the subset of homes from Figure 2b along with the marginal grid price (dashed line) for consumption. Optimal installation sizes are indicated with “ $*$ ” for each house.

more panels (from reduced irradiance due to the best locations being taken first). Figure 3 plots the per-kWh leveled cost over the number of panels for three of the four home profiles from Figure 2 (one home is removed to simplify the figure). These leveled cost curves are the upward sloping lines. Figure 3 also shows the weakly decreasing step functions illustrating the cost of the marginal unit of grid electricity for each home. Drops in these step functions occur where the number of panels on each rooftop generates a sufficient amount of electricity for the household to drop down to a lower electricity rate tier.

The intersection of each step function with the upward-sloping leveled cost curve is marked with a letter for the household, and it refers to the optimal solar system size where the marginal benefit of another panel equals the marginal cost. We divide our sample into five equal electricity consumption bins based on average consumption over the sample period. Panel (a) assumes that the households that are in the highest bin, while panel (b) assumes that the households in the 2nd bin.

To better understand Figure 3, begin with panel (a). Consider home D (green dashed line). The upward-sloping marginal cost per kWh dashed line crosses the electricity rate step function when the system size contains six panels (see the D^* note). Home D receives much less irradiance than home B, and thus home B has a much lower marginal cost per kWh (yellow upward-sloping line). The electricity rate step function for home B steps down to a

lower tier at a solar system size of 21 panels. This system size is also where the step function crosses the marginal cost per kWh line, thus indicating that the optimal system size for home B is 21 panels. Home C falls in between, with an optimal system size of 13 panels.

Panel (b), which shows the same four homes if they had electricity consumption in the second consumption bin, illustrates much smaller optimal system sizes. Home B and C both have optimal system sizes of seven panels, while home D has such poor irradiance that it has an optimal system size equal to the minimum installation size.⁹ In other words, it would not make sense to install a solar system on this rooftop if the electricity consumption was in the second consumption bin due to the lower electricity rates consumers in this consumption bin face. The basic logic described here underpins our optimal sizing model.

3.3 Relationship between Effective Irradiance and Adoption

In Figure 4 we provide model-free evidence of the relationship between the probability of adopting solar and the drivers of the expected stream of benefits that results from solar irradiance reaching a given rooftop. Panel (a) shows the relationship based on the the solar generation of the first panel of the system, as that provides a good measure of the overall sunlight reaching the rooftop in its best locations after accounting for trees and the shape of the roof. Panel (b) shows the relationship based on the total generation from a 15-panel array which can be thought of as a reasonable approximation of the relevant irradiance for an actual installation.

Figure 4 shows two main relationships. First, adopting shares increase over all wealth levels when irradiance increases, as one would expect. Second, the rate of increase is higher for medium- and high-wealth households relative to the low-wealth households. This indicates a wealth-based *differential* response to increases in the flow payoff of solar. If low-wealth households are less responsive to increases in the flow payoffs, as is suggested in this figure, then low-wealth households put less value on payoffs that occur in the future relative to the present. This descriptive result provides intuition for some of the key variation in the data that will be identifying our implied discount rate estimates.

4 Model

We develop a dynamic discrete choice model of residential solar installations. The motivation for including dynamics to estimate implicit discount rates is that consumers have a “buy-or-

⁹We set the minimum installation size to five panels which corresponds to the smallest observed installation in our data.

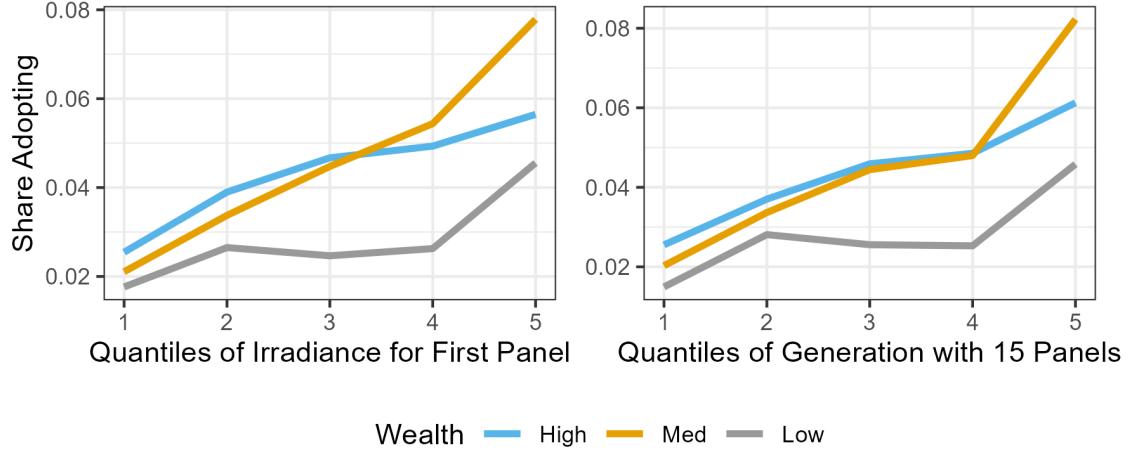


Figure 4: **Model free evidence.** Observed share adopting over quantiles of measures of irradiance by wealth. (Left) shows the change in observed share adopting as first panel irradiance increases. (Right) the change in observed share adopting as total generation at 15 panels increases. High and Medium wealth households respond more to irradiance than does the Low wealth bin, evidenced by the more positive slope for High and Medium.

wait” decision about adopting solar, with expectations about future electricity prices and solar panel prices. A key innovation in our model is to include a static optimal solar system size decision based on setting the marginal benefits of an additional panel from reduced use of grid electricity equal to the marginal costs of installing that panel. Because of the granularity of our data, we can calculate what the optimal installation size is for every potential adopting household as a function of electricity consumption, as is illustrated in Figure 3.

The optimal system sizing model is important in our setting both for correctly calculating the payoffs from installing solar for a given consumer and for running counterfactuals that change upfront versus future payoffs, and thus affect the optimal system size. Once the household and installer determine the optimal solar system size for the home, the household then decides whether to install solar using a discounted net present value calculation. This calculation explicitly accounts for consumer expectations of future electricity prices and solar prices. Details are in Appendix B.

4.1 Solar Installation Decision

Our dynamic discrete choice model of solar installations, conditional on the optimal system size, follows the literature in treating the adoption of solar as an exit action (e.g., de Groot and Verboven (2019)). A distinguishing feature of our model is that it leverages variation in household characteristics and climate zones for identification.

The consumer decides whether or not to install solar, $j \in \{0, 1\}$, where $j = 1$ is the decision to install. The flow utility for choice j at time t is given by $u_{jt}(q_0, q^*) + \sigma\epsilon_{jt}$. q_0 is the household's baseline electricity consumption prior to installing solar and q^* is the electricity generated by an optimally-sized solar system. The ϵ_{jt} is a stochastic structural error term with scaling parameter σ .

We normalize the flow utility of not adopting solar to $u_{0t} = 0$; accordingly, we include the savings from using less grid electricity in the value of adopting solar. In what follows, we will derive an expression for the value of both adopting solar and not adopting. Since we treat adopting solar as an exit action, the expression for adopting solar will capture the discounted stream of expected utility for all periods subsequent to the adoption; i.e. $u_{1t} = v_{1t}$, where v_{jt} is the choice-specific value function for choice $j \in \{0, 1\}$ at time t (absent the additive stochastic shock). The value of not adopting will be equal to the continuation value, as there is the option of adopting later.

The total expected utility at time t is given by:

$$V_t(p_t, C_t, F_t) = \sum_{\tau=t}^{\infty} \rho^\tau \mathbb{E} \left[\max_{j \in \{0,1\}} (u_{j\tau} + \sigma\epsilon_{j\tau}) \right], \quad (1)$$

where ρ is the household's discount rate and p is the electricity price. C_t is the variable cost of installing solar to the consumer and F_t is the fixed cost of the system. Both C_t and F_t are inclusive of rebates and the tax credits.

By Bellman's optimality principle, we can also define the value function recursively as:

$$\begin{aligned} V(p, C, F) &= \max_{j \in \{0,1\}} (v_j + \sigma\epsilon_j), \text{ where} \\ v_j &\equiv \mathbb{E}[u_j | p, C, F] + \rho \mathbb{E}[V(p', C', F' | p, C, F)]. \end{aligned}$$

The prime notation indicates the next period's value of the state variables (and we drop the t subscript for notational clarity). We include an expectation term for u_j in addition to the next period's continuation value because solar adoption is treated as a terminal choice whose payoff also depends on the evolution of the state variables (p , C , and F). We follow de Groote and Verboven (2019) and assume rational expectations. One minor difference is that we use fitted prices from a linear regression over the range of the data, rather than realizations of prices (we discuss this further in Section 5.2). We define a period in our model as a quarter.

In order to derive an expression for the choice-specific value function of adopting, v_1 , we start with the total expected utility from the adoption of solar over its lifespan relative to not adopting (not inclusive of the ϵ_j):

$$\delta_1 = \int_{q_0-q^*}^{q_0} \sum_{\tau=1}^T (\rho(1+\zeta)(1-\lambda))^{\tau-1} p_\tau(x) dx - C(K^*) - F + X\beta. \quad (2)$$

The integrand in (2) reflects the present value of future costs of grid electricity avoided given solar generation of q^* over the lifespan of the array, which is given by T .¹⁰ It is determined by the per unit price of grid electricity, $p(x)$, which potentially varies (as a step function) in x , and by the grid electricity consumed, which is the difference in total electricity consumption per period, q_0 , and the electricity generated by the optimally sized solar PV system q^* . Consistent with the sizing model, we assume that consumers expect future changes in electricity prices, allowing for an additive, mean zero, stochastic short run prediction error; electricity prices are expected to evolve according to $p'(x) = (1+\zeta)p(x) + \epsilon^p$.¹¹ We also assume that consumers expect panels to depreciate each year by λ , such that $q' = (1-\lambda)q + \epsilon^q$, with $Cov(\epsilon^p, \epsilon^q) = 0$. This is incorporated in our model via a discounting of the stream of benefits of adopting.

The $C(K^*)$ and F are the variable and fixed costs of the solar installation of optimal size K^* . Upon examination of the data, the decline in solar PV costs appears to be in the variable costs, such that $C(K^*)' = \eta C(K^*)$ and F appears to be constant over time.¹² We assume that consumers expect an AR(1) process for the decline in variable costs (details are in Appendix D). Finally, the $X\beta$ is the heterogeneous utility from electricity consumption and ancillary utility derived from solar adoption, such as from a warm glow effect (Andreoni, 1990). Specifically, $X\beta$ includes time-invariant demographic variables and home characteristics, as well as an area fixed effect and a time fixed effect, both of which we assume consumers expect to remain constant in future periods.

The expression for the expected economic value of adoption over the life of the solar array can thus be simplified to:

$$\delta_1 = \omega [\theta q^* \bar{p} - C(K^*) - F] + X\beta, \quad (3)$$

in which we define:

$$\theta \equiv \sum_{\tau=1}^T ((1+\zeta)(1-\lambda)\rho)^{(\tau-1)} \quad (4)$$

¹⁰There is a very small approximation here: we treat the average price of offset grid electricity as not changing as a result of the very small rate of panel depreciation, given by λ , leading to slightly less consumption at the household's lower tier.

¹¹We estimate a climate zone and consumption bin-specific ζ , with results in Appendix D.

¹²This is consistent with cost declines that relate to either panel costs or increased labor efficiency. We allow that the fixed price component will vary by boundary group.

The θ term can be interpreted as the number of current period payoffs that the household values as equivalent to the stream of solar net benefits over T periods (similar to an indifference break-even period but accounting for panel depreciation and rate increases). The \bar{p} is the current average cost of grid electricity avoided by adoption of an optimally-sized installation that produces q^* .¹³ Thus, $\theta q^* \bar{p}$ captures the direct utility of solar electricity consumption over the installation's life. Since we are interested in differences in implicit discount rates between wealth levels, we incorporate a wealth-specific marginal utility of income ω to allow for heterogeneity in utility from any cost or savings after discounting. Households with higher wealth may have a lower marginal utility of income, even holding implicit discount rates constant.

Next, we need to make some assumption of what consumers expect to do after the lifetime of their solar array. In de Groote and Verboven (2019), the authors argue that they do not have to take a stand on whether the dynamic problem is finite time or infinite time. This is technically true, but if consumers view the problem as an infinite-time problem and the problem is treated as a finite-time problem, this implicitly assumes that there is zero utility and zero continuation value after T periods if you adopt solar. The reason for this is that the value function for adoption is only the utility over the lifespan of the solar array. But after time T , the household must either again consume electricity from the grid or adopt solar again. Treating an infinite horizon problem as a finite horizon problem ignores the value in period $T + 1$, thus potentially underestimating the total present value of adopting solar in the current time period.

Assuming a finite-time problem also leads to a disconnect between how the adoption and non-adoption decisions are treated when modeling the problem as a finite-time problem. Specifically, the value of non-adopting can include payoffs past $T + 1$ because the option value of adopting in any future period is calculated out for T further periods. This issue may not be important if implicit discount rates are sufficiently high, but at lower levels of discounting or when electricity rates increase considerably over time, allowing the decision variable to affect the time over which utility is calculated can appreciably impact the estimated parameters.

Thus, we formulate the problem as an infinite-time dynamic problem, with the simplifying assumption that once a household makes the decision to adopt solar, the household will re-adopt after the solar installation reaches the end of its working life, i.e. every T quarters. While this may not always be the case, we believe it more reasonable than setting the value to zero after the life of the solar array, which does not capture either the net benefits of a new solar system or the cost of consuming grid electricity in those later periods.

¹³As solar output declines gradually, it is possible for \bar{p} to also change slightly with tiered pricing, but we will account for this in the estimation of how average price changes for different consumption bins over time.

We further assume that the infinite re-adoption applies to the flow payoff and costs of adoption, but the heterogeneous ancillary utility from adoption $X\beta$ is a one-time payoff of adoption. The reason for this is two-fold: first, it would be consistent with a green glow from adoption, where the act of installing itself provides the utility. Second, some demographics in X are mechanically correlated with time (i.e., length of residence) or may change over time (i.e., presence of children in the home). Thus, we model the ancillary utility as non-recurring when re-adopting.

Under these assumptions, the expected value of installing solar is given by the stream of benefits from installing solar again every T quarters:

$$v_1 = \omega \left[\frac{1}{1 - (\rho(1 + \zeta))^T} \theta q^* \bar{p} - \frac{1}{1 - (\rho\eta)^T} C(K^*) - \frac{1}{1 - \rho^T} F \right] + X\beta.$$

As a reminder, since adopting solar is an exit action, $u_1 = v_1$.

Now that we have expressions for the choice-specific value function of both adopting and not adopting solar, we can close the model. We assume ϵ_0 and ϵ_1 are distributed Type 1 extreme value with scale variance of σ . With these assumptions, we can write the below expression for the value of non-adoption using conditional choice probabilities (Hotz and Miller 1993), treating adoption as an exit state, as in de Groote and Verboven (2019) and Bollinger and Gillingham (2023):

$$v_0 = \rho (v'_1 - \sigma \ln(Pr'_1) + \sigma\gamma), \quad (5)$$

in which v' is the next period value of adopting, γ is Euler's constant, and Pr'_1 is the adoption probability next period. Thus, the value of non-adoption can be written as a function of the expected value of adopting in both the current period and next period, as well as the probability of adopting in the next period.

The difference in the expressions for v_1 and v_0 in equations (3) and (5) yields the difference in the value of adopting versus not adopting:

$$\begin{aligned} v_1 - v_0 &= \omega \left[\frac{1 - \rho(1 + \zeta)}{1 - (\rho(1 + \zeta))^T} \theta q^* \bar{p} - \frac{1 - \rho\eta}{1 - (\rho\eta)^T} C - \frac{1 - \rho}{1 - (\rho)^T} F \right] \\ &\quad + (1 - \rho)X\beta + \sigma\rho(\log(Pr') - \gamma) \end{aligned} \quad (6)$$

The probability of adoption conditional on consumption bin and being in the market for making a purchase is:

$$Pr^p = \Lambda \left(\frac{1}{\sigma} (v_1 - v_0) \right), \quad (7)$$

in which Λ is the standard Logit cdf. We can estimate σ since we normalize the scale by setting the marginal utility of income to one for high-wealth households.

4.1.1 Leased systems

A substantial number of adopters during our study period used a third-party “leased” system wherein the lessor bears all up-front cost to install the rooftop system, and the lessee agrees to pay a price per unit of consumption during the life of the lease. In terms of up-front costs and benefits over time, the adoption decision for a lessee is distinctly different from that of a purchaser. Specifically, leasing has the effect of amortizing the cost of installing over the life of the panels. We are the first in the literature modeling solar demand to explicitly model the lease option.

For leased systems, the economic value of the lease over its lifespan is:

$$\delta_1^l = \omega_w [\theta q^* \bar{p} - \theta^{ppa} q^* p^{ppa}] + X\beta, \quad (8)$$

in which we define:

$$\theta^{ppa} = \sum_{\tau=1}^T ((1 + \zeta^{ppa})(1 - \lambda)\rho)^{(\tau-1)}, \quad (9)$$

and in which p^{ppa} is the starting price of solar electricity and ζ^{ppa} captures the annual change in the electricity price guaranteed by the PPA, which we set at 0.04 based on industry standards (we show the results from a robustness check using 0.03 in Appendix I.2).

We assume that the price the installer charges reflects the levelized cost of installing the system:

$$p^{ppa} = \frac{C(K^*) + F}{\theta^I q^*} + markup, \quad (10)$$

in which the θ^I captures the discounted sum of benefits per kWh using the installer’s implicit discount rate, set at 6%: $\theta^I = \sum_{t=1}^T ((1 + \zeta^{ppa})(1 - \lambda)\rho^I)^{(t-1)}$. We also allow for a transfer of *markup* to the installer for fronting the installation costs. We parameterize this transfer by letting κ^{TC} denote the profit margin based on the cost of providing the capital for the

installation, and κ^p a per-kWh markup. We can write (10) as:

$$p^{ppa} = (C(K^*) + F)(1 + \kappa^{TC})\frac{1}{\theta^I q^*} + \kappa^p. \quad (11)$$

The first multiplicative factor in (11) applies the markup to the installation cost and then divides by θ^I , which amortizes the marked-up cost over 25 years at the installer's implicit discount rate. Finally, the amortized cost is divided by the per-period generation q^* , plus a per-kWh markup.

By substitution, for leased systems, the economic value of the lease over its lifespan can thus be written:

$$\delta_1^l = \omega \left[\theta q^* \bar{p} - \theta^{ppa} q^* \kappa^p - \frac{\theta^{ppa}}{\theta^I} (1 + \kappa^{TC})(C(K^*) + F) \right] + X\beta, \quad (12)$$

We assume all of the markup is through the κ^{TC} , which captures the full resolution of p^{PPA} and set $\kappa^{TC} = 0.7$ based on the observed markup reported by a prominent solar leasing company's annual reports during our study period;¹⁴ correspondingly, we assume κ^P is equal to zero. These assumptions together yield prices p^{ppa} that are consistent with observed lease terms, approximately \$0.18-0.19 per kWh (we have tested and found results that are robust to other combinations of κ^{TC} and κ^{PPA} that together yield similar total markups).

Using (12), we can write analogous expressions to (6) and (7) for the total value of leasing solar, v_1^l , the continuation value of not leasing, v_0^l , and for the probability of leasing, Pr^l .

5 Identification and Estimation

5.1 Identification of Implicit Discount Rates

There are two key identifying assumptions that allow us to estimate the implicit discount rate. First, we assume that the profile of irradiance hitting each rooftop is exogenous with respect to the utility of adopting solar, conditional on household/home characteristics, household electricity consumption, and a set of geographic fixed effects, including climate zone boundary fixed effects. Second, we assume that homes on one side of a climate zone are similar to homes on the other, after conditioning on this same set of controls. Rooftop irradiance provides plausibly exogenous variation in q^* , and climate zone borders provide additional variation in \bar{p} , allowing us to identify discount rates from variation in the value of grid electricity

¹⁴See <https://ir.tesla.com/press-release/solarcity-announces-first-quarter-2014-financial-results>, which states a markup of 50-55%. We assume markup is pre-ITC, and add 15% for the ITC to total 70%

that solar offsets, $q^* \bar{p}$.¹⁵ We use these sources of variation to 1) assess how consumers weigh upfront costs versus long-term benefits, and 2) to convert the value of the grid electricity that solar offsets into dollar terms (discrete choice models only identify parameters up to a scale transformation).

There are possible issues with our first identifying assumption. One concern could be endogenous sorting, whereby homeowners intentionally purchase homes that are better suited for solar (in a way our controls do not already address). We consider this to be small concern given the high cost of California real estate in comparison to the value of solar, and the fact that solar installations were still relatively uncommon in the empirical setting. Furthermore, the average length of residence for households in the sample is 13.6 years, indicating that most households in our data purchased homes well before solar could have become a consideration.

Another potential concern with our first identifying assumption is the possibility that households manipulate their local environment to improve solar irradiance reaching their rooftop. For example, households could cut or trim trees. This would lead us to underestimate the fixed costs of adopting solar and would be an issue for us if households with smaller implied discount rates are more likely to incur the same fixed cost than those with higher discount rates. However, much of our sample has few tall trees in residential neighborhoods due to small lot sizes and relatively dry landscapes in California. In addition, we include wealth fixed effects, which should help address any selection issue in tree trimming/cutting across wealth bins.

One aspect of our model that impacts our identification might be apparent to the careful reader: the discounting enters into the value of adopting (shown for purchasers in equation (6)) via θ and the ρ in front of the Pr' term.¹⁶ The Pr' term describes the probability of adopting in the next period. Our empirical setting covers a period with few changes over time in regulations or electricity rates that could affect Pr' . We certainly expect substantial

¹⁵There is a burgeoning literature showing how quasi-experimental strategies for identification can be used when decisions (pricing, advertising, etc.) are made at a more aggregate level than unit at which conversion is measured (Shapiro, 2018; Li et al., 2019). Pricing within a climate zone is driven by average climate within that zone.

¹⁶Note that differences in θ across wealth groups are not separately identified from differences in T , the expected life of the solar array. Although the life of a system is not expected to vary across wealth bins, consumers who expect to move sooner could treat T differently than those who expect to live in their house longer. If the residual value of the solar array at the time of their move is recognized in the expected transaction price, then this distinction is not important, so long as consumers expect is that the transaction price of the house is higher by this amount. The amount may be smaller if the full value of the array is not recognized, or larger if the household has a larger discount rate than the expected buyer. Since there is previous work showing that purchased solar systems are recognized in home transaction prices (Dastrup et al., 2012; Qiu et al., 2017), and since it seems likely to us that the buyer of the same home is likely to have similar demographics and thus a similar implicit discount rate, we prefer to treat T as 25 years for all households and interpret the differences in θ as differences in the implicit discount rate.

variation in Pr' due to household differences in q^* and p , but we would expect little variation in Pr' over time. This differentiates our identification strategy from the approach in previous work that draws entirely from policy changes as temporal shocks to future values (de Groot and Verboven, 2019; Bollinger, 2015), and it implies that we are not as dependent on the variation in the estimated Pr' for identification of the implicit discount rate. We also identify σ using variation in Pr' , which further reduces the role of Pr' for the identification of the implicit discount rate. This allows us to focus our discussion of identification of θ for pinning down implicit discount rates.

For intuition on the variation identifying our results, recall Figure 4. This figure provides a sense of the cross-sectional variation in irradiance that is driving the variation in q^*p , along with variation in electricity consumption and electricity rates (from the climate zones). A key takeaway from the figure is that while higher irradiance on a rooftop leads to more adoption, the rate of increase in adoption is much steeper for high-wealth and medium-wealth households than low-wealth households. In other words, greater payoffs over the life of the solar system increase adoption more for high-wealth and medium-wealth households than low-wealth households. This fundamentally is the variation identifying the differences in implicit discount rates across wealth groups that we observe. The figure is based on irradiance, but the basic pattern is the same if we also bring in electricity rates and electricity consumption and look at adoption shares over per-period payoffs from solar.

5.2 Estimation

5.2.1 State Variable Evolution

As discussed in the model section, we assume households have rational expectations. However, rather than use realizations of the state variables in the next period, we incorporate rational expectations into the model by assuming that consumers make decisions based on expectations that follow simple models of state variable evolution using the range of the data. By construction, $\mathbf{E}[X_{it}] = \hat{x}_{it}$.

Our approach allows for market-level shocks that are anticipated via fixed effects and for common unanticipated shocks as well. A different approach could follow de Groot and Verboven (2019), who assume rational expectations by modeling the expected ex ante value function as the *realized* ex ante value function plus a prediction error. This is convenient in that it allows the authors to use the realized next period states as the expected states. A downside is that it implies that the unobserved shocks would be correlated with any market-level shock that impacts all consumers the same. This is one important reason why we prefer modeling the expectation process. Another reason is that it allows us to use the model

to extrapolate beyond the range of the data. Doing so requires an additional stationarity assumption, but in our setting we have a relatively short panel, so the additional assumption is necessary (Arcidiacono and Miller, 2020). Details regarding the estimation of the state variable transitions are in Appendix D.

5.2.2 Integrating over Consumption and Lease Type

Estimation of the household-level adoption model can be performed via maximum likelihood estimation. If we could observe the purchase/lease type $e \in \{\text{lease, purchase}\}$ and consumption bin $b \in \{1, \dots, 5\}$, then each household's contribution to the likelihood would be written simply as:

$$\mathbb{L}_{ibe} = \prod_t [Pr_{ibt}^e]^{y_{it}} [1 - Pr_{ibt}^e]^{(1-y_{it})}, \quad (13)$$

where Pr_{ibt}^e is the probability of household i adopting in time t , conditional on being type e and bin b . In practice, we do not observe the consumption bin b , nor the type e for non-adopting households. To address this, we integrate over consumption and lease types. Specifically, we use the method laid out in Arcidiacono and Miller (2011), treating the combination of consumption bin b and type e as permanent, unobserved heterogeneity. Estimation details are in Appendix E.

6 Results

6.1 Parameter Estimates

The estimates of our structural model include a large set of coefficients, most of which are controls, such as demographic and voting variables. This paper is about the implicit discount rate and thus we focus our discussion on these findings, but all of the parameter estimates can be found in Appendix Table F.1.

Table 2 presents our primary estimation results. We divide up the sample into the high-, medium-, and low-wealth groups. First, we present our estimated marginal utility of income (ω) across the wealth groups, as this parameter is very important for our counterfactuals and provides context for our implicit discount rate results. We observe that the high-wealth group has a much lower marginal utility of income, at 0.03, than the low-wealth group, at 0.20. The medium-wealth group falls in between. The marginal utility of income is an ordinal

rather than cardinal parameter, so we interpret the difference between the wealth groups. The low-wealth group has a marginal utility over six times higher than the high-wealth group.

Table 2: Primary Estimation Results

Wealth	Marginal Utility of Income	Annual Discount Rate	$\bar{\theta}$	Ratio
High	0.03 (0.02)	10.0% (0.44%)	52.6	1.5
Med	0.11 (0.14)	13.9% (1.76%)	39.0	1.1
Low	0.2 (0.07)	15.3% (3.29%)	35.8	1
All		13.1%	42.5	—

Heteroskedasticity-robust standard errors in parentheses, calculated by the delta method. The difference between the high-wealth and low-wealth underlying marginal utility of income structural parameters is statistically significant, with a p-value of 0.012. The difference between the high-wealth and low-wealth underlying discount rate structural parameters is statistically significant, with a p-value of 0.042.

Some of our most important results are the annual discount rates in Table 2.¹⁷ We find that the high-wealth households have an annual implicit discount rate of 10.0%. Medium-wealth households have a somewhat higher rate of 13.9%. And low-wealth households have an even higher rate of 15.3%. All three of these estimates are significant, and the difference between the low-wealth and high-wealth, as well as medium-wealth and high-wealth groups, are also significant (as can be seen in the coefficients α_{low} and α_{med} in Appendix Table F.1). The average rate for all groups is 13.1%. This finding is remarkably close to the average finding in de Groote and Verboven (2019) of 15%, estimated based on households in Belgium.

The final two columns in Table F.1 provide a way to understand the implications of the implicit discount rate results. Recall from our model that θ converts a \$1 payoff from solar that occurs each period over the panel lifespan from lower electricity costs into a present value. This calculation takes into account the implicit discount rate, rate of panel depreciation, and expected electricity price increases. The difference between the high- and low-wealth groups is substantial, with high-wealth households valuing the \$1 flow payoff at \$52.6, while the low-wealth households value it at only \$35.8. The ratio of the value of the two is 1.5.

This level of implicit discount rates and the remarkable difference in how consumers of different wealth groups value the future payoffs from solar has very important implications for our counterfactual results. To highlight this, consider how crucial the valuation of the future payoffs of solar is for the decision of whether to adopt solar. For solar adopters, the average present value of the flow of benefits for solar adopters is \$16,658 given the observed implicit discount rates. In contrast, if a 4% rate is used, which reflects the approximate borrowing cost for a government entity, the present value of the flow of benefits would be

¹⁷We calculate these by transforming the structural coefficients, e.g., for high-wealth households $\Phi(\rho_i)^{-4} - 1$, since the time step is a quarter.

\$37,251, a massive difference. This alone provides an indication of the inefficiency of NEM policy relative to upfront subsidies, and in light of our results of higher implicit discount rates for low-wealth households, it also suggests that the NEM policy would be much less effective at increasing adoption by low-wealth households than higher-wealth households.

6.2 Price Elasticity of Demand

The implicit discount rate and the price elasticity of demand are two of the most important parameters driving our counterfactuals. Our model is flexible enough to accommodate price elasticities of demand that vary by wealth group. Since one cannot simply read off the price elasticity from the structural parameters, we recover the elasticities by simulating adoption (incorporating resizing) under a 1% reduction of the system cost over the entire sample period. We cover the entire sample period because consumers can expect costs in the future to decline. Table 3 reports the recovered own-price elasticities of demand by wealth group and lease type.

Table 3: Price Elasticity of Demand

Wealth	Rate	All	Purchase	Lease
High	10.0%	-0.8	-0.4	-1.6
Med	13.9%	-1.9	-1.3	-2.4
Low	15.3%	-2.6	-2.4	-2.8
All	13.1%	-1.7	-1.1	-2.3

In the table, we observe price elasticities of demand in the range of -0.4 to -2.8. What is most notable is that the elasticities of demand for high-wealth households are much smaller than for low-wealth households. These price elasticities should be interpreted as the response over a quarter to a long-lasting price change, affecting both current and future prices. Thus, they would be expected to be slightly larger (in absolute value) than estimates in the existing reduced-form literature. Indeed, this is the case. Other studies, using different time frames and often other settings, tend to find price elasticities in the range of -0.65 to -1.2 (Gillingham et al., 2016; Hughes and Podolefsky, 2015).

6.3 Model Fit

While examining price elasticities is one way to gauge the reasonableness of the model, we also examine the model fit. We predict adoption probabilities for each household, time period, consumption bin, and type, and aggregate the probability of adopting within the study time

period by wealth level. We can then compare our model-predicted aggregate probabilities to the data. Overall, we find that our model fits the data well, with total installations only overpredicted by 2.5%. The gap between predicted and data is slightly larger for purchased systems than leased systems, but in all cases is relatively small. Appendix F includes more detail.

7 Counterfactuals

We explore two counterfactual policies. First, we develop a scenario that reduces the compensation for excess solar generation fed back into the grid. Instead of compensation at the retail rate, as under standard NEM, we use an estimated levelized avoided cost of energy of \$0.062/kWh.¹⁸ This first scenario is roughly approximating some of the changes under California’s NEM 3.0 reform. The second scenario again reduces the compensation rate for excess solar generation, but accompanies it with an alternative upfront subsidy. The upfront subsidy is chosen to keep the total capacity of solar installed roughly the same in the counterfactual as in the observed data. This scenario uncovers the potential efficiency and equity improvements possible from changing the policy, while avoiding any political fallout (and reduced environmental gains) from diminishing the solar industry.

Before turning to our counterfactual results, it is worth a brief discussion of how we estimate the outcomes in our counterfactual scenarios. One first key point is that state transitions may change under our counterfactuals. To address this, we follow similar assumptions as in our parameter estimation. We again assume that consumers expect a deterministic evolution of the state variables with a short-run prediction error, using the same functions as in our estimation. Further details can be found in Appendix G. We construct counterfactuals such that the policy changes are expected to remain in place for the future. Changes in policy will also likely result in changes in the optimal solar system size, which we incorporate into the counterfactual using the optimal sizing model. The baseline that we compare our policy counterfactuals to is the observed data.

7.1 Lowering Compensation for Exported Solar

Following the NEM 3.0 reform, our first counterfactual compensates solar adopters for excess solar electricity above consumption that is fed into the grid at the avoided cost, which we assume to be \$0.062/kWh (E3, 2022). This leads to a leftward shift of the demand curve for

¹⁸This estimate is from a typical solar generation profile in the California Public Utilities Commission Avoided Cost Calculator derived by E3 Consulting (E3, 2022)

solar installations because the pecuniary value of solar is reduced. One challenge in running this counterfactual is that the change in the net present value of a given system on a home depends on how much solar electricity is consumed by the household (and thus offsets buying electricity at the retail rate) versus being exported to the grid. For example, on one extreme, one could imagine a household that uses all of the electricity generated by the solar system, so that none of the electricity is fed into the grid. For this household, a NEM reform that lowered the compensation rate for excess electricity would not change the net present value of adopting solar. On the other extreme, a household that fed nearly all of the electricity into the grid would have a much lower net present value from adopting solar after the reform.

We report our results for several potential “splits” between solar generation that offsets consumption and solar generation that is exported. Specifically, we calculate results for $\{0, 30, 50, 70, 99\}$ percent exported. For each percent exported split, we allow for re-sizing, then predict adoption conditional on the resized flow benefits and up-front costs.

Table 4: Percent Change of Solar Installations in Counterfactual Relative to Baseline

Wealth	Rate (%)	% solar exported				
		0	30	50	70	99
High	10.0	0	-6	-14	-24	-36
Med	13.9	0	-8	-16	-24	-31
Low	15.3	0	-7	-14	-21	-29
All	13.1	0	-7	-15	-23	-33

Table 4 presents the first key results of the counterfactual analysis, showing the percent change in solar adoption for each of the three wealth groups and for the entire sample. For reference, the second column presents the implicit discount rate results, as they play a crucial role in the counterfactual results. The following rows show the percent change in adoptions in the counterfactual relative to the baseline based on the assumption of the percent of generated solar electricity that is exported to the grid. In the trivial case where none of the solar is exported to the grid, the counterfactual is identical to the baseline.

Consider the last column in Table 4 where we assume that 99% of generated solar electricity is exported to the grid (the remainder is consumed by the household). We observe that high-wealth households, who value the offset electricity bill savings more than other wealth groups, adopt 36% fewer solar systems under the counterfactual. In contrast, the low-wealth households adopt 29% fewer solar systems under the counterfactual. Clearly, the reduced future NEM payoffs affect high-wealth households much more than low-wealth households. This is due to the lower implicit discount rate for high-wealth households and the tiered rate

structure, which compensates high-usage households more than low-usage households under the current regime. High-wealth households tend to consume more electricity and tend to be on a higher electricity rate tier.

Shifting from 99% of electricity being exported to the grid to 50% of electricity being exported to the grid increases the importance of the tiered rate structure, mitigating some of the effect of the lower counterfactual compensation rate. With 50% of the electricity consumed by the household, more higher-wealth households are still going to be interested in solar under the counterfactual because they tend to consume more electricity at a higher electricity rate tier. This means that the reduction in solar installations in the counterfactual is not as severe for the high-wealth group, and indeed is the same as the low-wealth group at 14%. This second force affecting the results due to the electricity rate tiers is even stronger once the percent of solar exported to the grid is 30%.

These results show when the implicit discount rate plays the strongest role by influencing how the flow payoffs from solar are valued by consumers. We have not seen any reliable evidence on the average percent of solar exported, although if solar systems are sized to fully or nearly fully offset annual electricity consumption, we would anticipate something on the order of 30-50% of electricity being exported for a typical household whose members generally leave the home for work during the day. The seasons play a major role in this, as most solar systems overproduce relative to consumption during the summer and underproduce in the winter.

7.2 Replacing NEM Compensation with Upfront Subsidy

Our second counterfactual reduces the NEM compensation, as in Counterfactual 1, and adds an upfront subsidy, effectively swapping a flow payoff for an upfront subsidy. This policy swap raises the question of what the government's interest rate is. We assume a standard 4% government interest rate. For each solar adopter, we calculate the change in the net present value from reducing the NEM compensation from the retail rate to the avoided cost, as in our first counterfactual. We sum over all adopters to provide an estimate of the present value of revenues no longer being used for the NEM subsidy that can be reallocated to other purposes.

We then solve for the government revenues used for an upfront subsidy to ensure that the total solar capacity installed (in MW) remains roughly equal to the baseline capacity. In other words, we hold the overall solar market size approximately constant. One could view this as a political constraint. We find that roughly 50% of the savings from the reduced NEM compensation would be sufficient to hold the total solar capacity installed constant if it is allocated to upfront subsidies.

There are two common variations in the design of upfront subsidies. One common approach is to provide an incentive based on the solar system size (a per-watt capacity subsidy). Under a capacity subsidy, more of the government subsidy outlays would go towards adopters who install larger systems. These are likely to be wealthier households. Alternatively, the government could provide a fixed upfront subsidy that is the same for all adopters. Fixed upfront subsidies are much less common, but they might have preferable distributional consequences. We explore scenarios that employ a per-watt capacity subsidy and one where 50% of the upfront subsidy is per-watt and 50% is a fixed upfront subsidy that everyone receives.

In our analysis, we calculate the welfare effects using both a 30% and 50% grid export rate. For the case in which 30% of generation is exported to the grid, the subsidies used are \$703 per installation and \$0.13 per watt. For 50% of generation exported, the subsidies are \$1,923 and \$0.38 per watt.¹⁹ Table 5 presents the counterfactual results for each wealth group and for the total population.

Table 5: Percent Change of Solar Installations and Capacity in Second Counterfactual Relative to Baseline

Wealth	Rate (%)	No subsidy		Per-W		Per-install and per-W	
		Installs	Capacity	Installs	Capacity	Installs	Capacity
30% exported to grid							
High	10.0	-6	-9	-2	-3	-2	-4
Med	13.9	-8	-10	1	0	1	-1
Low	15.3	-7	-11	3	2	5	2
All	13.1	-7	-10	1	0	1	-1
50% exported to grid							
High	10.0	-14	-24	-3	-4	-3	-9
Med	13.9	-16	-25	7	7	7	2
Low	15.3	-14	-25	13	13	21	12
All	13.1	-15	-24	5	4	7	0

‘Adopted’ refers to number of adoptions, ‘Capacity’ refers to MW installed

In Table 5 we again present the implicit discount rates for reference in the second column. Then we present the percent change between the counterfactual and baseline for the number of installations and the amount of solar capacity installed under the three scenarios: no subsidy (this repeats the results in Table 4 for reference), savings from reducing NEM compensation

¹⁹The fraction rebated is approximately 50% of the revenues no longer used for NEM, but varies somewhat due to the resizing that occurs in response to different subsidy levels.

used for an upfront capacity-based per-watt upfront subsidy, and the savings used for an upfront subsidy split evenly between a level adopter subsidy and a capacity-based subsidy. Note that the total aggregate value of the upfront subsidy is identical between the capacity subsidy and the mixed capacity and adoption subsidy. The capacity-based subsidy is \$0.26/W for the 30% export rate case and \$0.76/W for the 50% export case.

The first observation from Table 5 is that by repurposing only about half of the present value of the savings from reducing the solar export compensation rate, we can hold the counterfactual solar market size to the roughly the same as the baseline market size. Indeed, the solar market can even *expand* under the counterfactual because the upfront subsidy is so much more effective per dollar spent at inducing new solar installations. This can be seen in the positive values of solar adoptions for medium-wealth and low-wealth groups for both the capacity per-watt subsidy and the mixed subsidy. Indeed, the aggregate adoptions increase by 5% for the capacity-based subsidy and 7% for the mixed subsidy.

A second observation follows from the first. The upfront subsidy scenarios lead to greater solar installations by low-wealth and medium-wealth households. The higher implicit discount rates are one reason for this finding, as the upfront subsidies are not discounted. Another important reason is the differences across wealth groups in the marginal utility of income (Table 2). Medium-wealth households value upfront payments half as much as low-wealth households, and high-wealth households value upfront payments 15% as much. The increase in adoptions by low-wealth households is even more notable under the mixed subsidy scenario that includes a fixed installation subsidy. Low-wealth households tend to have smaller systems, so a fixed subsidy will provide greater benefits than a capacity-based subsidy.

A third observation is that there are some differences when comparing the number of installations and the solar capacity installed across the scenarios. This is an interesting aspect of our analysis because we account for the different system sizes by wealth group (recall Table 1) and allow for optimal resizing of solar systems. The difference is most striking in the 50% export case, where low-wealth households observe a 21% increase in installations, but only a 12% increase in additional solar capacity. The explanation here is that, even after resizing, the low-wealth household system sizes are substantially smaller than for higher-wealth households.

7.3 Marginal Value of Public Funds

Changes in welfare are crucial inputs to the policy process, but are very complicated in the electricity market. It is essential to quantify the distortions from raising revenue either through taxes or by increasing electricity rates. Moreover, it is complicated by the fact that the present value calculation may be different across wealth groups and for the government,

due to the use of different discount rates. It is also tricky due to the fact that policy changes affecting utility revenues can lead to adjustments to the electricity rate, including changes to the entire tiered rate structure. Given the difficulty in ascertaining how such changes might occur, our analysis holds the electricity rate structure fixed (future work could relax this by estimating a new equilibrium). Thus, our analysis should be seen as short-run or medium-run, prior to any new rate cases that would revise electricity rates.

We begin exploring the welfare effects by first calculating the gross post-subsidy changes in consumer surplus for each household in our sample and for each counterfactual scenario. We calculate this by integrating under each consumers' *new* demand curve, inclusive of the subsidies and accounting for the possibility of system resizing. The change in the compensation rate shifts each household's demand curve for adopting solar to the left, and the size of the shift depends on their discount rate, their irradiance curve, their electricity consumption, and the initial tiered pricing structure. We carefully account for heterogeneity by calculating the welfare effect for each consumer (integrating over the unobserved consumption state with the estimated weights) and then aggregate, rather than assuming a representative consumer.

We also calculate the changes in government expenditures from changes in payouts of the investment tax credit and upfront rebates, as well as the changes in utility expenditures from changes in NEM subsidies. Finally, we calculate the aggregate avoided environmental and health damages resulting from changes in solar installations using the monetized values of the externalities in Sexton et al. (2021).²⁰ Further details on our calculations can be found in Appendix H.

We present the results for each of these welfare-relevant variables for our sample of zip codes for each wealth group and for the entire sample in Table 6, for a 50% export rate (the analogue for a 30% export rate is in Table H.3). Importantly, the numbers for each wealth group are for the outcomes *attributed to* the solar adoption decisions of each of the wealth groups, rather than the welfare-relevant effects on that group, as in a standard distributional analysis. Recall that our final sample consists of 183,667 households, which represents 3.2% of all owner-occupied single-family detached homes in California, so the results would have to be scaled up by a factor of 31 to cover all of the state.

In Table 6, we observe that lowering the compensation rate for exported solar to the avoided cost reduces consumer surplus by \$26.3 million, reduces government tax credit expenditures by \$13.3 million, reduces utility expenditures by \$75 million, but also means that the environment and health externalities increase by \$7.0 million. The bulk of the impacts are due to the decisions of the high-wealth group. When we take 50% of the savings

²⁰We use the “dollarization” method from this paper and do not split up the calculation by wealth group as this is infeasible.

from reducing the NEM compensation and allocate them towards the mixed subsidy, consumer surplus declines on net by -\$11.5 million, but increases for the low-wealth households by \$1.5 million. This demonstrates a clear equity tradeoff. Government tax credit outlays increase by \$26.6 million, but utility expenditures decrease by \$41.6 million. Environmental and health externalities barely change. The key takeaway here is that switching from an NEM subsidy to an upfront subsidy can maintain the level of the solar market, maintain the environmental and health benefits, improve the consumer surplus for low-wealth households and reduce utility expenditures (which could reduce the cost-shift and potentially also benefit low-wealth households).

Table 6: Changes in Welfare-Relevant Outcomes (Millions \$; % Change)

Wealth	Δ Consumer Surplus	Δ Government Expenditures	Δ Utility Expenditures	Δ Avoided Damages
Lowered Compensation for Exported Solar				
High	-\$14.4 (-63%)	-\$4.7 (-31%)	-\$27.3 (-66%)	-\$2.4 (-31%)
Med	-\$9.0 (-38%)	-\$5.7 (-32%)	-\$31.9 (-68%)	-\$3.0 (-32%)
Low	-\$2.9 (-26%)	-\$2.9 (-31%)	-\$15.7 (-72%)	-\$1.6 (-33%)
All	-\$26.3 (-46%)	-\$13.3 (-31%)	-\$75.0 (-68%)	-\$7.0 (-32%)
Replacing 50% of NEM Savings with Mixed Subsidy				
High	-\$10.4 (-39%)	\$6.6 (25%)	-\$19.6 (-40%)	-\$0.9 (-10%)
Med	-\$2.7 (-9%)	\$11.6 (33%)	-\$16.6 (-27%)	\$0.2 (2%)
Low	\$1.5 (10%)	\$8.4 (41%)	-\$5.4 (-17%)	\$0.8 (11%)
All	-\$11.5 (-16%)	\$26.6 (32%)	-\$41.6 (-29%)	\$0.1 (0%)

All estimates under 50% export to the grid assumption.

It is important to note that one cannot simply add up the columns in the table to get an estimate of the overall change in social welfare under each scenario. Under NEM, there is a transfer from governments and utilities to consumers. This transfer is associated with a deadweight loss from raising the funds. A major challenge is determining the deadweight loss.

One promising approach to gain insight into the welfare effects of policy counterfactuals without making assumptions about the deadweight loss from raising funds is to calculate the marginal value of public funds (MVPF) (Finkelstein and Hendren, 2020). The MVPF is the ratio of the policy beneficiaries' willingness to pay for a policy to the government expenditures of the policy. It is a measure of the effectiveness of government expenditures. The gains to the beneficiaries include the change in consumer surplus and electric utility expenditures (accounting for taxation, which goes to the government) plus the externality damages avoided. The government expenditures account for the changes in the incentive payments shown in Table 6, and also account for changes in tax revenues. A MVPF of greater than one indicates

that the government expenditure is less than willingness to pay, providing an indication that the policy is net beneficial.

In our MVPF calculations, we focus on the MVPF of our second counterfactual relative to our first to provide evidence on the effectiveness of using some of the savings from reducing NEM compensation for additional subsidies. We calculate the MVPF for both a 30% and 50% share of solar generation exported to the grid. We calculate the MVPF for subsidies that might be targeted to each wealth group. We follow Hahn et al. (2024) in how we handle the electricity markup and corporate taxes on both the electric utility and government expenditures, using the same assumptions (a 10% corporate tax rate and the 8% industry-wide economy-wide markup found by De Loecker et al. (2020)).²¹

Table 7: Changes in Outcomes (Millions \$) and Marginal Value of Public Funds from Comparing the Two Counterfactual Scenarios

Wealth	Consumer Surplus	Government Expenditures	Utility Expenditures	Avoided Damages	MVPF
30% exported to grid					
High	\$1.6	\$4.3	\$2.0	\$0.5	0.95
Med	\$2.4	\$6.6	\$4.5	\$1.2	1.21
Low	\$1.6	\$4.2	\$3.0	\$0.8	1.30
All	\$5.6	\$15.1	\$9.4	\$2.5	1.16
50% exported to grid					
High	\$4.0	\$12.0	\$5.5	\$1.5	0.92
Med	\$6.3	\$18.8	\$10.8	\$3.2	1.08
Low	\$4.5	\$12.3	\$7.3	\$2.3	1.14
All	\$14.8	\$43.1	\$23.6	\$7.1	1.05

Table 7 presents the results of our MVPF calculations. We include the estimates of the components of the calculations in the first set of columns. For the 50% exported to the grid case, these estimates are the differences between the top panel and bottom panel in Table 6. The numbers are all correspondingly lower in the 30% export case in the top panel of Table 7 because the NEM outlays are correspondingly lower with less electricity exported to the grid. Again, these estimates are divided up into the expenditures or damages due to the decisions made by individuals in each of the wealth groups.

²¹Our calculations would be the same with government-mandated transfers of the post-tax utility savings back to consumers – pre-tax transfers would lead to small changes in the effect on government revenues. Another possible transfer mechanism is a small downward adjustment in utility rates, which would have a secondary effect of reducing installations to some degree since the value of the offset utility bills would be reduced. We anticipate that the MVPF calculations would not change appreciably.

We observe MVPF values ranging from 0.92 to 1.30, with the lowest values for high-wealth households and the highest for low-wealth households. These findings indicate that additional subsidy spending provides more total marginal value when targeted to low-wealth households than to high-wealth households. The intuition behind this result is that high-wealth households are less price-sensitive than low-wealth households (recall our differing price elasticities in Table 3). The notable fact that the MVPF estimates are greater than one for low-wealth and medium-wealth households suggests that such targeted policies are valued by consumers and society more than the expenditures.

8 Conclusion

In this paper, we use a novel identification strategy that leverages plausibly exogenous cross-sectional variation in irradiance to identify implicit discount rates used by households in California in their solar installation decisions. We provide model-free evidence that high-wealth and medium-wealth households are more responsive to the value of the solar flow payoff obtained by investing in solar panels than low-wealth households, highlighting the features of the data that drive our results. We then estimate a structural dynamic model that pins down an average implicit discount rate for residential solar adopters of 13% and demonstrates clear heterogeneity in the implicit discount rate by wealth, with high-wealth households making decisions consistent with a 10% rate and low-wealth households a 15% rate. Our results help explain disparities in solar adoption rates between low-wealth and high-wealth households.

A natural question that arises when considering these results is how they might generalize to other products. Some products may have product-specific borrowing costs, such as manufacturer promotions. If the borrowing costs for some products differ from others, we would not be able to generalize our results. However, if the borrowing costs are similar, and the payoffs over time follow a similar pattern, we should expect similar implicit discount rates. Green technologies such as solar, electric vehicles, and heat pumps all share similar characteristics. We are cautious about extrapolating our results too far beyond solar, but we believe that the heterogeneity across wealth groups that we find likely extends to many durable goods.

It is also interesting to consider what mechanisms underlie the differences in implicit discount rates. Like much of the existing literature using observational data, we do not have variation in the data to identify the mechanisms that drive our results. It is possible that there are differences in the pure rate of time preference across groups. But differences in borrowing costs may also play a role, as wealthy households are more likely to have greater

access to credit at lower interest rates than poorer households. Thus, a limitation of our study is that we cannot analyze policies focusing on shifting factors that affect the implicit discount rates, such as low-interest loan programs for low-wealth households. We leave this for future work.

Fortunately, we can analyze a set of highly policy-relevant counterfactuals and the implicit discount rates we estimate should be invariant to these counterfactuals. We show that reducing NEM compensation to the avoided cost in California would reduce the size of the solar market substantially, and would reduce installations across all wealth groups, but would reduce consumer surplus of the high-wealth households much more than low-wealth households. If roughly half of the savings from reducing NEM compensation are allocated to an upfront subsidy (half per adoption and half per capacity installed), this would maintain the size of the solar market, reduce government and utility expenditures, and even lead to an increase in consumer surplus for low-wealth households. In short, the higher discounting of future payoffs by households than the government provides an opportunity to exploit this difference to reduce utility expenditure (and the potential associated cost-shift of solar), and by carefully structuring the upfront incentives, there is the potential to also improve equity.

As California and many other states reform NEM policies to better reflect the actual value of solar generation, and to address equity issues with legacy utility costs, it is important for policymakers to understand how consumer responses to net metering reform may vary by household wealth. Our analysis aims to provide a contribution to the economics literature through well-identified estimates of the implicit discount rate across wealth groups, while at the same time providing guidance to policymakers on the effects of different actions they might take by integrating over the household-specific welfare impacts of counterfactual policies.

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Online Appendix

A Data Assembly

A.1 Sample Selection

We assemble the study sample by first identifying zip codes in California that are located within the Pacific Gas and Electric service territory. We identify the climate zone associated with each zip code in the Pacific Gas and Electric service territory and extract from the sample home in those zip codes that lie on a climate zone boundary²². The 28 zip codes contained in the sample are shown in Figure 1.

Our base dataset of potential solar adopters is the set of all single-family detached non-mobile home residences that were built before 2014 in the 28 zip codes we identified.

A.2 Google Project Sunroof Matching

We match each household in our data to the nearest Google Project Sunroof record with a greedy spatial matching algorithm. We drop the 5% of households with the largest distance between the geocoded home address and the Google Sunroof record. For each matched household, our data contains the panel-by-panel expected generation. Generation is largely decreasing as panels are ordered by generation, though contiguity requirements may result in some increases. Figure 2b shows the previous four randomly selected rooftops' generation profile.

A.3 Household Consumption Profiles

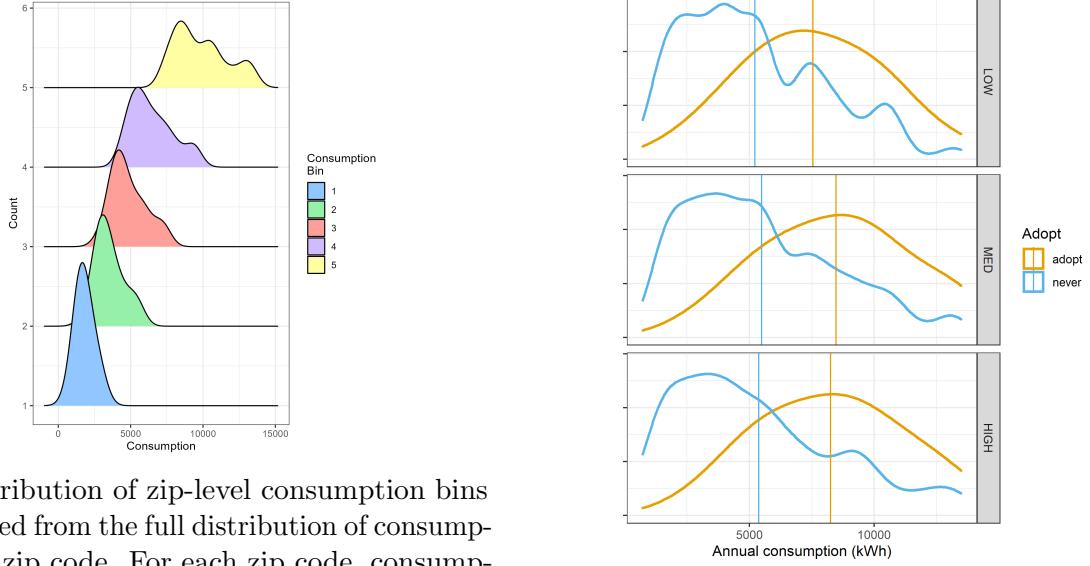
The PG&E data are anonymized and do not include addresses. They do include the 5-digit zip code, as well as grid interconnection IDs that identify solar adopters. Thus, for solar adopters, we observe the annual consumption prior to the installation of solar and can designate the closest consumption bin for each adopter. For non-adopters, we see only the full distribution of consumption across the zip code. For each zip code, we remove known adopters and bin all consumption into five equal-sized consumption bins. In estimation, we will integrate over the observed empirical distribution of consumption within each zip code (sampling without replacement).

The study period is 10 quarters, from Q1 2014 through Q2 2016, so we treat consumption as fixed over the study period. We calculate the mean consumption for each bin within each zip code. A density plot of zip-level consumption is shown in Figure A.1a. Figure A.1b shows the consumption levels of adopters and non-adopters by wealth. Across all three wealth bins, adopters have higher consumption on average. As wealth increases from low- to medium, the separation between average consumption of non-adopters and average consumption of adopters becomes larger, consistent with lower implicit discount rates and higher sensitivity to the flow of benefits from installing solar

A.4 PG&E Rates

While all households in the PG&E service territory share the same block pricing steps at any given time, CEC climate zones vary in the *width* of a block tier pricing step – hotter inland zones are allowed more baseline consumption before stepping up to the next higher marginal rate relative to

²²During the study period, PG&E designated CEC climate zones as “baseline territories”. We use PG&E published rates by territory, but note that these territories follow the CEC climate zone boundaries.



(a) Distribution of zip-level consumption bins calculated from the full distribution of consumption by zip code. For each zip code, consumption is grouped into one of five bins (1 is lowest consumption, 5 is highest) and the mean consumption is calculated for each bin. Plot shows the distribution across zip codes of the five bin's mean consumption.

(b) Density of consumption by adopter status and wealth. To calculate density of non-adopters, we assign equal weight to each of the five consumption bins for the household's zip code.

Figure A.1: Consumption Summary Statistics

cooler coastal zip codes. Our sample includes homes in 28 zip codes that are wholly contained in one of three unique CEC climate zones (PG&E territories S, T, and X). While all homes initially face the same price per kilowatt-hour for their first unit of consumption, homes in warmer CEC climate zones will, as consumption increases, face lower retail rates than will homes in cooler CEC climate zones due to the higher threshold for stepping to the next block tier price. Average retail price per kilowatt-hour is weakly lower in warmer CEC climate zones with higher baseline thresholds.

During the study period, baseline thresholds were adjusted once. Thresholds are shown over time in Figure A.3. The sample contains 34,796 households in zip codes in Territory S, 57,790 households in zip codes in Territory T, and 91,081 households in zip codes in Territory X, for a total sample size of 183,667 representing approximately 3.2% of all owner-occupied single-family detached homes in California.

In addition to spatial CEC climate zone variation in block tier step width, retail electricity rates for each step of block tier pricing vary over time, as shown in Figure A.2. Although rates at lower consumption levels (Tiers 1 and 2) steadily increased during the study period shown (2014–2016), higher tier prices decreased slowly over the same time period. Thus, higher-consumption households experienced smaller total increases in the average cost per kilowatt hour during this time period.

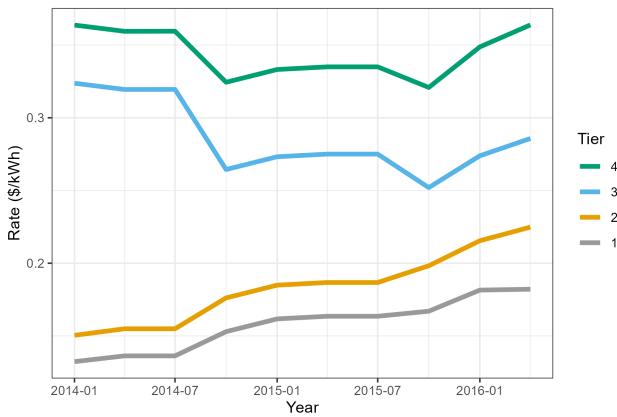


Figure A.2: **Retail Rates.** Retail rates by tier over time in dollars per kilowatt-hour.

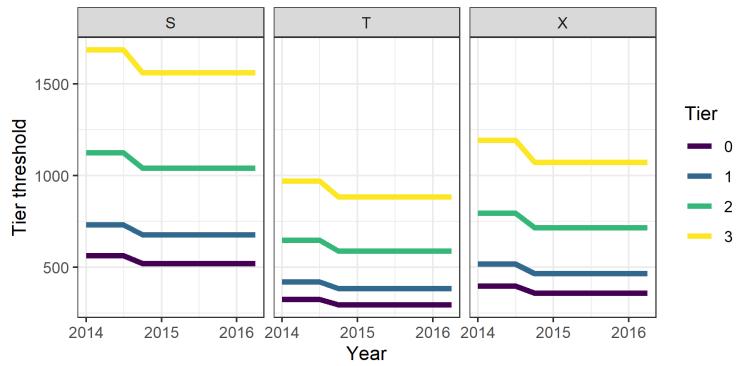


Figure A.3: **Rate tier climate zone thresholds.** CEC climate zone thresholds over time in kilowatt-hours per month. Corresponding rates are shown in Figure A.2

B Sizing Model

In this section, we describe the optimal sizing decision for solar purchasers. The optimal size of the system is a function of the system costs (inclusive of upfront subsidies), system generation (as a function of size), and the price of grid electricity, which depends on a household's electricity consumption due to the tiered pricing structure. As a robustness check, we also incorporate the possibility of a solar rebound that increases electricity consumption after the solar installation (Oliver et al., 2024).²³

Let $TC(K)$ denote the total cost to a household of a solar installation of size K . It is comprised of the fixed cost, FC and a cost per panel, V , charged by the installer. A per-kWh of solar capacity rebate subsidy, S can reduce the upfront cost of the panels. The total cost of the system net of rebates is reduced by a fraction I equal to the investment tax credit.²⁴ Thus, $TC(K) = (K \cdot (V - S) + FC)(1 - I) = K \cdot C + F$. We define $C = (V - S)(1 - I)$ as the cost per kilowatt of solar capacity faced by consumers (i.e., the post-subsidy variable cost of adding further panels) and $F = FC(1 - I)$ as the fixed cost faced by consumers.

If the leveled cost of electricity generation from the marginal unit capacity is less than or equal to the lowest electricity rate, p_0 , we assume that the household that purchases solar will optimally install a system large enough to exactly offset all consumption.²⁵ Details are in Appendix B. The household installs a minimum installation of 4 panels (1 kW) if the leveled cost is greater than the highest grid electricity rate. And if leveled costs of the marginal solar capacity are less than the highest grid electricity rate but higher than the lowest grid electricity rate, then the household optimally sizes the solar array to offset just the fraction of grid electricity consumed at the highest rate.

Leased systems in the data are much more likely to be sized equal to current consumption, and indeed the firm incentives are such that installers would prefer recommending the largest system size up to fully offset consumption. Thus, we size purchased systems according to the optimal sizing model, and leased systems according to full offset, which minimizes the absolute error in sizing. Fit statistics are shown in Appendix B.

Let $Q(K)$ be the quarterly electricity generated by a new solar system of size (installation capacity) K (in units of kWh), and let λ be the quarterly depreciation of panels each quarter. We define Q^* as the annual electricity produced by a new system of optimal size K^* . Let $q(K) = \frac{dQ}{dK}$ be the marginal generation at size K , i.e., the electricity produced by an incremental kilowatt of capacity. Following our descriptive evidence, we assume $q(K)$ is weakly decreasing in K because solar panels are installed first on the best (i.e., highest irradiance) ares of a rooftop. Thus, $q(K) \geq 0$ and $\frac{dq(K)}{dK} \leq 0$. Let the lifetime of the solar panel be given by T quarters.

We define a household's initial grid consumption as Q_0 , such that for an installations producing Q kW of electricity with $Q(K) < Q_0$, the remaining grid consumption is $Q_0 - Q(K)$. The interior solution to the sizing problem equates the present value of the lifetime stream of offset utility payments that results from an additional unit of capacity to the cost of that capacity. :

$$C(K) = \sum_{t=1}^T \left(\frac{(1 + \zeta)(1 - \lambda)}{1 + r} \right)^{t-1} p(Q_0 - Q(K))q(K), \quad (14)$$

²³For our main results we do not include a solar rebound due to the fact that our model fit is better without including the rebound effect.

²⁴We assume that all homeowners have sufficient tax liabilities to qualify for the 30% tax credit offered on solar during this period.

²⁵Excess generation under NEM policies is not compensated, or is compensated as a much lower level.

in which $p(Q_0 - Q(K))$ is the quarterly cost of the monthly marginal unit of electricity consumption, r is the quarterly discount rate used for sizing, and ζ is the expected increase in real electricity costs.²⁶

We define:

$$c(K) = \frac{C(K)}{\left(\sum_{t=1}^T \left(\frac{(1+\zeta)(1-\lambda)}{1+r} \right)^{t-1} q(K) \right)}, \quad (15)$$

which is effectively an average, discounted price of solar electricity that consumers compare to the price of grid electricity, $p(Q_0 - Q(K))$, which accounts for the expected increases in both solar and grid prices over time.

Because q is decreasing in K and $p(Q_0 - Q(K))$ is decreasing in K with constant and increasing block rate prices, there will be a unique solution to the first order condition (if any). With increasing block prices, the first units of displaced grid electricity bear the highest marginal costs, and marginal costs of displaced electricity decline discretely as solar capacity increases.²⁷ The optimal size is a function of upfront incentives and the feed-in-tariff rate, is increasing in q , p , S , and I , and is decreasing in r and V .²⁸

Because of the tiered nature of grid prices, the optimal sizing function is not always an interior solution; it is a piece-wise function defined according to the number of tiers in the tariff structure. We illustrate this in the context of a tariff with two distinct tiers of volumetric charges. We abstract from consideration of fixed charges because we assume no households prefer to disconnect from the grid. Let τ be the monthly grid consumption threshold at which rates change from p_0 to p_1 for $p_0 < p_1$, and let q_0 denote monthly household consumption.

The marginal price of grid electricity p depends upon the residual grid demand, i.e., consumption net of solar generation, such that:

$$p = \begin{cases} 0 & Q_0 - Q \leq 0 \\ p_0 & 0 < Q_0 - Q < \tau \\ NSOp_1 & Q_0 - Q \geq \tau \end{cases}$$

We define the minimum size installation considered as \underline{K} .²⁹ The piece-wise-defined solution to the optimal sizing problem for increasing block rates and a household consuming at the highest rate

²⁶We follow de Groote and Verboven (2019) by using a constant and deterministic value for ζ , which we estimate using an AR(1) model with fixed effects. This can also be interpreted as assuming rational expectations, discussed further in Section 5.2.

²⁷For decreasing block prices, the opposite is true, and the interior optimum may not be unique.

²⁸For the sizing model, we use the Google Sunroof default rate of 4%. This rate is considerably lower than the household rates we estimate. However, the optimal sizing decision is generally not made by consumers alone, but rather by the installation contractor who presents the cost and expected payoff when generating a quote for homeowner consideration. A lower discount rate tends to increase the savings relative to up-front costs, which favors the installer using the lowest reasonable rate. Optimal sizing also must assume an expected rate of increase in electricity prices, which we estimate from the data, as described in Appendix D and apply to the sizing decision.

²⁹We set \underline{K} equal to the smallest observed installation in the data – 5 panels, or 1.250kW.

is defined as:

$$K^* = \begin{cases} K & c(0) > p_1 \\ q^{-1} \left(\frac{C}{\sum_{t=1}^T \left(\frac{(1+\zeta)(1-\lambda)}{1+r} \right)^t p_1} \right) & c(0) \leq p_1, c(Q_0 - \tau) \geq p_1 \\ Q^{-1}(Q_0 - \tau) & p_0 \leq c(Q_0 - \tau) < p_1 \\ q^{-1} \left(\frac{C}{\sum_{t=1}^T \left(\frac{(1+\zeta)(1-\lambda)}{1+r} \right)^t p_0} \right) & c(Q - \tau) < p_0, c(Q_0) \geq p_0 \\ Q^{-1}(Q_0) & c(Q_0) \leq p_0 \end{cases}.$$

Figure B.1 depicts these cases, moving in order from the top curve to the bottom, for given alternative q 's that define c . The weakly decreasing step function (indicated in red) is the leveledized cost of the marginal unit of grid electricity as a function of grid consumption, and the intersection points with each curve indicates the generation from an optimally size installation. Solar generation $q(K)$ is increasing left to right, and remaining grid consumption is increasing right to left.

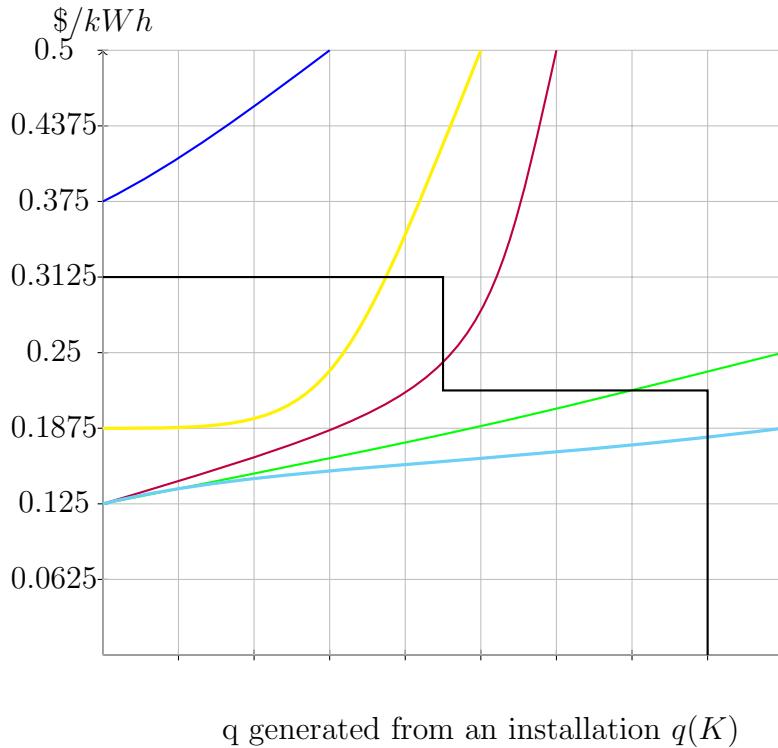


Figure B.1: **Optimal sizing.** Optimal sizing of solar PV arrays is depicted as a function of alternative modeled q' functions, i.e., the electricity generation of marginal units of solar capacity. Depicted are the costs per kWh for alternative q 's and a tariff with two tiers of volumetric charges. Grid consumption increases from right to left. Solar capacity increases left to right.

Figure B.2 shows the fit of the optimal sizing model fit over purchased (left) and leased (right) systems, which use the two different assumptions. For purchasers, we use the optimal sizing model, and for leasers, we assume full offset. For non-adopters, we observe only the zip-level distribution of consumption, and thus size each household conditional on consumption at one of five zip-level

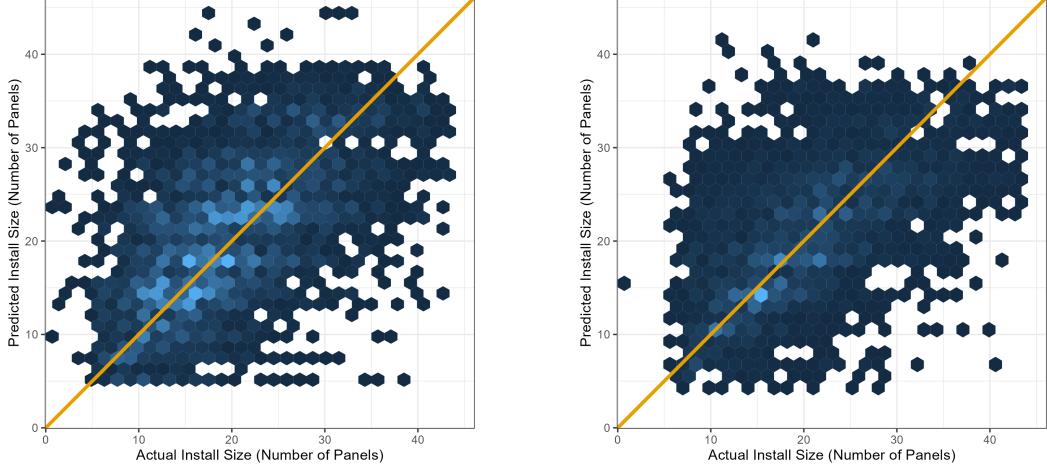


Figure B.2: **Sizing model accuracy.** Density plot of Google Sunroof-method predicted (y-axis) and actual (x-axis) installed system capacity for (left) purchased systems and (right) leased systems. The diagonal represents correct predictions of the optimal installation size.

Table B.1: Optimal sizing model fit by type. This table reports the difference between the predicted and actual observed installations. Positive numbers indicate sizing greater than observed. Does not include reported installations with greater than 44 panels (95th percentile).

Type	Mean Sizing Error		Mean Absolute Sizing Error	
	count panels	%	count panels	%
Purchaser	2.01	10%	5.72	29%
Leaser	1.19	6%	4.97	24%
All	1.64	8%	5.38	27%

consumption bins. In Figure B.3, we graphically present the sizing model fit using average annual consumption (left) and the same sizing model fit using the *closest* consumption bin level for the adopting household’s zip code. The horizontal striation on the right is due to discretization to the nearest consumption bin. The right panel, despite not using actual consumption, provides a close fit to observed installation sizes, despite the discretization.

Table B shows a low average error in sizing expressed in number of panels. The average error of 1-2 panels is 5-10% of the average installation size (20 panels). This is consistent with installers using similar tools (electricity bills and roof profiles) and assumptions to size a system.

Our preferred sizing model does not account for rebound effects. As a robustness check, we allow for rebound effect, which may either increase the amount for grid consumption, or it may lead to larger panel sizes. For consumers not sizing their array to offset full consumption, any rebound will be through increased grid consumption, if the marginal cost of electricity is reduced due to the solar installation by placing the household on a lower rate tier. For consumers sizing their array to offset full consumption, the levelized cost of added solar generation will be weakly less than the cost of grid electricity, and there will be some scope to increase the size of the installation due to rebound. To do so, we calculate the consumer surplus using a constant price elasticity of $\varepsilon = .1$

and allow the system size to increase so long as the cost of the increase is lower than the increased surplus. Details are in Appendix C.³⁰

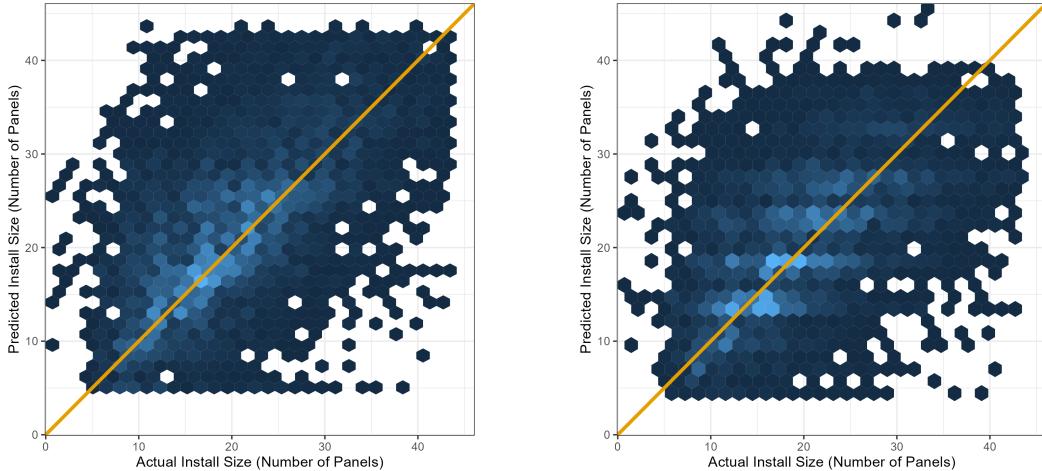


Figure B.3: Density plot of Google Sunroof-method predicted (y-axis) and actual (x-axis) installed system capacity sized using (left) actual consumption and (right) using assigned closest consumption bin. The diagonal represents correct predictions of the optimal installation size.

C Sizing with Rebound

We account for rebound effects using a constant demand elasticity for electricity, ε . Let:

$$\log(q) = \varepsilon \log(p) + \log\left(\frac{q_0}{(p_H)^\varepsilon}\right), \quad (16)$$

in which the second term is an intercept that sets observed pre-installation consumption to q_0 at the observed pre-installation marginal price of electricity, p_H^H . We can expect demand to increase by Δq , which is the maximum value of r such that:

$$r \leq -\varepsilon \left(\frac{p_H - p_L(r)}{p_H} \right) q_0, \quad (17)$$

in which p_L is the effective marginal electricity rate with rebound r using the discount rate used to size the installation:

$$p_L(r) = \min_{r^S} \left(\min \left(p(q_0 - q^* + r - r^S), \frac{C/T}{q' (K(q^* + r^S)) \left(\sum_{t=1}^T \frac{1}{(1+\delta)^t} \right)} \right) \right), \quad (18)$$

³⁰When including rebound with a price elasticity of $\varepsilon = .1$, the mean error for purchasers increases to 16%, while the mean absolute error increases to 32%. Thus, we use the no-rebound sizing model for our main estimation due to the high degree of fit and little evidence of the systematic under-sizing that would indicate sizing for rebound. We report results using $\varepsilon = .1$ in Appendix C.

in which $r^S \leq r$ is the amount of the rebound electricity generated from increasing the installation size and q^* is still defined as the optimal solar generation ignoring rebound. Let Δq^S be the optimal amount of this rebound solar electricity. For households not offsetting full consumption with their installation, the entirety of the rebound effect is through higher grid consumption at the new marginal rate, $p(q_0 - q^* + \Delta q)$, and equation (17) holds with equality except at a point in which the rebound pushes the household to the next price tier. For those households offsetting full consumption prior to rebound, the cheapest increment of additional electricity may be (and will almost always start with) the leveled marginal rate of additional solar electricity, but as the installation size increases and the leveled cost or marginal generation increases, it may switch to additional grid consumption.

For households whose rebound consumption is grid electricity (those who don't offset their full consumption), the value of the generated electricity in each period is equal to the offset cost of q^* plus the added surplus from the rebound effect:

$$\begin{aligned}\Delta S^R &= \int_{p_L}^{p_H} q(p)dp - (p_H - p_L)q_0 + \int_{q_0}^{q_0 + \Delta q - \Delta q^S} (p_L - p(q - q^*))dq \\ &= \int_{p_L}^{p_H} p^\varepsilon \frac{q_0}{(p_H)^\varepsilon} dp - (p_H - p_L)q_0 + \int_{q_0}^{q_0 + \Delta q - \Delta q^S} (p_L - p(q - q^*))dq \\ &= \left(\left(\frac{1}{1 + \varepsilon} \right) \left(\frac{(p_H)^{1+\varepsilon} - (p_L)^{1+\varepsilon}}{(p_H)^\varepsilon} \right) - (p_H - p_L) \right) q_0 \\ &\quad + \int_{q_0}^{q_0 + \Delta q - \Delta q^S} (p_L - p(q - q^*))dq.\end{aligned}\tag{19}$$

The first two terms are the additional surplus of consumption when the cost of this electricity is p_L . The third term is equal to zero unless the rebound consumption is at multiple price levels (i.e. at multiple price tiers), in which case we need to account for the fact that some of the grid rebound consumption is at a price lower than p_L .

Households who currently offset full consumption may consume from the grid, and they may not. They will also increase the size of their installation, in which case we need to adjust this surplus term by:

$$p_L(q_0 + \Delta q^S) - (TC(K(q^* + \Delta q^S)) - TC(K(q^*)). \tag{20}$$

This term is the leveled value of the solar rebound minus the cost. It is equal to zero if the discount rate used in sizing is the same as that when making installation decisions. Since most sizing decisions are heavily influenced by the installer (using a discount rate of 4%), we allow for these to be different.

As a robustness check, we re-size the optimal sizing model using an elasticity of $\varepsilon = .1$, motivated by the literature. We apply the rebound only to purchased systems under the assumption that leased systems are sized to full consumption, as in the main body.

Relative to table B, sizing with rebound over-sizes purchased systems, leading to greater mean sizing error (16%) and greater mean absolute error (32%). Leased systems are sized to offset full consumption, and thus have the same error as in table B.

Nevertheless, we re-estimate our preferred specification and calculate the counterfactual-implied elasticity as in 7. Results are in Appendix I

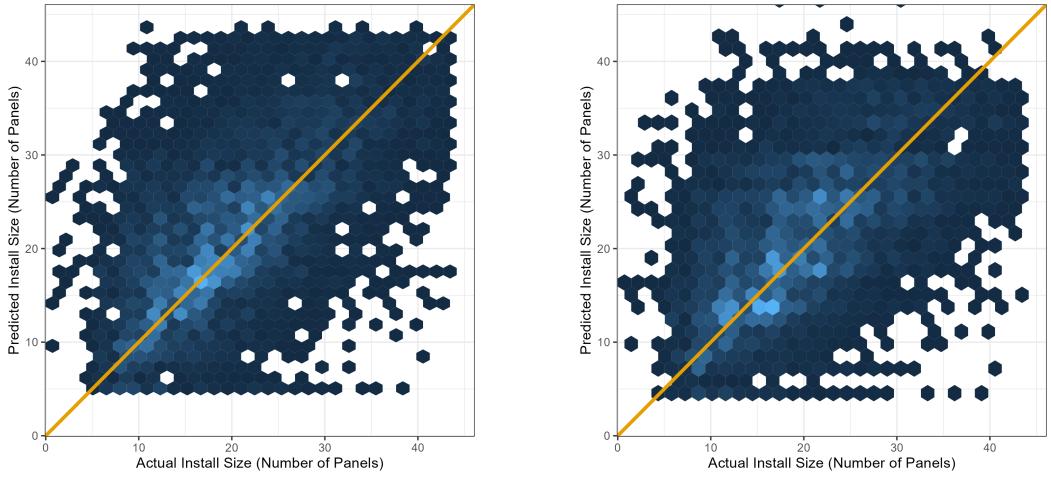


Figure C.1: Density plot of Google Sunroof-method predicted (y-axis) and actual (x-axis) installed system capacity sized using (left) actual consumption and (right) using assigned closest consumption bin, both inclusive of rebound. The diagonal represents correct predictions of the optimal installation size.

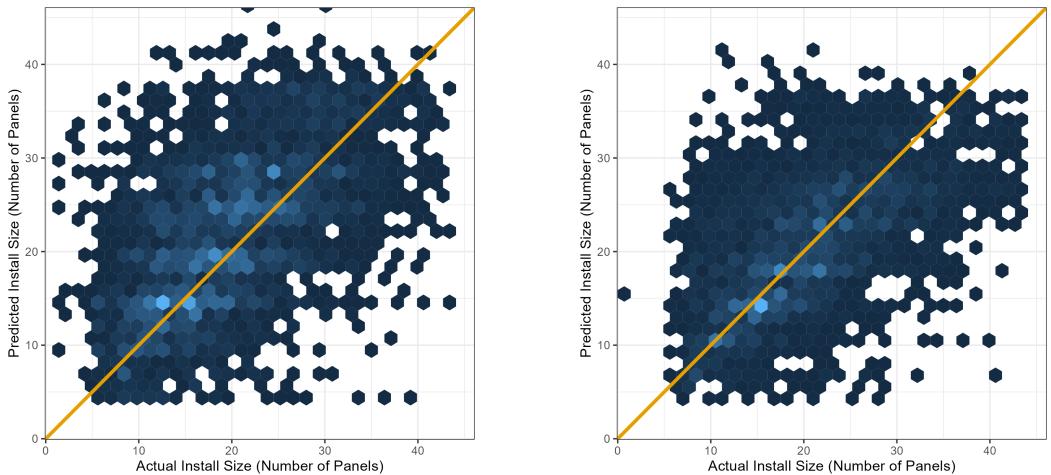


Figure C.2: Density plot of Google Sunroof-method predicted (y-axis) and actual (x-axis) installed system capacity for (left) purchased systems inclusive of rebound and (right) leased systems. The diagonal represents correct predictions of the optimal installation size.

Table C.1: Optimal sizing model fit by type. This table reports the difference between the predicted and actual observed installations. Positive numbers indicate sizing greater than observed. Does not include reported installations with greater than 44 panels (95th percentile).

Type	Mean Sizing Error		Mean Absolute Sizing Error	
	count panels	%	count panels	%
Purchaser	3.13	16%	6.21	32%
Leaser	1.19	6%	4.97	24%
All	2.25	11%	5.65	28%

D Electricity and Solar Price State Evolution Estimates

D.1 Cost of Solar Installation

We need an estimate of the cost of adopting solar for all potential adoptions, which may be a function of installation size, time, and location. To do so, we estimate the fixed and variable (per-watt) components of price using TTS data for each boundary group and quarter in our sample. We assume that the fixed price component will vary by boundary group, and that a common variable price per watt will decline over time at a constant rate η , to be estimated. The decline of panel prices on a per-watt basis is well-documented in the literature. Heterogeneous fixed costs reflect relative wealth and cost of labor across the study areas.

We estimate the solar price model on a sample that includes our study period, as well as the year prior (2013). We deflate costs using the Bureau of Labor Statistics quarterly CPI using the fourth quarter of 2016 as the base period. Our decomposition of total reported price into fixed costs, variable costs, and a common η uses the following specification, which we estimate by nonlinear least squares (NLS):

$$SystemCost_{it} = \sum_b \kappa_b \mathbb{1}_{b=b(i)} + \beta_W SystemW_{it} \cdot e^{\beta_T(t-t_0)} + \varepsilon_{it}, \quad (21)$$

in which $SystemCost$ is the cost exclusive of subsidies or tax credits, $SystemW$ is the size of the system, $t - t_0$ is the elapsed time since the beginning of the cost model estimation sample, Q1 of 2013.

Estimated fixed costs range from \$998 to \$1,622. Per-watt panel estimates start at \$5.12 in the first quarter of 2013, and decline at a rate of $e^{-0.014t}$. A value of $\beta_T = -.01403$ yields an estimated quarterly $\eta = 0.986$. We use the estimates in table D.1 to predict fixed and variable installation costs for adopters and non-adopters.

Table D.1: **Cost Model Estimation:** Results from estimation of equation 21 using the sample of all installations in the study area during the study period and the previous year. Results show boundary group-specific fixed cost intercepts, per-watt costs κ in first quarter 2013, and quarterly rate of decline in per-watt costs, η , estimated as $\eta = 1 - \beta_T = .986$. All costs are deflated using BLS CPI-U.

	(1)
κ_A	1622.238 (154.807)
κ_B	1527.982 (244.818)
κ_C	1124.275 (185.183)
κ_D	1119.103 (164.510)
κ_E	998.059 (283.709)
κ_F	1212.440 (148.897)
β_W	5.122 (0.034)
β_T	-.014 (0.000)
Num.Obs.	9163
Log.Lik.	-89988.246

D.2 Electricity Prices

We use an AR(1) model with fixed effects to estimate the expectation of the rate of increase in average electricity rates for each consumption bin and in each zipcode's CEC climate zone, $\zeta_{b,z}$, using deflated quarterly data. To account for CPUC orders requiring that the block-tiered price system reduce the gap between high- and low-consumers that resulted in a significant one-time decreases in tiers 3 and 4 and increases in tiers 1 and 2 which took effect in Q3 of 2014, we include a break term in the AR(1) specification as follows:

$$avgprice_{t,bz} = \zeta_{bz} avgprice_{t-1,bz} + \zeta_{bz}^b avgprice_{t-1,bz} \mathbb{1}(t = 2014Q3) + \varepsilon_{t,bz} \quad (22)$$

Table D.2 shows results from equation 22. ζ_{bz} estimates range from 2.67 to 5.62 percent annually (.66 to 1.37 percent quarterly).

Table D.2: **Electricity Rate Model Estimation:** To estimate equation 22, we calculate the average electricity rate for each quarter from Q1 2012 to Q3 2016, which captures the two years prior to the study period. We calculate this average rate using annual consumption that reflects the distribution of consumption in each zipcode and deflate using the BLS CPI-U. For each level of consumption and CEC climate zone, designated by $\{S, T, X\}$, we calculate the total variable cost portion of the bill and divide by the annual consumption. The unit of observation is defined by the combinations of zipcode, consumption level, and CEC climate zone. Consumption bin 5 is the highest quintile of consumption.

	(1)
$\zeta_{1,S}$	1.012 (0.003)
$\zeta_{2,S}$	1.012 (0.003)
$\zeta_{3,S}$	1.013 (0.003)
$\zeta_{4,S}$	1.014 (0.003)
$\zeta_{5,S}$	1.007 (0.003)
$\zeta_{1,T}$	1.012 (0.002)
$\zeta_{2,T}$	1.012 (0.002)
$\zeta_{3,T}$	1.014 (0.002)
$\zeta_{4,T}$	1.011 (0.002)
$\zeta_{5,T}$	1.007 (0.002)
$\zeta_{1,X}$	1.012 (0.002)
$\zeta_{2,X}$	1.013 (0.002)
$\zeta_{3,X}$	1.012 (0.002)
$\zeta_{4,X}$	1.010 (0.002)
$\zeta_{5,X}$	1.008 (0.002)
Num.Obs.	3610
R2	0.999
R2 Adj.	0.999
Std.Errors	HC Robust
Time step	Quarterly

E Estimation Details

Each non-adopter household is one of ten possible consumption \times type combinations $\{1, \dots, 5\} \times \{\text{lesser, purchaser}\}$. We specify weights w_{ibe} as the probability that household i consumes in consumption bin b and is of type e . With weights w_{ibe} , we integrate the likelihood function over the unobserved heterogeneity:

$$\mathbb{L} = \prod_i \sum_b \sum_e w_{ibe} \prod_t [Pr_{ibt}^e]^{y_{it}} [1 - Pr_{ibt}^e]^{(1-y_{it})} \quad (23)$$

which requires evaluating ten conditional likelihoods per observation of household i and time t .

We posit the weights w_{ibe} as $w_{ib} \times w_{ie}$, where the following adding up constraints apply:

$$\begin{aligned} \sum_{e'=1}^2 w_{ie'} &= 1 \\ \sum_{b'=1}^5 w_{ib'} &= 1 \\ \sum_{i \in z} w_{ib} &= \frac{N_z}{5} \end{aligned} \quad (24)$$

The first two constraints require that each household i have weights that sum across consumption bin b and type e to equal 1. The constraint in 24 requires that, within a zipcode z , the weights must sum to 1/5th of the number of households in the sample for that zipcode (due to the use of quintiles). This guarantees that the moments of the consumption distribution match the empirical distribution. Type e weights have no analogous restriction, only that they sum to unity.

The constraint in 24 makes w_{ibe} dependent on w_{jbe} for any $i \in z, j \in z$. Methods of calculating these weights such as those in Arcidiacono and Miller (2011) are not appropriate for dependent weights, and an alternative is employed here. To account for dependence, we integrate over randomly drawn allocations of b that comport with the empirical distribution.

1. Draw $R = 1000$ random allocations of b that place $\frac{1}{5}$ of the households into each bin, guaranteeing that $b^{(r)}$, the r^{th} allocation, satisfies the constraint in 24 for each allocation r
2. Evaluate the conditional likelihood for every $\{b, e\}$ combination for every household i and time t , then taking the likelihood as the product over t , calling this $L_{ibe} = \prod_t L_{ibet}$
3. Calculate $w_{ie|b}$, the type-weight, for each L_{ibe} as $\frac{L_{ie|b}}{L_{ie|b} + L_{ie'|b}}$, following Arcidiacono and Miller (2011)
4. Calculate L_{ib} as the $w_{ie|b}$ -weighted sum of L_{ibe}
5. Turning to the b weights, for each r , calculate the likelihood of observing r conditional on the parameters and $w_{ie|b}$. To do so, take the product of $L_{ib^{(r)}}$ where $L_{ib^{(r)}}$ is the likelihood for household i conditional on being in the bin drawn in allocation r . Formally, $L_r = \prod_i L_{ib^{(r)}}$
6. Calculate allocation weights $w_z^{(r)} = \frac{L_r}{\sum_r L_r}$
7. Calculate $L_z = \sum_r w_z^{(r)} L_r$
8. Log-likelihood $L = \sum_z \log(L_z)$

Allocations r where households are better allocated to consumption bins b that better explain the observed outcome are weighted higher than allocations that poorly explain the observed outcome. All weights sum to 1 within household i , and all weights satisfy 24 by definition.

E.1 Conditional Choice Probabilities

In estimation we utilize the state transition estimates shown in Appendix D. The final component of 23 is the conditional choice probability (CCP), which is the predicted probabilities of adopting in the next period. We again follow Arcidiacono and Miller (2011) and use a flexible logit to estimate the probability of adopting for household h at time t .³¹ Weights w_{ibt} are used in the flexible logit and a separate probability of adopting is estimated for leasers and purchasers. In estimation, the next-period probability of adopting $Pr_{ib}^{e'}$ is updated in a third step using updates of w_{ibe} to re-weight the logit estimation and following the update of the weights. The flexible logit is specified using all interactions of the variables in X , interactions between all X and a second-degree polynomial in time, and a 3rd degree polynomial in time. The CCP's (predicted probabilities of adopting in the next period) are generated by advancing the time by 1 period and predicting the logit response.

E.2 Estimation Transformations

For estimation, σ is estimated using an exponential transformation e^σ to preserve positive variance. The parameters for the marginal utility of income are transformed using $e^{\omega_0 + \omega_{low}1(\text{wealth}_i=\text{low}) + \omega_{med}1(\text{wealth}_i=\text{med})}$. This ensures positive marginal utility of income, but does not restrict results to be monotonic or decreasing in wealth. The parameters of ρ_i , the household discount factor, are estimated with a Normal cdf transformation $\rho_i = \Phi(\rho + \alpha_{low}1(\text{wealth}_i=\text{low}) + \alpha_{med}1(\text{wealth}_i=\text{med}))$. All dollar amounts are scaled to be in thousands of dollars.

³¹A bin estimator would be feasible, but components of 6 and the leaser analogue are continuous

F Structural Parameter Results

The full set of results are shown in Table F.1. In addition to the results discussed in the main text, we find that having one or more available lines of credit is positive and significant, but the linear term on additional lines of credit is positive but indistinguishable from zero. Length of residence and the number of children are negative but insignificant. While previous literature has indicated these demographics correlate with adoption, these other papers did not condition on the economic value of adopting solar.³² We condition on the house being listed as owner-occupied in the Corelogic data, but not all of these are coded as owner-occupied in InfoUSA; the indicator for being listed as non-owner-occupied in the InfoUSA data has a large and significant negative intercept. Square footage is positive in the linear term and close to zero in the quadratic, while 2+ stories is negative indicating single-story homes receive more utility from adopting relative to equal-sized two-story homes, possibly due to greater roof area for optimal solar panel siting.

The γ terms capture differential effects across boundary zones across wealth and type, which is of particular concern if solar installers use wealth for lead generation or targeting. Intercept shifts for consumption bins show a U-shaped form: the lowest consumption bin, ϕ_{bin1} is closest to the omitted category, bin 5, while ϕ_{bin2} is the lowest. This is consistent with households that are highly energy-cognizant investing in energy efficiency *and* solar adoption. Consumption bin intercept shifts for leases are positive, but only one is significant, and then only at the 10% level.

³²The lack of significance (and negative sign) may also be the result of conditioning on wealth and consumption since households with children tend to have higher consumption. Households with longer length of residence tend to be higher wealth as well.

Table F.1: Structural parameter results

Param. Grp	Parameter	Estimate	se	t	pval
$\sigma; \omega$	σ	-0.958	0.002	-549.337	0.000 ***
	ω_0	-3.388	0.463	-7.321	0.000 ***
	ω_{med}	1.199	0.827	1.450	0.147
	ω_{low}	1.773	0.708	2.503	0.012 *
ρ	ρ_0	1.985	0.017	113.817	0.000 ***
	α_{med}	-0.134	0.048	-2.825	0.005 **
	α_{low}	-0.172	0.085	-2.029	0.042 *
β	β_0	11.464	0.240	47.777	0.000 ***
	Wealth: middle 1/3rd	-2.261	0.803	-2.815	0.005 **
	Wealth: lowest 1/3rd	-2.081	0.095	-21.863	0.000 ***
	Lease	-6.535	1.074	-6.082	0.000 ***
	Lease x Wealth: middle 1/3rd	2.170	0.089	24.415	0.000 ***
	Lease x Wealth: lowest 1/3rd	2.473	0.419	5.899	0.000 ***
	Voter affiliation: D	-0.696	0.392	-1.774	0.076 .
	Voter affiliation: D + lease	0.809	1.006	0.804	0.421
	Has 1 or more lines of credit	0.780	0.053	14.760	0.000 ***
	Lines of credit	0.328	0.591	0.555	0.579
	Length of residence	-0.148	0.685	-0.215	0.830
	Has children	-0.145	0.298	-0.487	0.626
	Listed as renter-occupied in InfoUSA	-15.225	0.306	-49.749	0.000 ***
	Sqft (1,000's)	1.295	0.169	7.685	0.000 ***
γ_{area}	Sqft ² (1,000's)	-0.063	0.835	-0.075	0.940
	Stories	-1.879	1.452	-1.294	0.196
	γ_B	-2.660	0.088	-30.368	0.000 ***
	γ_C	1.967	0.960	2.050	0.040 *
	γ_D	0.741	0.181	4.097	0.000 ***
	Wealth: lowest 1/3rd: γ_B	4.386	0.420	10.432	0.000 ***
	Wealth: middle 1/3rd: γ_B	2.639	1.578	1.673	0.094 .
	Wealth: lowest 1/3rd: γ_C	0.393	0.722	0.544	0.586
	Wealth: middle 1/3rd: γ_C	-2.342	0.226	-10.370	0.000 ***
	Wealth: lowest 1/3rd: γ_D	0.801	1.698	0.472	0.637
	Wealth: middle 1/3rd: γ_D	-1.721	1.513	-1.138	0.255
	Wealth: lowest 1/3rd x Lease: $\gamma_{B,lease}$	0.383	0.951	0.403	0.687
	Wealth: lowest 1/3rd x Lease: $\gamma_{C,lease}$	-0.511	0.850	-0.602	0.547
	Wealth: lowest 1/3rd x Lease: $\gamma_{D,lease}$	-0.542	0.448	-1.211	0.226

0 *** 0.001 ** 0.01 * 0.05 . 0.1 ' 1

Includes consumption bin and time fixed effects. Robust std. errors from Arcidiacono and Miller (2011)

Table F.2: Model predicted and actual adoption shares

Wealth	Households	Total			Purchases			Leases		
		Predicted	Actual	Predicted:Actual	Predicted	Actual	Predicted:Actual	Predicted	Actual	Predicted:Actual
High	61,229	2,567	2,445	1.050	1,714	1,553	1.104	854	892	0.957
Med	61,223	3,094	3,052	1.014	1,589	1,540	1.032	1,505	1,512	0.996
Low	61,215	1,767	1,747	1.011	694	711	0.977	1,072	1,036	1.035
All	183,667	7,428	7,244	1.025	3,997	3,804	1.051	3,431	3,440	0.997

To assess model fit, we use parameter estimates in Table F.1 to predict adoption probabilities for each household, time period, consumption bin, and type. We then calculate the probability of adoption within the study period as one minus the product of the probability of non-adoption in each time period. We then aggregate across consumption bin and type for each household using the weights from estimation. As in estimation, for adopters we observe the type (lesser vs. purchaser) and consumption bin with certainty, which is reflected in the weights. Finally, we aggregate by wealth bins and type to summarize total predicted adoption during the study period, which can be directly compared to observed adoptions.

G Counterfactual Methodology

All counterfactual scenarios report the ratio of predicted counterfactual adoptions to baseline predicted adoptions occurring within the study sample and during the study period. In all cases, we calculate adoption as one minus the joint probability of choosing “do not adopt” in each of the 10 time periods in the study window. This allows us to report the total number of adoptions predicted over the period, rather than examining across time periods. In the following, we dive into the details of the counterfactual methodology.

The value of adoption, δ_1 , is a terminal state and so there is no continuation value. To calculate δ_0 , we need to calculate the value function. We do this by taking the infinite sum given in 1. In practice, we forward simulate the state variables many periods in the future (S periods), assume $V(p_S, VC_S, FC_S) = \delta_1(p_S, VC_S, FC_S)$ (i.e. treat the value as if everyone who had not yet adopted solar at period S purchases solar), which is a benign assumption if S is large enough. We then backward iterate to calculate δ_0 in the current period using the below expression for the inclusive value of adoption in each period:

$$\begin{aligned} & E [\max(\delta_0 + \sigma\epsilon_0, \delta_1 + \sigma\epsilon_1)] \\ &= \sigma E [\max(\delta_0/\sigma + \epsilon_0, \delta_1/\sigma + \epsilon_1)] \\ &= \sigma [\log(\exp(\delta_0/\sigma) + \exp(\delta_1/\sigma)) + \gamma] \end{aligned} \tag{25}$$

Under counterfactual regimes, we must account for the fact that the probability of adopting in the next period will also change. I.e., counterfactuals require counterfactual CCP’s – as the utility payoff of adopting changes (in one or all periods), the probability of adopting in the next period also changes. Here, we use model estimates to update both $\delta_1 - \delta_0$ and $\log(Pr')$ as well.

Our strategy for calculating counterfactual $\log(Pr'^+)$ is to calculate the *difference* in adoption utility implied by the estimated parameters of the model. Arcidiacono and Miller (2020) discuss identification of counterfactual CCPs and show conditions under which counterfactual CCPs are identified. Under strong assumptions of stationarity, counterfactual CCPs are identified as the “choice probabilities from the past fully capture anything that might happen in the future.” We assert that the progression of electricity prices and solar costs form a stationary environment, allowing us to identify both model parameters and CCPs in our setting. We leverage the flexible logit estimate of $\log(Pr')$ and the stationary environment to construct future values of counterfactuals $\log(Pr'^+)$ by re-writing future changes in the probability of adopting as an infinite series of (known) flow utility payoffs.

Let A capture the scaled (by $1/\sigma$) utility of adopting today relative to the discounted utility of adopting tomorrow, $A = (u - \rho u')/\sigma$, and B capture the next period adoption probability and Euler constant, so that we can write the value of adopting as:

$$\begin{aligned} \frac{1}{\sigma} (\delta_1 - \delta_0) &= \underbrace{\frac{1}{\sigma}(1 - \rho(1 + \zeta))\theta q^* \bar{p} - \frac{1}{\sigma}(1 - \rho)FC - \frac{1}{\sigma}(1 - \rho\eta)VC + \frac{1}{\sigma}(1 - \rho)X\beta}_A \\ &+ \underbrace{\rho(\log(Pr') - \gamma)}_B \end{aligned}$$

Under a counterfactual scenario, we change the utility of adopting today by Δu and the expected utility of adopting tomorrow by $\Delta u'$, so that $\Delta A = (\Delta u - \rho\Delta u')/\sigma$.

The counterfactual change in the probability of adopting, Pr^+ , is determined by the change in A plus the change in B :

$$Pr^+ = \Lambda \left(\frac{1}{\sigma} (\delta_1 - \delta_0) + \Delta A + \Delta B \right) \quad (26)$$

Note we can write:

$$\Lambda^{-1}(Pr) = \log \left(\frac{Pr}{1 - Pr} \right)$$

and thus

$$\begin{aligned} \log(Pr') &= \Lambda^{-1}(Pr') + \log(1 - Pr') \\ &= \frac{1}{\sigma} (\delta'_1 - \delta'_0) + \log(1 - Pr'), \end{aligned} \quad (27)$$

where δ'_1 is the next-period utility of adopting and δ'_0 is the next period utility of non-adoption.

Using this expression, we can write B as:

$$B = \rho(\log(Pr') - \gamma) = \rho \left(\frac{1}{\sigma} (\delta'_1 - \delta'_0) + \log(1 - Pr') \right) - \rho\gamma$$

and we can write B^+ (the value of B under the counterfactual) as:

$$B^+ = \rho \left(\log(Pr'^+) - \gamma \right) = \rho \left(\frac{1}{\sigma} (\delta'^+_1 - \delta'^+_0) + \log(1 - Pr'^+) \right) - \rho\gamma$$

By plugging in the values for δ and δ^+ , we can write the change in B as:

$$\begin{aligned} \Delta B &= B^+ - B \\ &= \rho \left(\frac{1}{\sigma} (\delta'_1 - \delta'_0) + \Delta A' + \Delta B' + \log(1 - Pr'^+) \right) - \rho\gamma - B \\ &= \rho \left(\frac{1}{\sigma} (\delta'_1 - \delta'_0) + \Delta A' + \rho(\log(Pr''^+) - \log(Pr'')) + \log(1 - Pr'^+) \right) - \rho\gamma \\ &\quad - \rho \left(\frac{1}{\sigma} (\delta'_1 - \delta'_0) + \log(1 - Pr') \right) - \rho\gamma \\ &= \rho\Delta A' + \rho^2(\log(Pr''^+) - \log(Pr'')) + \rho(\log(1 - Pr'^+) - \log(1 - Pr')) \\ &= \rho\Delta A' + \rho\Delta B' + \rho(\log(1 - Pr'^+) - \log(1 - Pr')) \end{aligned} \quad (28)$$

where $\Delta A'$ is the next-period difference between counterfactual and actual A . ΔB can be rewritten using the following recursion:

$$\begin{aligned} \Delta B &= \rho\Delta A' + \rho(\log(1 - Pr'^+) - \log(1 - Pr')) + \rho\Delta B' \\ &= \rho\Delta A' + \rho^2\Delta A'' + \rho(\log(1 - Pr'^+) - \log(1 - Pr')) \\ &\quad + \rho^2 \left(\log(1 - Pr''^+) - \log(1 - Pr'') \right) + \Delta B'' \end{aligned} \quad (29)$$

where we denote the next period's next-period logged probability of adopting as $\log(Pr'')$ and $\log(Pr''^+)$, and additional future probabilities of adopting as $\log(Pr'^s)$ and $\log(Pr'^s+)$.

The expression for ΔB in (29) is a recursive sum that can be rewritten as:

$$\Delta B = \sum_{s=1}^{\infty} \rho^s \Delta A'_s + \sum_{s=1}^{\infty} \rho^s \left(\log \left(\frac{1 - Pr_s'^+}{1 - Pr_s'} \right) \right), \quad (30)$$

The s subscript on A'_s and Pr_s' indicates that A , Pr , and Pr'^+ change in future periods based on the evolution of the state variables and are affected by the counterfactual changes (electricity prices, solar prices, etc.). Each recursion produces $\Delta A'$ that is equal to ΔA scaled by ρ ,³³ as well as a discounted logged ratio of the probability of not adopting in the next period under the counterfactual to the probability of not adopting in the next period under the baseline. While this ratio is close to unity, a positive ΔA , for example, will result in a higher probability of adopting in subsequent periods, decreasing the probability of not adopting and decreasing the logged ratio.

To calculate the second term in equation (30), we forward-simulate the deterministic progression of VC , FC , and $q^* \bar{p}$ to the period $s = S = 151$ using the estimated state transitions $\{\eta, \zeta_{b,z}\}$. We assume that all households will make a terminal choice at this time period, and calculate the expected value of that choice as $\log(\exp(\frac{\delta_1^{(S)}}{\sigma}) + \exp(0)) + \gamma$. Setting $s = 150$, we substitute the expected value of not adopting as the previous quantity scaled by ρ and calculate the probability of adopting at $s = 150$. We record the log of one minus that probability, scaled by ρ^s . We then iterate from $s = 150$ to $s = 0$, taking a cumulative sum of $\log(1 - Pr)$ at each value of s . At $s = 0$, we discard the continuation value in favor of using equation 30, and substitute the cumulative sum of $\log(1 - Pr)$ for the denominator of the second term. We then calculate δ_1 under the counterfactual – a straightforward task for any counterfactual that re-scales VC , FC , and/or $q^* \bar{p}$, and repeat the process to calculate the numerator of the second term in 30.

The first term in equation (30) is straightforward. Adding $\Delta A'$ to 30, we see:

$$\Delta A + \Delta B = \sum_{s=0}^{\infty} \rho^s \Delta A'_s + \sum_{s=1}^{\infty} \rho^s \left(\log \left(\frac{1 - Pr_s'^+}{1 - Pr_s'} \right) \right),$$

which allows for closed form calculation of the infinite sum of the first term, including cases where $\Delta A' = \eta \Delta A$, as is the case when counterfactual changes apply to the variable cost term.

Finally, with $\Delta A + \Delta B$ in hand, we calculate the counterfactual Pr'^+ using equation 26.

H Counterfactual Welfare

H.1 Welfare Calculation Methodology

We formulate demand as the probabilistic quantity of capacity installed as a function of the fixed and variable costs of installation.

$$d_{ibet}(C_t) = K^*(C_t, p_t; \gamma_i, e_i, b_i) \tilde{Pr}^{adopt}(C_t, FC_i, p_t, e_i, b_i, X_i, K^*(C_t, p_t; \gamma_i, e_i, b_i)) \quad (31)$$

in which K^* is the optimal sizing function, C_t is the per-Watt cost of a panel at time t , p_t are the retail electricity rates, γ_i represents the roof profile of household i , and b_i and e_i are household

³³For example, under a counterfactual price change that scales the variable cost of solar by some amount in every period, ΔA is equal to that difference in the variable installation costs and we have that $\Delta A' = \eta \Delta A$. A counterfactual change in the fixed costs of solar leads to $\Delta A' = \Delta A$.

consumption bin b and type e , respectively. This represents quantity (in watts of solar capacity) demanded conditional on adopting. FC_i is the fixed cost of installation which does not enter the optimal sizing K^* . \tilde{Pr}^{adopt} is the unconditional probability of adopting conditional on K^* , household demographics X_i , time t , type, consumption bin, C_t , and p_t . Model predictions yield a conditional probability of adopting Pr^{adopt} . Thus, we calculate \tilde{Pr}^{adopt} using the following:

$$\tilde{Pr}_t^{adopt} = \prod_{s=1}^t \left(1 - \mathbb{1}(s \geq 2) Pr_{t-s+1}^{adopt}\right) Pr_t^{adopt}$$

For each household, type, consumption bin, time period, and value of C_t , we calculate K^* as a function of price, generate $q^* \bar{p}$ and TC , and use the adoption model to calculate the probability of adopting.

Consumer surplus. Household surplus is calculated by integrating equation 31 over average cost per Watt, defined as:

$$\tilde{C}_t = \frac{FC + K^* C_t}{K^*}$$

$$CS_{ibe} = \sum_{t=1}^{10} \int_0^m (\tilde{C}_t + x) d_{ibet}(\tilde{C}_t + x) dx$$

The upper limit of integration m is chosen to approximate the intercept of the demand curve. Because T1EV shocks are unbounded, the probability of adopting never reaches 0. In practice, we numerically integrate over the range of $[0, 5.60]$, and assume that the probability of adopting when \tilde{C}_t is \$5.60 per Watt larger than what is observed in the data is negligible.³⁴ The consumer surplus, weighted by the unconditional probability of adopting, is summed over the 10 time periods in the sample.

Because K^* , q^* , and other important quantities vary over time within a household and type, we calculate the expected capacity installed, generation, government expenditures including counterfactual subsidies and expenditures on the federal investment tax credit (ITC), utility expenditures, and avoided damages using a similar equation, which appropriately weights each time period by the probability of not adopting prior to that period and the probability of adopting:

$$K_{ibe}^* = \sum_{t=1}^{10} \tilde{Pr}_t^{adopt} K_{ibet}^* \quad (32)$$

Finally, we take the weighted sum across type and consumption bin using w_{ibe} , resulting in a total for each household in our sample.

Government expenditures. Counterfactual 3 explores the replacement of the NEM embedded subsidy with an explicit subsidy paid per-Watt and per-installation. In addition to explicit subsidies, payment of the federal ITC will change under counterfactual 2 (as fewer households adopt smaller systems) and counterfactual 3, as more households adopt larger systems relative to 2. We report these expenditures as $\Delta GovernmentExpenditures$. Changes in private expenditures are accounted for in CS_i .

Utility expenditures. We evaluate the change in utility expenditures by considering the subsidies embedded in the NEM policy. Because current NEM policy provides electric bill savings in excess of the avoided cost savings, the difference between the avoided cost and \bar{p} is an embedded subsidy. Furthermore, critics of NEM policy note that the embedded NEM subsidy is substantial,

³⁴the maximum value of \tilde{C}_t in our data is \$4.17/W

is primarily paid to high-wealth solar adopters, and increases electricity prices on lower-wealth non-adopters. Counterfactuals 2 and 3 are based on a reform of NEM policy that does not entirely eliminate the embedded subsidy – under these counterfactuals, households can no longer “bank” excess instantaneous generation (and are instead paid at the avoided cost rate for export to the grid), but can still reduce their electricity bill by amounts in excess of the value of generation. Thus, we calculate the change in utility expenditures as the change in the embedded subsidy, calculated as:

$$\Delta Utility Expenditures_{ibet} = \theta_{4\%} \left((1 - s) \times q^{*'} (\bar{p}' - .062) - q^* (\bar{p} - .062) \right)$$

in which $\theta_{4\%}$ is the value of θ with a 4% discount rate, s is the export share $s \in \{.30, .50\}$, $Subs^W$ and $Subs^I$ are the explicit subsidies, $q^{*'}$ and \bar{p}' are counterfactual generation and average value of offset electricity after resizing. $\bar{p}' \geq \bar{p}$ as the average value of non-grid-exported electricity increases as more is exported to the grid. We calculate total $\Delta Subsidy_i$ using equation 32 and then summing over type and consumption using w_{ibe} . To explore the distributional criticisms of NEM policy, we report $\Delta Utility Expenditures$ over wealth bins.

Environmental damages avoided. A primary goal of NEM policy is to encourage the adoption of renewable energy in order to decrease negative externalities associated with fossil-fuel based electricity generation. Counterfactual welfare calculations include a “dollarization” of environmental and health damages avoided based on Sexton et al. (2021), which calculates the hourly marginal emissions factors for all dispatchable generators capable of serving, *inter alia*, the relevant portion of the grid operated by the California Independent System Operator (CAISO) during the period including 2014-2016. These marginal emissions factors for each potentially responding plant are calculated as dollars of damages per unit of emissions of three criteria pollutants: NOx, SOx, and PM2.5, plus CO2 emissions³⁵. Yearly damages are calculated for each potentially responding plant based on emissions location, local dispersion, and local population density and composition. Dollarized yearly damages are then summed over all potentially responding plants based on estimated responsiveness. Hourly generation profiles for each zip code in the sample are used to convert one watt of capacity K to avoided emissions, and yearly damages are summed to the 25-year lifetime of the panel using a 2% social discount rate, the value of $\lambda = .8\%$, and an expected decline in grid emissions equal to 1.75% per year. Finally, we sum expected environmental damages avoided over sample time and type as noted before.

³⁵a Social Cost of Carbon of \$41/ton is used

H.2 Counterfactual Welfare Results

Table H.1: Total Welfare for a 50% export rate.

Wealth	CS	Adoptions	Total Capacity kW	Total Generation MWh	Gov Subsidy Expenditures \$1,000's	Gov ITC Expenditures \$1,000's	Utility Expenditures \$1,000's	Avoided Damages \$1,000's	Total Surplus \$1,000's
Baseline									
High	\$37,070	2567	14,167	21,277	\$0	\$19,798	\$68,926	\$10,129	-\$41,524
Med	\$32,616	3094	17,043	26,955	\$0	\$23,799	\$79,002	\$12,254	-\$57,931
Low	\$14,353	1767	8,708	13,702	\$0	\$12,244	\$37,622	\$6,275	-\$29,238
All	\$84,039	7428	39,917	61,934	\$0	\$55,841	\$185,549	\$28,657	-\$128,694
NEM \$.062, no subsidies									
High	\$22,708	2214	10,789	16,474	\$0	\$15,141	\$41,605	\$7,713	-\$26,325
Med	\$23,608	2596	12,864	20,560	\$0	\$18,063	\$47,092	\$9,250	-\$32,296
Low	\$11,426	1524	6,549	10,433	\$0	\$9,321	\$21,900	\$4,720	-\$15,076
All	\$57,742	6334	30,202	47,468	\$0	\$42,525	\$110,598	\$21,683	-\$73,698
NEM \$.062, per-install and per-W subsidy									
High	\$26,704	2493	12,929	19,607	\$9,767	\$16,630	\$49,288	\$9,243	-\$39,739
Med	\$29,933	3322	17,337	27,536	\$13,031	\$22,327	\$62,422	\$12,463	-\$55,384
Low	\$15,876	2143	9,762	15,438	\$7,905	\$12,741	\$32,192	\$7,032	-\$29,929
All	\$72,514	7959	40,028	62,581	\$30,704	\$51,699	\$143,901	\$28,738	-\$125,052

Table H.2: Total Welfare for a 30% export rate.

Wealth	CS	Adoptions	Total Capacity kW	Total Generation MWh	Gov Subsidy Expenditures \$1,000's	Gov ITC Expenditures \$1,000's	Utility Expenditures \$1,000's	Avoided Damages \$1,000's	Total Surplus \$1,000's
Baseline									
High	\$37,070	2567	14,167	21,277	\$0	\$19,798	\$68,926	\$10,129	-\$41,524
Med	\$32,616	3094	17,043	26,955	\$0	\$23,799	\$79,002	\$12,254	-\$57,931
Low	\$14,353	1767	8,708	13,702	\$0	\$12,244	\$37,622	\$6,275	-\$29,238
All	\$84,039	7428	39,917	61,934	\$0	\$55,841	\$185,549	\$28,657	-\$128,694
NEM \$.062, no subsidies									
High	\$29,274	2418	12,902	19,501	\$0	\$18,055	\$57,845	\$9,225	-\$37,402
Med	\$28,529	2854	15,348	24,353	\$0	\$21,477	\$64,973	\$11,035	-\$46,885
Low	\$13,355	1639	7,777	12,280	\$0	\$10,989	\$30,473	\$5,604	-\$22,502
All	\$71,158	6911	36,027	56,134	\$0	\$50,521	\$153,290	\$25,864	-\$106,789
NEM \$.062, per-install and per-W subsidy									
High	\$30,847	2524	13,597	20,519	\$3,581	\$18,485	\$60,690	\$9,721	-\$42,188
Med	\$30,928	3136	16,954	26,858	\$4,448	\$23,053	\$71,334	\$12,189	-\$55,719
Low	\$14,974	1863	8,918	14,054	\$2,495	\$12,240	\$34,715	\$6,425	-\$28,049
All	\$76,748	7523	39,469	61,430	\$10,524	\$53,778	\$166,738	\$28,335	-\$125,956

Table H.3: Welfare Effects for a 30% export rate.

Wealth	Δ CS \$1,000's (%)	Δ Gov Expenditures \$1,000's (%)	Δ Utility Expenditures \$1,000's (%)	Δ Avoided Damages \$1,000's (%)	Δ Total Surplus \$1,000's (%)
NEM \$.062, no subsidies					
High	-\$7,796 (-27%)	-\$1,743 (-10%)	-\$11,081 (-19%)	-\$904 (-10%)	\$4,123 (-11%)
Med	-\$4,087 (-14%)	-\$2,322 (-11%)	-\$14,030 (-22%)	-\$1,219 (-11%)	\$11,047 (-24%)
Low	-\$999 (-7%)	-\$1,255 (-11%)	-\$7,149 (-23%)	-\$670 (-12%)	\$6,735 (-30%)
All	-\$12,882 (-18%)	-\$5,320 (-11%)	-\$32,259 (-21%)	-\$2,793 (-11%)	\$21,905 (-21%)
NEM \$.062, per-install and per-W subsidy					
High	-\$6,223 (-20%)	\$2,268 (10%)	-\$8,236 (-14%)	-\$408 (-4%)	-\$664 (2%)
Med	-\$1,688 (-5%)	\$3,702 (13%)	-\$7,669 (-11%)	-\$65 (-1%)	\$2,213 (-4%)
Low	\$621 (4%)	\$2,491 (17%)	-\$2,907 (-8%)	\$151 (2%)	\$1,188 (-4%)
All	-\$7,291 (-9%)	\$8,461 (13%)	-\$18,811 (-11%)	-\$322 (-1%)	\$2,737 (-2%)

I Robustness Checks

I.1 Model Estimates with Rebound

We resize optimal installations assuming a rebound of $\varepsilon = .1$ for purchased systems, holding leased systems sized to full offset as before (see Appendix C for sizing results). Using updated sizes, we re-estimate the model. Results are largely robust to sizing with rebound and are qualitatively identical to results presented above. With resizing, the estimated implicit discount rates across wealth are 8.7%, 12.2%, and 13.4%, which can be compared to results in Table 2 of 10.0%, 13.9%, and 15.3%. Differences between high- and low-wealth household implicit discount rates remain significant. While estimated implicit discount rates are lower at all wealth levels, the ratio of θ for high to low wealth remains identical at 1.5.

 Table I.1: Implicit Discount Rates: Rebound elasticity for $\varepsilon = .1$

Wealth	Marginal Utility of Income	Annual Discount Rate	$\bar{\theta}$	Ratio
High	0.04 (0.02)	8.7% (0.71%)	59.3	1.5
Med	0.12 (0.21)	12.2% (1.57%)	44.2	1.1
Low	0.18 (0.11)	13.4% (3.44%)	40.7	1
All		11.4%	48.0	—

Heteroskedasticity-robust standard errors in parentheses, calculated by delta method. The difference between the high-wealth and low-wealth underlying implicit discount rate structural parameters is statistically significant, with a p-value of 0.041.

I.2 Model Estimates with Alternative Increase in Power Purchase Rates

We assume the rate of increase in power purchase rates for leased systems is contracted at 4%, and in this section, we sensitivity test this assumption using $\zeta^{PPA} \in \{.03, .05\}$. Based on the data,

we assume lease customers are assumed to size to full offset. Thus, we do not re-size under the alternative values of ζ^{PPA} .

Results are qualitatively similar on implicit discount rates, with $\zeta^{PPA} = .03$ resulting in estimated implicit discount rates of 11%, 15.4%, and 16.8% for high, medium, and low-wealth households. At $\zeta^{PPA} = .05$, estimated rates are 8.8%, 12.3%, and 13.4%, slightly lower than main estimates of 10%, 13.9%, and 15.3%.

Table I.2: Implicit Discount Rates: $\zeta^{PPA} = .03$

Wealth	Marginal Utility of Income	Annual Discount Rate	$\bar{\theta}$	Ratio
High	0.01 (0.01)	11.0% (2.40%)	48.5	1.5
Med	0.17 (0.36)	15.4% (4.99%)	35.5	1.1
Low	0.33 (0.2)	16.8% (10.45%)	32.5	1
All		14.4%	38.8	—

Heteroskedasticity-robust standard errors in parentheses, calculated by delta method. The difference between the high-wealth and low-wealth underlying marginal utility of income structural parameters is statistically significant, with a p-value of 0.041. The difference between the high-wealth and low-wealth underlying implicit discount rate structural parameters is not statistically significant, with a p-value of 0.607.

Table I.3: Implicit Discount Rates: $\zeta^{PPA} = .05$

Wealth	Marginal Utility of Income	Annual Discount Rate	$\bar{\theta}$	Ratio
High	0.04 (0.01)	8.8% (0.35%)	58.9	1.5
Med	0.11 (0.13)	12.3% (1.56%)	44.1	1.1
Low	0.17 (0.07)	13.4% (3.08%)	40.5	1
All		11.5%	47.8	—

Heteroskedasticity-robust standard errors in parentheses, calculated by delta method. The difference between the high-wealth and low-wealth underlying marginal utility of income structural parameters is statistically significant, with a p-value of 0.035. The difference between the high-wealth and low-wealth underlying implicit discount rate structural parameters is statistically significant with a p-value of 0.0499.

I.3 Model Estimates with Alternative Scaling of η, ζ

In our main results, we estimate a value of η , the rate of decline of variable panel costs, from the data. We also estimate a zip code x consumption bin-specific value of ζ , the rate of increase in average electricity price. These estimates form the consumer expectations of future panel and avoided electricity rates associated with sizing and adopting. We sensitivity test around these results by scaling both η and ζ_{bz} by $\pm 20\%$, and by setting ζ_{bz} equal to a rate of 2.2% per year, a factor commonly used by solar installers for sizing calculations and used by Google Project Sunroof in calculating savings.

Estimated implicit discount rates for all three are little changed. Scaling η, ζ_{bz} by a factor of 1.2 results in estimated rates of 10%, 13.9%, and 15.3%, identical to the main results to the first decimal place. Scaling by a factor of .8 results in estimated rates of 10%, 14%, and 15.4% for high, medium, and low-wealth households.

Table I.4: Implicit Discount Rates with scaled-up ζ, η

Wealth	Marginal Utility of Income	Annual Discount Rate	$\bar{\theta}$	Ratio
High	0.02 (0.02)	10.0% (1.48%)	57.2	1.5
Med	0.11 (0.34)	13.9% (3.24%)	42.0	1.1
Low	0.2 (0.18)	15.3% (4.38%)	38.4	1
All		13%	45.8	—

Heteroskedasticity-robust standard errors in parentheses, calculated by delta method. The difference between the high-wealth and low-wealth underlying marginal utility of income structural parameters is not statistically significant, with a p-value of 0.227. The difference between the high-wealth and low-wealth underlying implicit discount rate structural parameters is statistically significant at the 10% level with a p-value of 0.060.

Table I.5: Implicit Discount Rates with scaled-down ζ, η

Wealth	Marginal Utility of Income	Annual Discount Rate	$\bar{\theta}$	Ratio
High	0.06 (0.17)	10.0% (3.93%)	48.7	1.5
Med	0.16 (1.01)	14.0% (4.37%)	36.1	1.1
Low	0.28 (0.36)	15.4% (4.49%)	33.2	1
All		13.1%	39.3	—

Heteroskedasticity-robust standard errors in parentheses, calculated by delta method. The difference between the high-wealth and low-wealth underlying marginal utility of income structural parameters is not statistically significant, with a p-value of 0.708. The difference between the high-wealth and low-wealth underlying implicit discount rate structural parameters is statistically significant at the 10% level with a p-value of 0.079.

Setting $\zeta_{bz} = 2.2\%$ for all consumption bins and areas primarily removes cross-sectional variation in energy price trends across consumption bins. Estimated implicit discount rates are slightly lower at 9.5%, 13.3%, and 14.7% for high-, medium-, and low-wealth households relative to our main results of 10%, 13.9%, and 15.3%, respectively.

Table I.6: Implicit Discount Rates with $\zeta = 2.2\%$

Wealth	Marginal Utility of Income	Annual Discount Rate	$\bar{\theta}$	Ratio
High	0.05 (0.02)	9.5% (0.50%)	44.8	1.4
Med	0.14 (0.17)	13.4% (1.65%)	34.0	1.1
Low	0.2 (0.08)	14.7% (3.02%)	31.4	1
All		12.5%	36.8	—

Heteroskedasticity-robust standard errors in parentheses, calculated by delta method. The difference between the high-wealth and low-wealth underlying marginal utility of income structural parameters is statistically significant at the 10% level, with a p-value of 0.084. The difference between the high-wealth and low-wealth underlying implicit discount rate structural parameters is statistically significant, with a p-value of 0.017.

I.4 Model Estimates including Race Covariates

Data from InfoUSA allow us to extract race and ethnicity for each household head. We group all households into four groups: Hispanic, White (non-Hispanic), Asian, and Black/Mixed and include indicators for this race variable in estimation. We allow indirect utility for adopting to vary by race, but do not interact it with implicit discount rate or marginal utility of income. Race is not used in the sizing model, and enters only in the adoption model.

Results are not qualitatively different from main results, though the statistical significance of the parameters estimating differences in implicit discount rates are no longer significant. Estimated implicit discount rates across wealth are 11.3%, 16%, and 17.6%. The ratio of average $\bar{\theta}$ between household wealth bins of 1.5:1 and 1.1:1 remains identical to the main results.

Table I.7: Implicit Discount Rates Including Race Covariates

Wealth	Marginal Utility of Income	Annual Discount Rate	$\bar{\theta}$	Ratio
High	0.02 (0.01)	11.3% (0.42%)	47.3	1.5
Med	0.11 (0.05)	16.0% (6.43%)	34.0	1.1
Low	0.22 (0.11)	17.6% (10.46%)	31.1	1
All		14.9%	37.5	—

Heteroskedasticity-robust standard errors in parentheses, calculated by delta method. The difference between the high-wealth and low-wealth underlying marginal utility of income structural parameters is statistically significant, with a p-value < .001. The difference between the high-wealth and low-wealth underlying implicit discount rate structural parameters is not statistically significant, with a p-value of 0.456.

I.5 Model Estimates Assuming Finite Time Horizon

We re-estimate the adoption model as a finite time model as in de Groot and Verboven (2019), which implicitly constrains the value function to include zero utility and zero continuation value at the end of the 25-year lifespan of the panels. In contrast, our main specification assumes re-adoption at $T = 25$. Results in Table I.8 imply higher implicit discount rates than our main results. The ratio between high- and low-wealth households valuation of the flow of NEM benefits, captured by θ , remain identical to the main specification results of 1.5:1, as does the ratio between medium- and low-wealth households.

Table I.8: Implicit Discount Rates Estimated Assuming Finite Time Model

Wealth	Marginal Utility of Income	Annual Discount Rate	$\bar{\theta}$	Ratio
High	0 (0)	13.2% (0.97%)	41.1	1.5
Med	0.26 (0.39)	18.5% (8.63%)	29.5	1.1
Low	0.72 (0.97)	20.1% (33.25%)	27.1	1
All		17.2%	32.6	—

Heteroskedasticity-robust standard errors in parentheses, calculated by delta method. The difference between the high-wealth and low-wealth underlying marginal utility of income structural parameters is statistically significant, with a p-value of < 0.001. The difference between the high-wealth and low-wealth underlying implicit discount rate structural parameters is not statistically significant, with a p-value of 0.807.

J Marginal Value of Public Funds (MVPF)

The MVPF is the ratio of the policy beneficiaries willingness to pay for a policy to the government expenditures of the policy (Finkelstein and Hendren, 2020). We calculate the MVPF for counterfactual 2 relative to counterfactual 1 as the addition of up-front subsidies along with the NEM reform provides an appropriate setting to evaluate those expenditures. We construct the MVPF for each wealth bin to separately examine the effectiveness of counterfactual 2 spending across the wealth distribution.

The MVPF takes the form of

$$(\Delta'CS + \Delta'UtilityExpenditures + \Delta'Damages) / \Delta'GovernmentExpenditures,$$

in which Δ' is the difference between counterfactual 2 and counterfactual 1 values of Δ . Under the 50% export assumption, direct changes in government expenditures via the ITC and subsidies increase from -\$4,657 to +\$6,600 (in \$1,000's, see table 6). However, the MVPF includes the fiscal externality of the change in government expenditures resulting from changes in tax revenues on utility profits. Following (Hahn et al., 2024) and noting that the utility in our case is an investor owned utility and thus $\alpha = 0$, we define the government fiscal externality as:

$$(P - [(LCOE + c_t) \cdot (1 + m)]) \cdot \tau$$

Further noting that $(LCOE + c_t)$ is equal to the avoided cost calculated in E3 (2022), we calculate the government fiscal externality as the sum across observations of $(P_i - .062)(1 + m)\tau$, weighted by the probability of adopting. We use a corporate tax rate of $\tau = .10$ and an economy-wide markup of $m = .08$. For high-wealth households, this totals -\$2,592 in Scenario 1, and -\$1,840 in Scenario 2, leading to a $\Delta'GovernmentExpenditures = \$11,257 + \$752 = \$12,008$. Results are shown in the “Government Expenditures” column of table 7

In the MVPF numerator, we take the change in Consumer Surplus, $\Delta'CS$ and the calculated change in damages $\Delta'Damages$ directly from table 6. We account for the change in utility expenditure as in table 6, but adjust for markup and the corporate tax rate using the same assumptions as before. We calculate utility expenditures for each potential adoption and sum over all observations, weighed by probability of adopting. In order to adjust for markup m and tax rate τ , we calculate the change in utility expenditures as:

$$(P - [(LCOE + c_t) \cdot (1 + m)]) \cdot (1 - \tau)$$

Results of this calculation are shown in the “Utility Expenditures” column of Table 7.