Valuing Solar Subsidies

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PRELIMINARY – PLEASE DO NOT SHARE OR CITE

Abstract

Individuals trade present for future consumption across a range of economic behaviors, and this tradeoff may differ across demographics. This study employs unique data on rooftop solar adoption and the expected returns from such adoption to estimate heterogeneous discount rates by wealth. We develop a dynamic model of optimal system sizing and adoption, and base identification on plausibly exogenous variation in the future savings from installing solar and electricity rates. We estimate implied discount rates of 19.8%, 10.3%, and 10.8% for low-, medium-, and high-wealth households in California. Counterfactual simulations demonstrate opportunities to reduce the regressivity of solar adoption and improve policy cost-effectiveness.

Keywords: solar, discount rates, energy policy, distributional impacts

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1 Introduction

The rate at which individuals trade future consumption for present consumption is important across a range of economic behaviors, including savings, human capital formation, investment in personal health, etc. It is also important for public policy, particularly amid claims that welfare of sometimes irrational consumers can be enhanced by reduced consumer choice, e.g., with respect to energy-consuming durable goods. Energy-efficiency standards for autos and household appliances, for instance, are credited with cost savings to consumers whose choices imply sufficiently high discounting of future energy costs that they are attributed to optimization mistakes. But these high implicit discount rates can be due to factors that are consistent with rational decision making. Furthermore, higher discount rates for some sub-populations will lead to substantial distributional differences of different policy incentives. Incentives that provide high up-front subsidies will greater relative impact than incentives that are accrued over time for sub-populations who discount this future stream of benefits to a greater degree.

Laboratory experiments on intertemporal decision-making are numerous, but credible quasi-experimental estimates of discount rates revealed by market decisions are relatively scarce (Hausman, 1979; Warner and Pleeter, 2001; De Groote and Verboven, 2019). Evidence on how discount rates vary demographically for policy-relevant sub-populations is even scarcer. In this paper, we employ rich and unique micro-data on rooftop solar panel adoption and on the rooftop expected returns from solar panel adoption to estimate heterogeneous discount rates as they depend on household wealth. Solar purchases entail an upfront cost to install panels that generate future electricity cost savings as a function of the sunlight that falls upon the panels and the retail electricity rates at which solar generation is compensated in California and many other states. Using proprietary Google Sunroof data for rooftop-specific expected electricity generation of optimal solar installations for every home in select California counties, in conjunction with household electricity consumption data from a California utility, we are able to calculate the value of installing solar as a function of household discount rate. We combine these data with the solar adoption decisions of these households (in data provided by the Lawrence Berkeley National Laboratory) and household-specific wealth, income and other demographic information from InfoUSA, in order to develop and estimate a structural model of solar adoption model. We estimate household preferences for the flows of benefits relative to the upfront costs of installing, accounting for optimal installation size and household consumption.

Implicit discount rates are identified from plausibly exogenous variation in future savings due to rooftop characteristics, such as pitch, orientation, and shading from trees and structures, and from discrete differences in electricity rates across administratively determined climate zones within the state. This identification strategy utilizes valuable cross sectional variation, which has some very attractive features that separates it from other empirical work estimating implicit discount rates. In some older papers, strong functional assumptions are made in order to infer discount rates. For example, Hausman (1979) need to assume an exact lifetime for air conditioners, no deterioration over time, no differential in expected inflation rates of purchase price and electricity, and constant utility over time for air conditioning. More recent strategies use arguably exogenous changes to the environment; (Warner and Pleeter, 2001) use the entry of a new choice option that was not available before to bound the discount rate implied by higher-than-expected choice of benefit packages with higher up-front payments; De Groote and Verboven (2019) and Bollinger (2015) identify discount rates using variation in upfront investment costs and future payoffs due to policy changes. Such strategies are effective but rely still on strong assumptions about agent expectations with regards to other potential environmental changes. In contrast, our approach identifies discount rates from cross sectional variation in the relative value of the upfront costs of installing solar and the long-term benefits that result from differences in solar irradiation, leaving us much less dependent on assumptions about unobserved consumer expectations.

More specifically, we consider how households trade off upfront solar PV system costs and future savings on grid electricity by exploiting both discrete differences in future energy savings across utility administrative borders, and plausibly exogenous variation in household system costs resulting from exogenous variation in solar irradiation from differences in roof exposure, house orientation, and shading. In doing so, we evaluate the efficiency of upfront capacity incentives that include a federal investment tax credit and state and local rebates relative to net energy metering (NEM) policies common to 43 U.S. states; NEM policies subsidize a future stream of electricity generated over the 20-25-year lifetimes of solar PV systems by requiring utility companies to roll back a household's meter by the generated solar electricity, in effect requiring the utility to purchase the solar electricity at the retail rate. However, this stream of economic benefits may be highly discounted by impatient households who are observed to under-invest in energy-saving durables in a phenomenon termed the "Energy Paradox" that is believed to yield an "Energy Efficiency Gap" (Hausman 1979; Dubin and McFadden 1984; Li et al. 2009; Bento et al. 2012; Allcott and Wozny 2014). If households exhibit discount rates higher than market rates, then policymakers interested in increasing solar electricity generation could redeploy public resources embodied in NEM policies in the form of upfront capacity rebates or expected generation rebates that effectively arbitrage household impatience.

We estimate statistically significant and economically meaningful differences in discount rates between low- and high-wealth homeowners: 20% versus 10%. This leads medium and high-wealth households to value the same stream of benefits 80% more than low-wealth households. Although the estimated implicit discount rates are the most policy-relevant measures in terms of calculating welfare impacts of different policies, it is important to note that these estimates capture more than just time preferences. Cohen et al. (2020) provide a nice review of the literature and explanations for how/when we can translate "money earlier or later" tradeoffs that are tested in the lab into discount rates. Coller and Williams (1999) show how consumer's real rate of return should equal their discount rate only if it lies between their borrowing and lending costs. Thus, the decline in rates with wealth is consistent with theories of credit constraints that bind more for low-income than high-income households.

Differences in the intertemporal tradeoffs also can be due to the increased ability to smooth consumption with more upfront money (Cubitt and Read, 2007). One value of our setting is that the trade-off is between an upfront cost and a smooth set of benefits/payments, which may reduce this complicating factor. Much of the literature assumes consume-on-receipt, often implicitly – Cohen et al. (2020) note that 90 percent of papers in their summary did not model substitution of consumption across time, assuming individuals consume money when it is received; the consume-on-receipt model assumes the marginal propensity to use cash immediately is equal to one. To interpret the implicit discount rate, we also need to consider how households evaluate the monetary costs and benefits of installing solar with respect to other cash flows and desired consumption patterns. In general, background consumption is not considered within the literature. Cohen et al. (2020) show that in a simple two-period tradeoff, risk aversion scales down the implied discount rate from the estimated indifference real rate of return, what we are referring to as the implicit discount rate.

Thus, reasons for the discrepancy in our estimated discount rates across wealth bins include: 1) differences in lending and borrowing costs; 2) differences in the marginal propensity to consume; 3) differences in risk aversion. Furthermore, as more background consumption is incorporated into the model, the role of risk aversion gets smaller. If lower wealth households have lower levels of background consumption than higher wealth households, then our higher estimated implicit discount rate for lower wealth households could theoretically be explained even with the same time preferences and risk aversion and higher wealth households, due to the interaction between background consumption and risk aversion. While the decomposition of the implicit discount rate has implications for the effect of policies than would alter the cost of borrowing or level of risk aversion, it is beyond the scope of this paper. The combined implicit discount rate is what determines the distributional effects and welfare changes from intemperately shifting subsidies.

Because solar panels produce a homogeneous input into utility, electricity, and because the intertemporal tradeoff of upfront costs for future cost savings is the dominant characteristic of the adoption decision (as opposed to comfort, safety, noise, size, brand, etc.), these estimates are likely unbiased by correlated unobservables or consumer inattention. Hence, they provide credible evidence that individual discount rates exceed market rates and that these vary by wealth in ways that have important implications for policy. First, these discount rates imply a smaller role for the energy paradox in explaining consumer decisions. Second, they indicate that current state net-energy-metering policies that subsidize future solar electricity generation could arbitrage differences in individual and market discount rates to increase solar adoptions per unit expenditure by offering upfront rather than future subsidies. Thirdly, our results suggest the current subsidy policies common to most states yield greater utility to high-income households than low-income households due to heterogeneous discount rates, highlighting a structural inequity in existing solar policy.

Despite the prevalence of NEM policies and the vigorousness with which they are defended, we are not aware of any previous research that has evaluated their effectiveness across wealth levels in spurring additional solar PV capacity or generation. Upfront rebates and financing mechanisms, on the other hand, have been studied by Kirkpatrick and Bennear (2014), Hughes and Podolefsky (2015), Rogers and Sexton (2015), Gillingham and Tsvetanov (2017) and Pless and van Benthem (2016). NEM policies have proven controversial because they are believed to shift costs from relatively wealthy households who preferentially adopt rooftop solar to relatively poor households who do not. Solar adopters avoid paying for fixed costs of grid investment and maintenance that are commonly incorporated into the volumetric charges of retail tariffs. Such cost-shifting is of concern to regulators for equity reasons alone. Also of concern, however, is the viability of traditional utility models if NEM policies are unreformed. As fixed costs are spread across smaller retail electricity sales, rates are likely to rise, inducing further grid defections that could yield a "utility death spiral" (Kind 2013).[1]

[1]We distinguish a subsidy mechanism from the funding sources in order to study the cost-effectiveness of NEM subsidies, i.e., the public cost per additional unit capacity or additional unit generation. Welfare analysis that accounts for transfers from some electric utility customers to solar adopters, as is customary in existing NEM policies, is beyond the scope of this paper. However, our interest in this research question centers on the potential for a policy innovation that spurs greater solar adoption without the cost-shifting that hinders utility fixed cost recovery and distributional objectives.

2 Background

Existing rooftop solar subsidy regimes have generated additional solar capacity and generation at relatively high cost partly due to take-up by infra-marginal adopters, i.e., free-riders who would have adopted solar in the absence of subsidies (Hughes and Podolefsky 2015; Gillingham and Tsvetanov 2014; Rogers and Sexton 2015. Moreover, the additional capacity may not be sited to yield maximum generation let alone maximum value of generation. Finally, as Borenstein and Davis (2016) show, the subsidy benefits accrue mostly to wealthy households who preferentially adopt solar, raising concerns about the distributional impacts of state and federal incentives for solar capacity and generation. This project considers opportunities for improving the efficiency and equity of existing solar policy.

Typically, a subsidy on the extensive (adoption) margin would sacrifice efficiency on the intensive (generation) margin. However, the feedstock for solar electricity generation is free, and so marginal costs of generation are negligible. Indeed, industry groups advise that rooftop systems don't even require any routine maintenance.[2] Moreover, our own preliminary analysis of monthly generation from rooftop systems receiving a California generation subsidy or an upfront subsidy for expected generation exhibit no output degradation over their lifetimes and no differential effects across subsidy mechanisms of system age.[3] Therefore, the decision to adopt solar is made as a "set it and forget it" decision requiring only consideration of up-front investment and the (constant) flow benefits.

Solar net metering acts as a flow or production subsidy by reducing a customer's electricity bill by more than the value of the electricity generated. This is due to the true-up period used in most net metering policies. A solar household may generate more electricity than is consumed during sunny afternoons, and the excess energy is injected into the grid. Increasingly, the wholesale value of that injection is low – when residential rooftop solar panels are producing at a high rate, so too are utility scale solar installations, which lowers the wholesale price of electricity that determines the value of the residential injection. Under net metering, this injected energy is credited against subsequent withdrawals from the grid, even when those withdrawals occur at high wholesale cost time periods, such as evenings just after sunset. The "wedge" can be in excess of $0.20/kWh. In effect, this is a subsidy for solar adopters with NEM. The

[2]See for instance https://www.energysage.com/solar/101/solar-panel-maintenance/.

[3]Aldy et al. (2017) estimate that wind farms choosing to receive a federal capital subsidy produce 8-13% less electricity per unit of capacity than wind farms selecting to receive a federal output subsidy, and that this effect is driven by incentives generated by these subsidies rather than selection. Like solar generation, the feedstock for wind generation is free. However, there are more operating margins for wind than for solar. Turbines, for instance, can be damaged by weather if they are spinning (and generating) in very high wind conditions.

policy is also regressive (even without any discrepancy in discount rates) due to the tiered pricing scheme used by California investor owned utilities, if there is a positive correlation between wealth and consumption. Higher consumption households consuming at a higher price tear will receive more compensation for the generated solar than households at lower price tier.

Solar panels generate electricity for more than 20 to 25 years, and NEM policies are generally "locked in" (though exceptions to this exist). Therefore, the net present value of the flow of subsidies varies greatly with the household's discount rate. This net present value of solar is the main comparison a household makes when weighing substantial up-front investment costs with the benefits of "going solar". Therefore, the key economic element in household solar decisions necessary to understand uptake, in addition to levels of flow payoffs and levels of net up-front costs, is the household discount rate. This paper empirically estimates these discount rates.

Notably, California has recently begun the process to amend its net metering policy to address the regressivity of the existing net metering policy. In November 2022, an administrative law judge in California issued a draft proposal for revisions to California's NEM policy as required under AB327 (2013). Previously, the California Public Utilities Commission (CPUC) had developed a set of priorities for net metering revision, in accordance with existing law, that emphasized, *inter alia*, that net metering payouts made to rooftop solar must reflect the *avoided cost* of generation based on the location and time of injection into the grid. Furthermore, the priorities sought to emphasize equity of burden as previous look-back studies had found that low-income households bore a large burden of fixed costs imposed by previous net metering programs 1.0 and 2.0 (Hymes, 2022). In December 2022, the CPUC voted unanimously to adopt this proposed "Net Metering 3.0" plan which would drastically decrease the payout for rooftop generation net of consumption and would provide an income-based glide-path of supplemental payments to encourage adoption of rooftop solar for a term of five to nine years. The need for reform has brought the issues of net metering, in particular the distribution of wealth amongst households that benefit. Counterfactuals in Section 7.1 are aimed at understanding the effects of some of the proposed reforms.

3 Data

Our main dataset is comprised of household-level data from six sources: CoreLogic, which provides property and house characteristics acquired from county recorders and assessors; Lawrence Berkeley National Laboratory's *Track The Sun* proprietary address-level dataset of all known solar installations; Google Project Sunroof, which provides house-level solar irradiance profiles; InfoUSA, which provides household demographics including wealth and income; Pacific Gas and Electric household consumption data; and the California Secretary of State's voter registration database, which provides address-level voter registration.

3.1 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. For a subset of these zipcodes described below, we extract from CoreLogic all single-family detached non-mobile home residences built before 2014 that are owner-occupied using CoreLogic's owner-occupancy flag. House data includes the year built, heated square footage, and the number of stories.

3.1.1 CEC Climate Zone Boundaries

Our identification strategy relies, in part, on leveraging differences in electricity prices across California Electric Commission (CEC) climate zones. 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 boundary[4]. The 28 zip codes contained in the sample are shown in Figure 1.

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 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 2. 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.

[4]During 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.

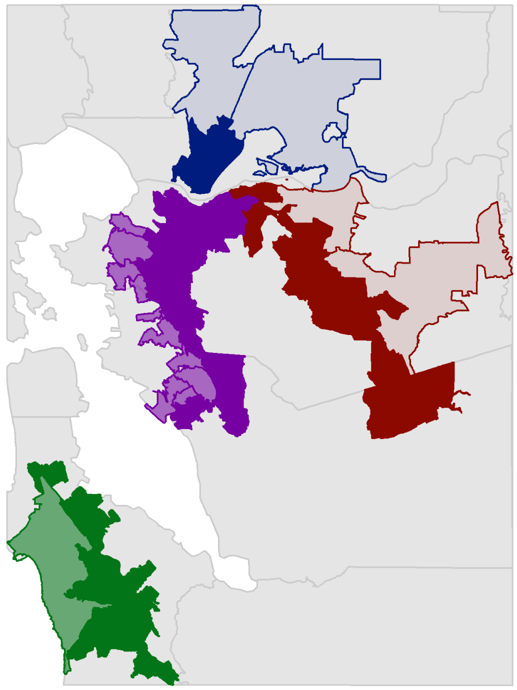

Figure 1: **Sample zip codes**. Zip codes in PG&E service territory that share a CEC climate zone boundary. Climate zones determine baseline allowances used to determine block pricing step “width”. Zip codes along a boundary face different average value of offset electricity when moving across the boundary. Color indicates boundary-spanning groups.

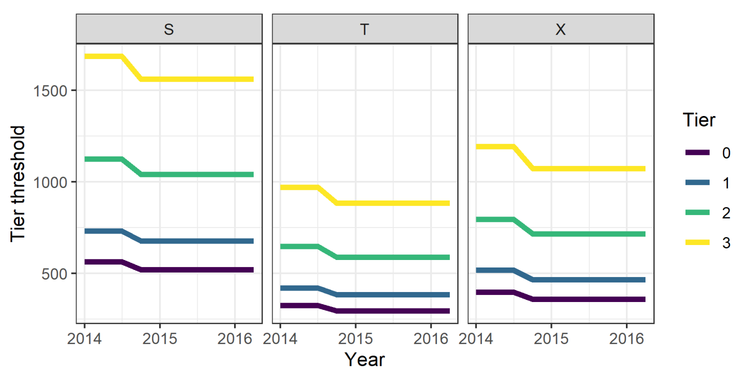

Figure 2: **Rate tier climate zone thresholds**. CEC climate zone thresholds over time in kilowatt-hours per month. Corresponding rates are shown in Figure 3

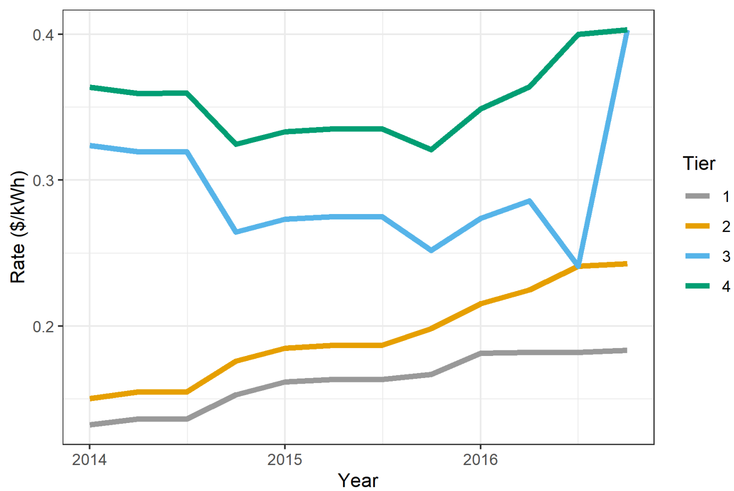

Figure 3: **Retail Rates**. Retail rates by tier over time in dollars per kilowatt-hour.

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.

3.2 Data Description

3.2.1 Household Characteristics

We merge publicly-available household voter affiliation provided by the California Secretary of State which indicate the voter affiliation of each person in the State. We match on address and generate a voter affiliation of the household by taking the affiliation of the two oldest registrations at an address that voted in the 2014 elections. We identify the household as registered Democratic if and only if all of the two longest-registered 2014 voters are registered Democrats or are registered with the Green Party.

Data from InfoUSA include the number of children, the length of time at the residence, the head of household's age and ethnicity, the number of open lines of credit, and the calculated wealth of the household. We merge by address and take only the individuals present from 2014-2016. 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.

Table 1 shows summary statistics for the homes and households in the sample by adopter status. Adopters tend to be middle- and high-wealth, are more likely to have children, and have larger homes. White households are over-represented among adopters, while Black, Asian, and Hispanic households are under-represented.

Table 1: Summary Statistics

			Adopters			Non-adopters		
		Pct. Sample	Mean	Std. dev	Pct. of Type	Mean	Std. dev	Pct. of Type
	Wealth	100.00	2654.65	945.81		2567.56	1055.69	
	Lines of credit	100.00	0.75	1.53		0.66	1.40	
	Children present	100.00	0.41	0.49		0.32	0.47	
	Length of residence	100.00	13.62	10.71		15.77	12.39	
	Square Footage	100.00	2.13	0.82		1.78	0.75	
Stories	1	69.38			57.54			69.98
	2+	30.62			42.46			30.02
Age	<40	16.58			16.99			16.56
	40-64	55.86			60.28			55.63
	65+	27.56			22.74			27.81
Ethnicity	Asian	10.31			8.99			10.38
	Black and Other	12.76			10.74			12.86
	Hispanic	15.90			14.84			15.95
	White	61.03			65.42			60.81
Voter affiliation (D)	Dem	41.90			45.23			41.74
	Rep, Mixed, or Unaffiliated	58.10			54.77			58.26
Wealth Bins	High	31.13			30.13			31.18
	Low	34.40			27.82			34.73
	Med	34.47			42.05			34.09

3.2.2 Household Irradiance Profiles

Each household faces an optimal installation size that depends on their initial electricity consumption, as well as the cost of installing solar. 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 is our main source of identifying variation. 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.

Figure 4 shows an example of the Google Project Sunroof website which shows the irradiance profile of two homes, one with a sunny, unobstructed, south-facing roof, and the other with low irradiance and no substantial south-facing roof. These homes are located in the same neighborhood in East Lansing, Michigan, and are served by the same electric utility.

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 5 shows six randomly selected rooftops' generation profile.

3.2.3 Household Consumption Profiles

From Pacific Gas and Electric (PG&E), we obtain confidential customer annual consumption for all customers in any of the 28 zip codes in the sample. Data is anonymized

Figure 4: **Google Project Sunroof display.**(Top) shows example readout for the home marked with location flag. This home enjoys unobstructed sunlight and has a large, flat, south-facing roof segment. Google Sunroof predicts substantial savings when installing solar on this home. (Bottom) this home has extensive shading and does not have a substantial south-facing roof segment. Google Sunroof predicts lower savings when installing solar on this home. These homes are in the same neighborhood in East Lansing, Michigan, and are served by the same electric utility.

and does not include address beyond the 5-digit zip code, but does include 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. We calculate the mean consumption for each bin within each zip code. The study period is relatively short (8 or 10 quarters), so we treat consumption as fixed over the study period. A density plot of zip-level consumption is shown in Figure 6.

Figure 7 shows the consumption levels of adopters and non-adopters by wealth. Across all three weath 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 discount rates and higher sensitivity to the flow of benefits from installing solar

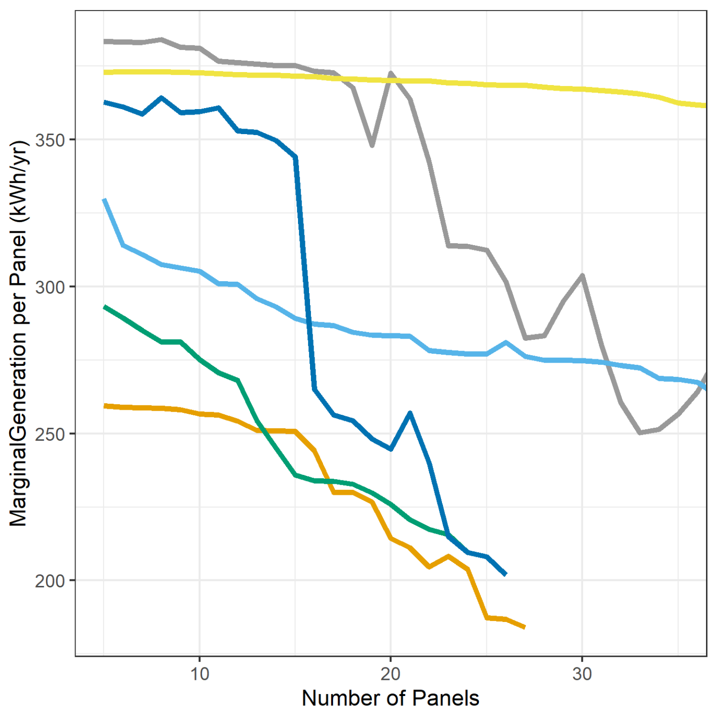

Figure 5: **Irradiance profiles** for six randomly selected rooftops. Figure shows marginal generation for each household on vertical axis per panel on horizontal axis. Contrast Orange, which exhibits low irradiance (260 kWh/yr) for the first panel and a slow decline up to 15 panels followed by a rapid decline, with Gray, which exhibits strong irradiance for the first 20 panels (340 kWh/yr) followed by a rapid decline.

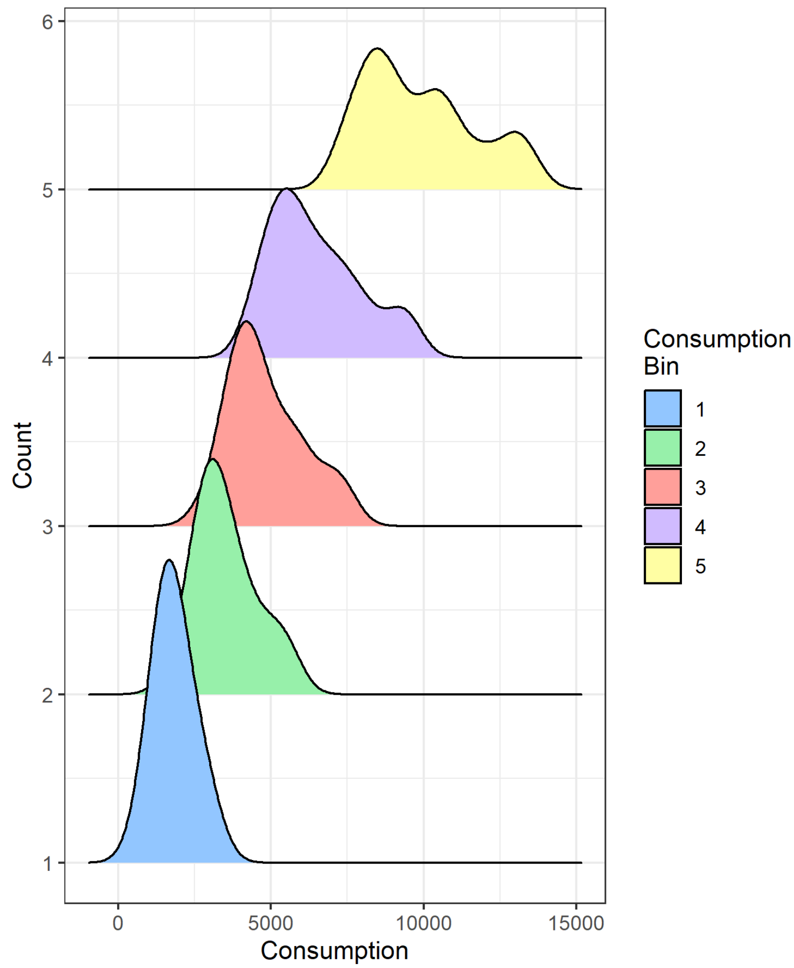

Figure 6: **Distribution of zip-level consumption bins** calculated from the full distribution of consumption by zip code. For each zip code, consumption is grouped into one of five bins (1 is lowest consumption, 5 is highest) and the mean consumption is calculated for each bin. Plot shows the distribution across zip codes of the five bin's mean consumption.

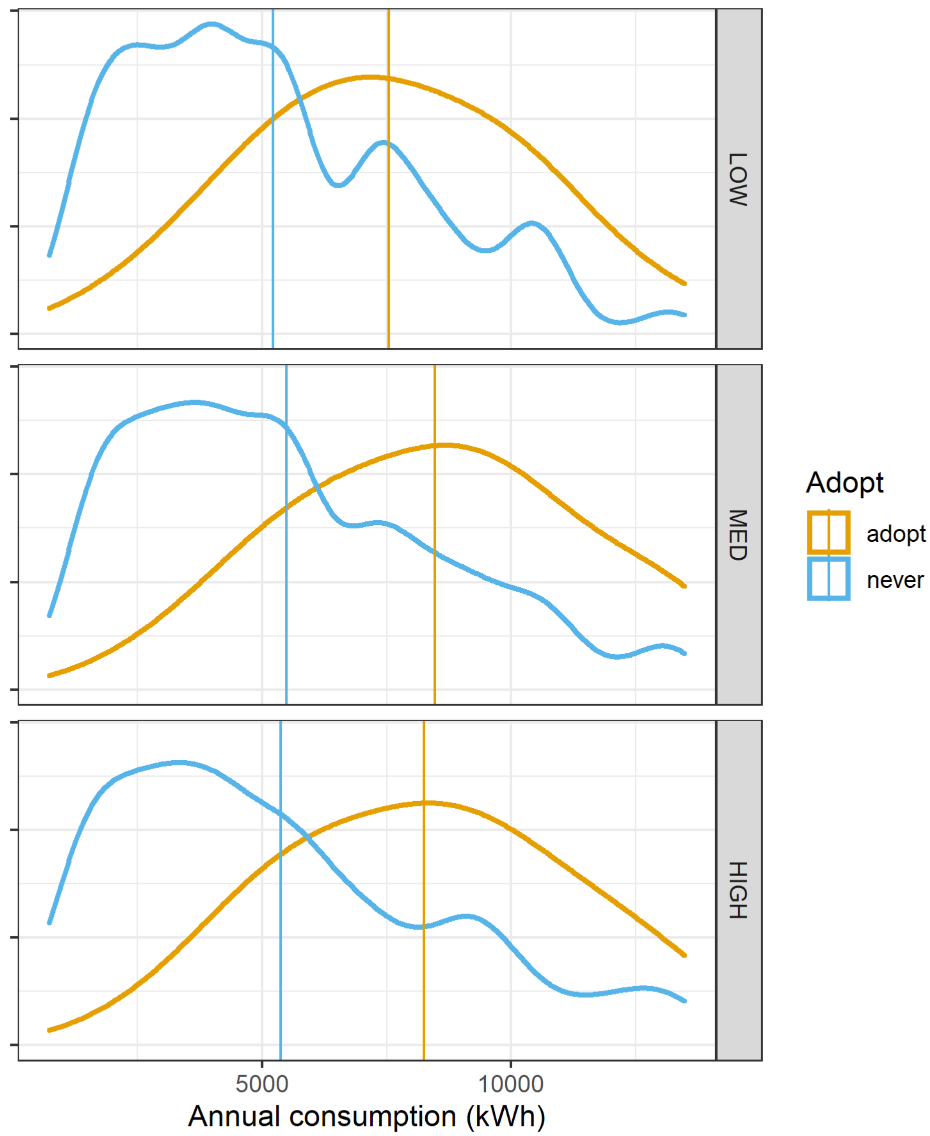

Figure 7: Density of consumption by adopter status and wealth. To calculate density of non-adopters, we assign equal weight to each of the five consumption bins for the household's zip code.

3.2.4 Solar Adoption

We assemble an installation-level dataset of solar adopters using a restricted-access version of the Lawrence Berkeley National Laboratories "Tracking the Sun" (TTS) database which contains address of installation in our study area, application date, installation date, system size (in watts), and total system cost exclusive of subsidies and tax credits. Our study window is exclusive of the California Solar Initiative (CSI) subsidy period, and we assume that all homeowners have sufficient tax liabilities to qualify for the 30% tax credit offered on solar during this period. We match by address to link adopters to households with a 96% success rate, and remove from the sample 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 households.

3.2.5 Cost of Solar Installation

We estimate fixed and variable (per-watt) costs of solar using TTS data for each boundary group and quarter in our sample. We assume that fixed costs will vary by boundary group, and that common variable costs per watt capacity will decline over time at a constant rate η to be estimated. The decline of panel costs 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 cost 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.

We decompose total reported costs into fixed costs, variable costs, and a common η, the per-period decrease in variable panel costs, using the following specification which we estimate by nonlinear least sqares (NLS):

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

Where *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 $e^{-.014t}$. A value of $\beta_T = -.01403$ results in an estimated quarterly $\eta = 0.986$. We use the estimates in table 2 to predict fixed and variable installation costs for adopters and non-adopters.

Table 2: **Cost Model Estimation**: Results from estimation of equation 1 using sample of all installations in study area during the study period and the previous year. Results show boundary group-specific fixed cost intercepts, per-watt costs in first quarter 2013, and rate of decline in per-watt costs, η, estimated as $\eta = 1 - \beta_T = .986$.

	(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

4 Model

4.1 Sizing

The decision to adopt solar depends upon a determination of the optimal system size conditional on adoption, and then a comparison of average electricity costs with and without solar adoption. The optimal size of the system is a function of system costs and upfront capacity rebates, the marginal cost of grid electricity, and system generation, which is a function of capacity and the effective solar irradiance of each portion of the optimal solar array. Effective solar irradiance is a function of the amount of sunlight that falls to the earth at the location of adoption. This irradiance varies considerably across the U.S. and around the world, and even within U.S. states, e.g., across zip codes. It is modeled from satellite imagery and is also a function of climate. The National Renewable Energy Laboratory models irradiance at the 10-square kilometer level. This irradiance, therefore, does not vary at the very local level. Effective irradiance, however, also accounts for the obstruction of some solar irradiance by surrounding structures and vegetation, as well as panel orientations and pitches that may fail to capture all irradiance due to rooftop characteristics. Effective irradiance, thus, admits 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.

Solar panel installation is characterized by economies of scale. This is true both for utility-scale and rooftop installations (Barbose et al. 2013). In both contexts, there are fixed costs associated with modeling the installation site to optimize size, orientation, and equipment, as well as obtaining permits and relevant regulatory approvals. These fixed costs cause the average cost of solar electricity to decline in system size, all else equal. Hence, utility-scale systems tend to be cheaper than rooftop systems, and the cost per watt of large rooftop systems is lower than the per capacity cost of small systems. However, because effective irradiance is non-increasing in system size and commonly decreasing in size, average solar electricity costs likely decrease over a range of rooftop capacity before increasing until rooftop surface areas is exhausted.

Let $TC(K)$ denote the total cost to a household of a solar installation of size K. It is comprised of a fixed cost, F and a cost per panel, V. The panel cost is reduced by available per-capacity subsidy, S. The total cost of the system net of rebates is reduced by a fraction I equal to the investment tax credit.[5] Thus,

$$TC(K) = (F + K \cdot (V - S))\,(1 - I)$$

Define $C = (V - S)(1 - I)$ as the constant marginal system cost (or cost per unit of capacity).

Let $q(K)$ be the annual electricity generated by a system of size K (and q^* is the annual electricity produced by a system of optimal size K^*). Then $q'(K)$ is marginal generation, i.e., the electricity produced by an incremental unit capacity. We assume $q'(K)$ is weakly decreasing in K because the first unit of solar capacity is installed on the highest solar irradiance surface of a rooftop, i.e., $q'(K) \geq 0, q''(K) \leq 0$. The cost per kWh of electricity generated by the marginal unit of capacity over its (25-year) lifetime, $c(K)$, is then equal to $(V - S)(1 - I)/25q' = C/25q'$. An interior solution to the sizing problem equates the present value of the levelized cost of electricity generated by the marginal unit capacity to the present value of the 25-year future stream of utility payments for the marginal unit of consumption from the grid.[6] Assuming annual discounting at a rate δ, the present value cost of the marginal unit of grid electricity consumption over the lifetime of the solar capacity is $\sum_{t=1}^{25} \frac{1}{(1+\delta)^t} p$, where p is the annual cost of the monthly

[5] This assumes federal income tax liability.

[6] We assume households take electricity consumption as given and seek the minimize the cost of that consumption.

marginal unit of electricity consumption. Thus, the optimal system size (in an interior solution to the first order condition) is implicitly defined by:

$$c(K) = \sum_{t=1}^{25} \frac{1}{(1+\delta)^{t-1}} p,$$

where $c(K)$ is increasing in K because q' is decreasing in K. Because q' is decreasing in K, for constant and increasing block rate prices, there will be a unique optimum. 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. For decreasing block prices, the opposite is true, and the interior optimum may not be unique. Optimal size is increasing in q', p, S, and I and decreasing in δ and V.

The optimal sizing of a system is a function of the NEM policy regime. Here we assume an NEM policy whereby rooftop system generation is compensated equivalently whether it is consumed in the household, thereby displacing grid imports, or whether it is exported to the grid, i.e., the NEM is equal to the retail rate. This assumption is consistent with the vast majority of NEM policies in effect in the U.S. Were exports not compensated at as great a rate as on-site consumption, or perhaps not compensated at all, then the optimal sizing decision would be different. In particular, optimal sizes would be smaller. Because most NEM policies restrict compensation for exports to annual or monthly quantities less than or equal to total consumption less on-site consumption of solar generation, households will not install solar capacity greater than that which is sufficient to fully offset electricity consumption.

The optimal sizing function is piece-wise 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:

$$p = \begin{cases} 0 & q_0 - q \leq 0 \\ p_0 & 0 < q_0 - q < \tau \\ p_1 & q_0 - q \geq \tau \end{cases} .$$

The piece-wise-defined solution to the optimal sizing problem for increasing block rates and a household consuming at the highest rate, is defined as:

$$K^* = \begin{cases} 0 & c(0) > p_1 \\ (q')^{-1}\left(\frac{C/25}{\sum_{t=1}^{25} \frac{1}{(1+\delta)^t} p_1}\right) & c(0) \leq p_1, c(q_0 - \tau) \geq p_1 \\ (q')^{-1}(q_0 - \tau) & p_0 \leq c(q_0 - \tau) < p_1 \\ (q')^{-1})\left(\frac{C/25}{\sum_{t=1}^{25} \frac{1}{(1+\delta)^t} p_0}\right) & c(q - \tau) < p_0, c(q_0) \geq p_0 \\ (q')^{-1}(q_0) & c(q_0) \leq p_0 \end{cases} .$$

The household will optimally install a system large enough to exactly offset all consumption if the levelized cost of electricity generation from the marginal unit capacity is less than or equal to the lowest electricity rate, p_0. It does not install any capacity if the levelized cost of electricity generated from the first unit capacity is greater than the highest grid electricity rate. And if levelized 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, $q_0 - \tau$. Figure 8 depicts these cases for given alternative q's that define c. Solar capacity K is increasing left to right, and grid consumption is increasing right to left.

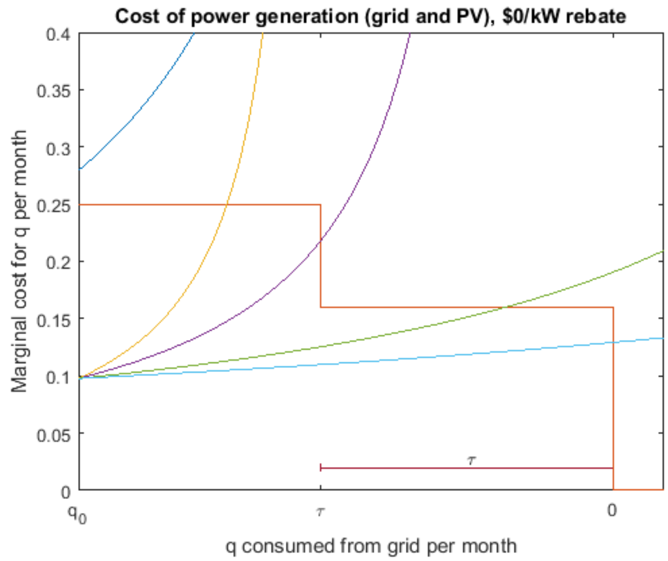

Figure 8: Optimal sizing of solar PV arrays is depicted as a function of alternative modeled q' functions, i.e., the electricity generation of marginal units of solar capacity. Depicted are the costs per kWh for alternative q's and a tariff with two tiers of volumetric charges. Grid consumption increases from right to left. Solar capacity increases left to right.

4.1.1 Sizing Model in PG&E Context

For the purpose of optimal sizing, we convert marginal DC generation to marginal cost per AC kilowatt-hour (kWh) by discounting the flow. This results in the upward-sloping solar price per kilowatt-hour shown in Figure 9, which shows the per-kWh price for three of the home profiles from Figure 5. The optimal installation size, depending on discount rate, is where the discounted marginal cost of solar electricity equals (or becomes higher than) the marginal cost of grid-provided electricity. Figure 10 (top) shows the same houses, but assumes consumption in the 4th bin for the zip code, shifting the dashed lines to the left. Lower consumption results in weakly smaller optimal installation sizes, even when the optimal size does not fully offset consumption. For some homes (e.g. Orange in Figure 10), the optimal installation may be zero panels, which occurs when the marginal cost of electricity generated by even the first panel exceeds the price of the first kWh of offset grid electricity.

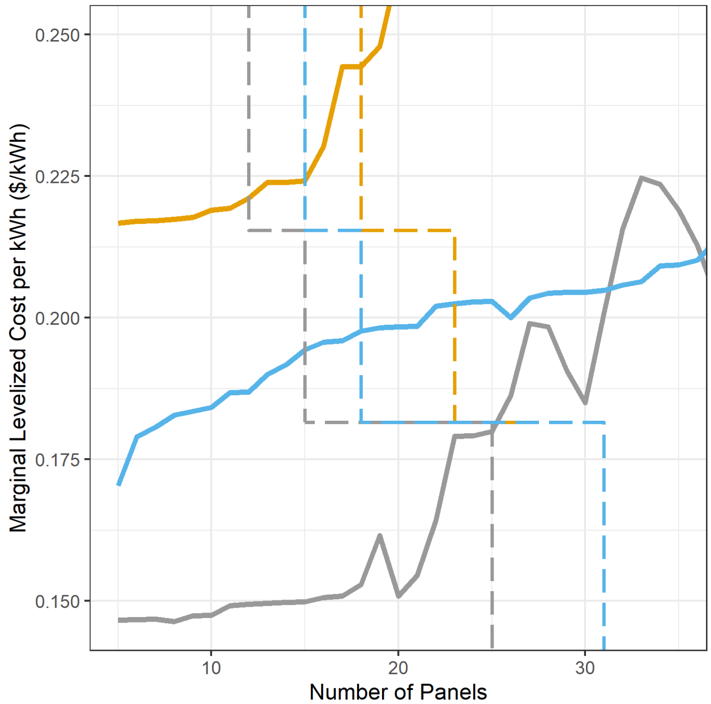

Figure 9: **Irradiance and optimal sizing** Figure shows the marginal per-kWh price of solar generation for a subset of homes from Figure 5 along with the marginal grid price (dashed line) for consumption in the 5th (largest) bin. Marginal grid price varies by climate zone. All homes initially generate solar electricity at a levelized cost below grid electricity. Gray reaches equality between grid and solar marginal cost at 25 panels corresponding to a full offset (Gray will, at optimum, install 25 panels and consume zero electricity from the grid per year). On the other hand, Orange reaches equality at 18 panels, approximately when remaining grid consumption is reduced to the second tier price of $0.215 per kWh. Orange, after an optimal installation, still purchases electricity from the grid, as does Light Blue.

The optimal installation size, K^*, and the corresponding optimal annual generation, q^*, are a function of consumption and irradiance profile of the house. Figure 10 illustrates how consumption and roof profile affect both the payoff of solar – the value of the offset grid electricity over the life of the panel – and the cost of solar. In Figure 9, both Orange and Light Blue are assumed to consume the same amount of electricity. Orange has low irradiance, and installs 18 panels at the optimal, which reduces Orange's grid consumption to τ_2, the level at which these households reach the second pricing tier (around $0.215/kWh). Light Blue also optimally installs 18 panels. However, Light Blue's 18 panels generate more electricity, offsetting grid consumption to the point that Light Blue consumes from the grid τ_1, the level at which these households reach the first pricing tier (around $0.18/kWh). Despite optimally installing the same number of panels at the same cost, Orange offsets less electricity, and Orange's flow benefits are much lower. Gray installs far more panels than Orange and Light Blue, facing a

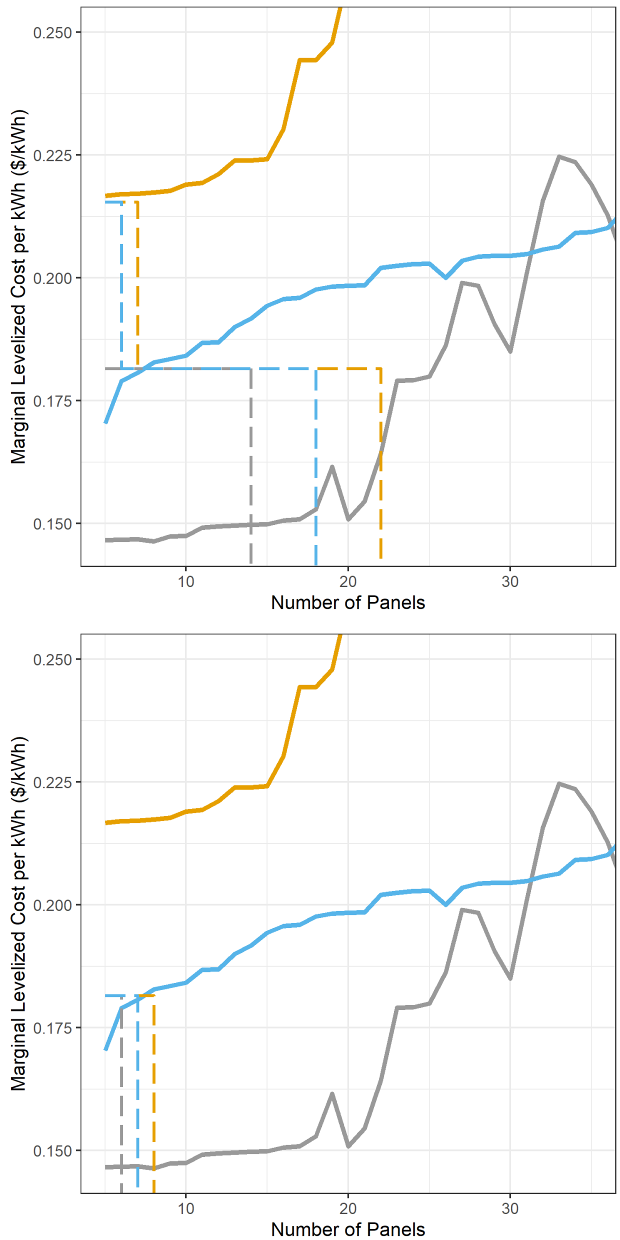

Figure 10: **Irradiance and optimal sizing in the 4th (top) and 2nd bin of consumption (bottom)**. (Top) the optimal installation is weakly decreasing in consumption. With lower consumption, marginal grid prices a lower due to increasing block pricing, the value of offset electricity steps down at smaller numbers of panels, and it reaches a full offset earlier as well. Note that Orange has no amount of generation where the marginal levelized cost per kWh is below the cost of grid electricity. For this consumption level, Orange's optimal installation size is 0. Gray still finds full offset to be optimal, but this occurs at 14 panels. (Bottom) Consumption in the 2nd bin results in small (Blue and Gray) or zero-sized optimal installations (Orange).

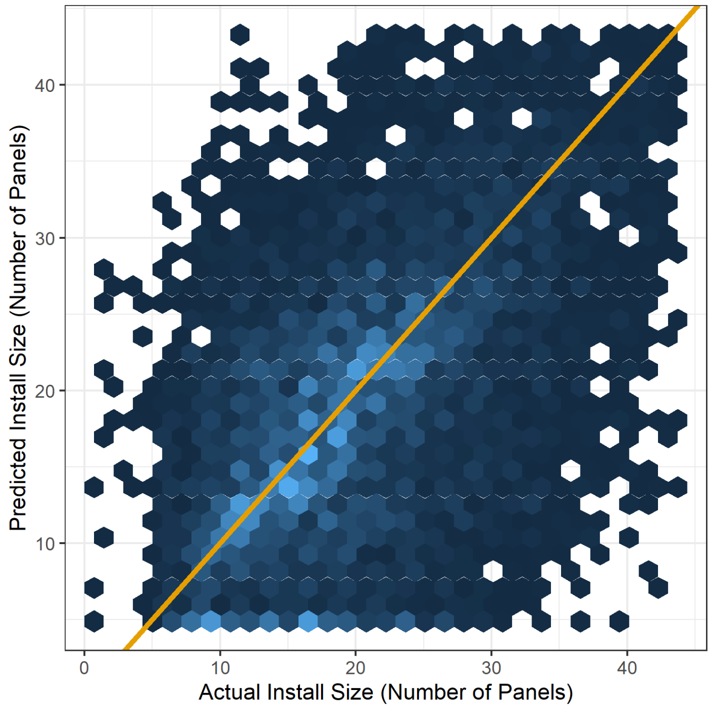

Figure 11: Density plot of Google Sunroof-method predicted (y-axis) and actual (x-axis) installed system capacity. The diagonal represents correct predictions of the optimal installation size.

much higher up-front cost, but also offsetting more electricity than Orange or Light Blue. Comparing Gray between Figures 9 and 10 clearly shows the variation owing to different consumption levels: Gray always fully offsets, but does so at 25, 14, and 6 panels for consumption in the 5th, 4th, and 2nd bin, respectively. Variation in the electricity rate structure across climate zones alter the optimal installation size (and thus benefit and cost) by compressing or extending the steps in the dashed lines in Figures 5 and 10, as is the case when California eliminated one of the four block pricing tiers. Changes in the rates (step heights) over time occur as well, which moves the steps along the y-axis (not shown).

The optimal sizing model can be compared to the observed installation sizes in the data as we observe the consumption of adopters. Figure 11 shows that the relationship largely holds. This is consistent with installers using similar tools (electricity bills and roof profiles) to size a system.

As a robustness check, we allow for rebound consumption, either through increasing the solar system size or through increased grid consumption, if the marginal rate of electricity is lower with an installation. Details of the implementation can be found in Appendix B.

4.2 Adoption Decision

Once the optimal size has been determined, consumers decide whether or not to install solar. We estimate a dynamic discrete choice model with some similarities to De Groote and Verboven (2019) and Bollinger and Gillingham (2018). We depart from these two papers in exploiting variation in household-level characteristics. We treat the adoption of solar as an exit action in formulating our discrete choice problem. We assume that electricity rates are relatively stable and known, and thus the importance of dynamics enters through changing solar PV prices net of rebates that can result from changing rebates over time. We specify the utility of adopting solar with a random utility expression such that:

$$v_1(q_0, q^*) = u_1(q_0, q^*) = \delta_1 + \sigma\epsilon_1, \tag{2}$$

where δ_1 is utility from adoption of solar, and ϵ_1 is a stochastic term (assumed type 1 extreme value) and σ a scaling parameter, since we normalize the scale through our specification of δ_1.

The utility from the adoption of a solar installation with a lifespan of T, relative to not adopting, is given by:

$$\delta_1 = \int_{q_0-q^*}^{q_0} \sum_{t=1}^{T} \frac{1}{(1+\rho)^{t-1}} p_t(x)dx - TC(K^*) + X\beta \tag{3}$$

The integrand in 3 reflects the present value of future costs of grid electricity avoided given solar generation of q^*. $TC(K^*)$ is the total cost of the solar installation of optimal size K^*, $X\beta$ is the heterogeneous utility from electricity consumption and ancillary utility derived from solar adoption. It is defined by the per unit price of grid electricity, $p(x)$, which potentially varies (discretely) in x, and by magnitude of grid electricity consumed, which is the difference in total electricity consumption per period, q_0 and the solar power generated by the optimally sized solar PV system q^*.

We omit subscripts for notational convenience and assume the determination of optimal panel size is a static decision in which the household chooses a solar array that minimizes the cost of generating the total quantity of electricity the household consumes, which depends upon electricity consumption and price, as well as rooftop irradiance.

Let us assume that electricity prices evolve according to $p'(x) = (1+\zeta)p(x)$ and panels depreciate each year by λ, such that $q' = (1-\lambda)q$. The expression for the economic value of adoption over the life of the solar array can be simplified to:

$$\delta_1 = \theta q^* \bar{p} - TC(K^*) + X\beta, \tag{4}$$

in which we define:

$$\theta = \sum_{t=1}^{T} ((1+\zeta)(1-\lambda)\rho)^{(t-1)} \tag{5}$$

$\theta q^* \bar{p}$ captures the utility of electricity consumption over the installation's life and $\bar{p}$ is the current average cost of grid electricity avoided by adoption.[7] We also need to make some assumption of what consumers expect to do after the lifetime of their solar array. We treat the dynamic problem as a fixed-time problem, as in De Groote and Verboven (2019). The value for installing solar is given by $V_1 = \delta_1 + \sigma\epsilon_1$.

When not adopting solar, the consumer pays the full cost of grid electricity in the current period (reflected in the avoided cost expression for δ_1) but gains the continuation value in the next period. Upon examination, the decline in solar PV costs appear to be in the variable costs such that $TC(K^*) = FC + VC(K^*)$ in which $VC(K^*)' = \eta VC(K^*)$. We assume type I extreme value shocks for ϵ_0 and ϵ_1. We can write an 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 (2018):

$$\begin{aligned} \delta_0 &= \rho\left(\int V_1' - \ln(Pr_1')dF(TC'|TC) + \gamma\right) \\ &= \rho(1+\zeta)\theta q^*\bar{p} - \rho FC - \rho\eta VC(K^*) + \rho X\beta - \sigma\rho\ln(Pr') + \sigma\rho\gamma \end{aligned} \tag{6}$$

in which γ is Euler's constant, V_1' is the next period adoption utility, and Pr_1' is the adoption probability next period, both of which are a function of the expected cost of the installation (net of any rebates) in the next period, TC'.

Thus, the value of non-adoption, $V_0 = \delta_0 + \epsilon_0$, is simply a function of the expected value of adopting, given by V_1, in both the current period and next period, as well as the probability of adopting in the next period.

[7] As 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 can calculate the difference in our expressions for δ_1 and δ_0 in equations (4) and (6) which yields the difference in the value of adopting versus not adopting:

$$\begin{aligned}\delta_1 - \delta_0 &= (1-\rho(1+\zeta))\theta q^* \bar{p} - (1-\rho)FC - (1-\rho\eta)VC \\ &+ (1-\rho)X\beta + \sigma\rho\left(\log(Pr') - \gamma\right) \end{aligned} \tag{7}$$

We can estimate the transition of the installation costs η, the transition of electricity prices ζ, and the probability of adoption in a first stage.

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

$$\delta_1^l = \theta q^* \bar{p} - \theta^{ppa} q^* p^{ppa} + X\beta, \tag{8}$$

in which we define:

$$\theta^{ppa} = \sum_{t=1}^{T} ((1+\zeta^{ppa})(1-\lambda)\rho)^{(t-1)} \tag{9}$$

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 .04 based on industry standards.

Now, the price the installer should charge for the solar electricity should reflect the levelized cost of installing the system:

$$p^{ppa} = \frac{TC(K^*)}{\theta^I q^*} + transfer \tag{10}$$

in which the θ^I reflects the discounted sum of benefits per kWh using the installer's discount rate:

$$\theta^I = \sum_{t=1}^{T} \left((1+\zeta^{ppa})(1-\lambda)\rho^I\right)^{(t-1)} \tag{11}$$

plus some extra transfer to the installer for fronting the installation costs. We might assume this transfer to be the same for all leases, but it is also likely it would be the same per dollar spent on the installation, i.e. it would scale by the system cost. It is also possible it may take the form of a per-kWh markup. Let us write 10 as:

$$p^{ppa} = TC(K^*)(1 + \kappa^{TC})\frac{1}{\theta^I}\frac{1}{q^*} + \kappa^p \tag{12}$$

κ^{TC} captures the profit margin based on the per dollar cost of providing the capital for the installation, and κ^p captures a per-kWh markup. The first multiplicative factor in 12 applies the markup to $TC(K^*)$, then divides by θ^I, which amortizes the marked-up cost over 25 years at the installers discount rate (just as θ converts a flow of benefits to a present value). Finally, the amortized cost is divided by the per-period generation q^*, plus a per-kWh markup.

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

$$\delta_1^l = \theta q^* \bar{p} - \theta^{ppa} q^* \kappa^p - \frac{\theta^{ppa}}{\theta^I}(1 + \kappa^{TC})TC(K^*) + X\beta, \tag{13}$$

The difference in the expression for δ_1^l and δ_0^l for consumers who would lease is:

$$\begin{aligned} \delta_1^l - \delta_0^l \;&=\; (1 - \rho(1 + \zeta))\,(\theta q^* \bar{p} - \theta^{ppa} q^* \kappa^p) \\ &-\; \frac{\theta^{ppa}}{\theta^I}(1 + \kappa^{TC})\Big((1 - \rho)FC + (1 - \rho\eta)VC\Big) \\ &+\; (1 - \rho)X\beta + \sigma\rho(\log(Pr^{l'}) - \gamma) + \sigma\epsilon \end{aligned} \tag{14}$$

Note that this expression is very similar to that for purchases, since the costs of the panels are reflected in the PPA price. The only difference is the $\frac{\theta^{ppa}}{\theta^I}(1 + \kappa)$ multiplier in front of the terms that capture the cost of the solar panels. Leasing has the effect of amortizing the cost of installing over the life of the panels. The term before the panel cost in 7 is less than 1 for households whose discount rates are sufficiently higher than the installer's discount rates to overcome the markup κ^{TC}. We assume a rate of return on investment (κ^{TC}) markup captures the full resolution of p^{PPA} and assume κ^P, a per-kWh markup in 15, is equal to zero.

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

$$Pr^p = \Lambda\left(\frac{1}{\sigma}\left(\bar{V}_1 - \bar{V}_0\right)\right) \tag{15}$$

in which $\bar{V}_1$ and $\bar{V}_0$ are the deterministic portions of the value of adopting shown in equation 7 and Λ is the standard Logit cdf. Similarly,

$$Pr^l = \Lambda\left(\frac{1}{\sigma}\left(\bar{V}_1^l - \bar{V}_0^l\right)\right) \tag{16}$$

is the probability of leasing, conditional on being in the lease market.

5 Identification and Estimation

5.1 Discount Rate Identification

Before we discuss estimation, it is important to consider the key identifying assumptions that allow us to estimate the discount rate. We assume that home irradiance profiles are exogenous to the utility of adopting solar, conditional on household characteristics, including household electricity consumption, and a set of geographic fixed effects, including climate zone boundary fixed effects. We secondly assume that homes on one side of a climate zone are similar to 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 responses to $q^*\bar{p}$.

The variation in irradiance and price tier cutoffs due to the different climate zones provide variation in the long term cost of offset grid electricity. Both sources of variation are used in order to 1) assess the relative valuation of upfront costs versus long-term benefits, and 2) to scale the value of the offset grid electricity in dollar terms (discrete choice models only identify parameters up to a scale transformation).

The main concerns that would violate this first identifying assumption is 1) endogenous sorting of home owners who intentionally purchase homes that are better suited for solar, and 2) manipulation of the local environment to improve the suitability of one's roof, e.g. cutting down or trimming a tree(s). With regards to sorting, 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 at this point of time; however, to help address this concern, we run a robustness check focusing only on households who had not moved in the last five years.

Regarding tree cutting/trimming or other changes to the local environment, this would lead us to ignore additional fixed costs of installing solar for those that did adopt after altering the environment and the ability of non-adopters to incur an additional upfront cost in order to increase their irradiance, which we do not observe (assuming the change to the environment only happens if the person decides to install). The resulting selection concern lies in the fact that households with smaller discount rates would be more likely to incur the same fixed cost than those with higher discount rates, all else equal.

Given that we account for actual irradiance, this increases the likelihood that we would see lower discount rate households with higher irradiance, since they value the increase in irradiance more. Given our primary interest is the difference in discount rates across wealth bins, our inclusion of wealth fixed effects helps address this selection issue to some degree. This concern about alterations to the local environment are also muted due to the lack of tall tress in residential neighborhoods in California and due to small lot sizes, such that most of the shade on one's roof is from trees on neighboring lots rather than one's own property. As a final robustness check, we restrict the sample to lots than are less than one quarter acre.

That said, as an additional robustness check, we include irradiance in the intercept as well, to control more fully for such selection effects, although this specification relies more on the functional form assumptions in the structural model in order to separate the effect of irradiance in the intercept from its effect via the stream of benefits from installing (namely the the interaction between irradiance and grid electricity prices in the future stream of benefits, $q^*\bar{p}$).

Regarding the use of climate borders, there 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.

The discount rate enters the value of adopting for purchasers and lessors in equations (7) and (14) in two places, via the θ and also in front of the Pr' term. One the advantages of our approach relative to papers that use temporal shocks to future values via policy changes, such as De Groote and Verboven (2019), is that we are not as dependent on the variation from the estimated Pr' term. We deliberately chose a period of time in which Pr' will not experience large changes over time in order to focus estimation more on the variation in q^* and $\bar{p}$; there will be substantial variation in Pr' across households due to these differences in q^* and $\bar{p}$.

Variation in q^* and $\bar{p}$ allow us to estimate the θ – but that is all. We operational the differences in θ across wealth through differences in the implied discount rate. But this is 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 may 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 the expectation 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 (Qiu et al., 2017), and since we would think that the buyer of the same home is likely to have similar demographics and thus a similar discount rate, we prefer to treat T as 25 years for all households and interpret the differences in θ as differences in the implied discount rate.

5.2 Model Free Evidence

The structural model in Section 4 formalizes the use of the variation in q^* from variation in rooftop irradiance and variation in $\bar{p}$ from the climate zone borders, but here we provide model-free evidence of this relationship. Figure 12 shows the share of observed adopters in the sample by quantiles of irradiance. We measure irradiance in three ways - the generation of the first panel, the rate of decline for each additional panel, and finally the total generation from a 15-panel array which can be thought of as a reasonable composite of the first two. Figure 12 shows the two main relationships. First, adopting shares increase over all income levels when irradiance increases. Second, the rate of increase is higher for medium- and high-wealth households relative to the Low wealth households. This indicates 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, then low-wealth households put less value on payoffs that occur in the future relative to the present.

Households with higher irradiance have either higher payoffs from adopting solar due to larger optimal size installations offsetting higher levels of consumption, *or* face lower total up-front cost due to smaller sized installations. To isolate the effect of $q^*\bar{p}$ on adoption by wealth, we may take a cross-sectional approach. In Figure 13, we restrict

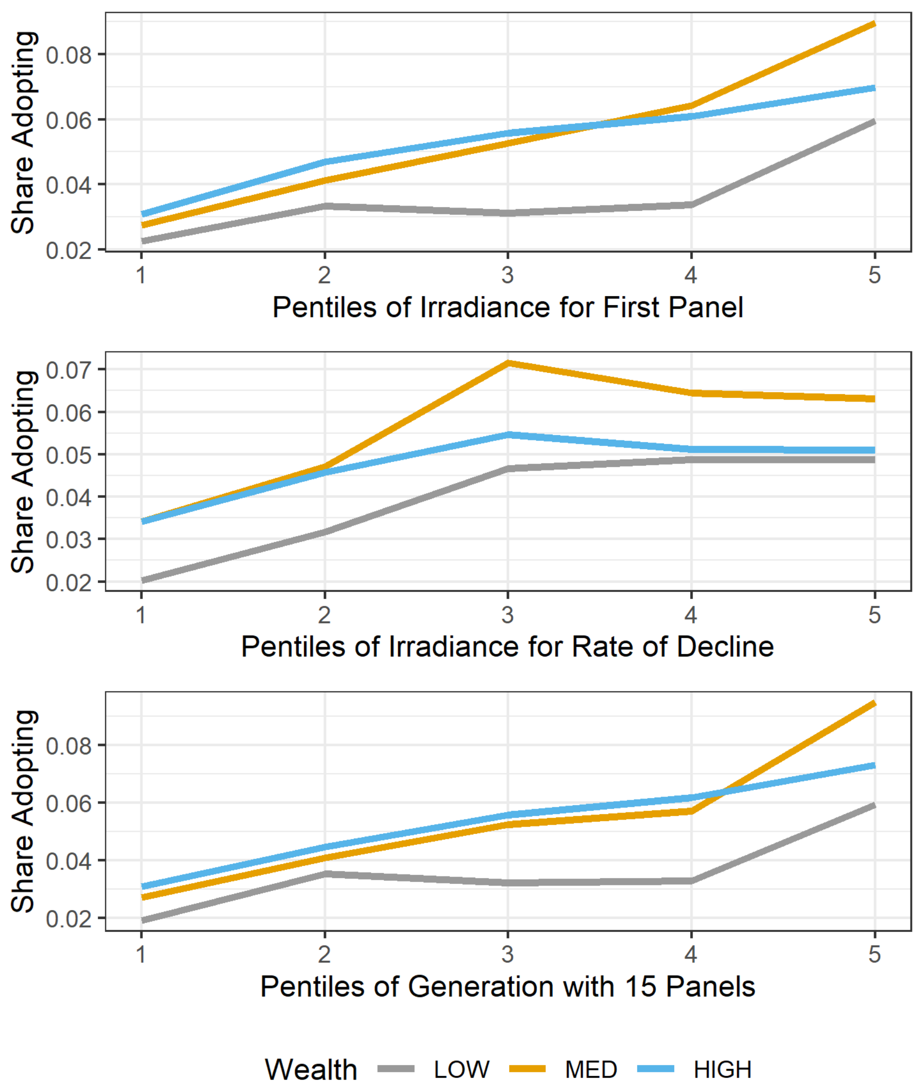

Figure 12: Observed share adopting over quantiles of measures of irradiance by wealth. (Top) shows the change in observed share adopting as first panel irradiance increases. (Middle) shows the change in observed share adopting as roof profile rate of decline decreases (higher generation read left-to-right).(Bottom) 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.

a sample to only those households with an optimal installation cost within a window around the mean total cost in the data. With the cost term fixed, we examine the cross-sectional variation in terciles of $q^*\bar{p}$, the flow payoff of installing, and the share observed to adopt. Variation in $q^*\bar{p}$ is the result of differences in rooftop irradiance, electricity rates, and consumption. Figure 13 shows two results. First, conditional on a fixed total cost, higher values of $q^*\bar{p}$ result in higher shares of adoption in the data. Second, high-wealth and medium-wealth households respond more positively to increases in $q^*\bar{p}$ than do low-wealth households. A more positive relationship between $q^*\bar{p}$ and share adopting indicates higher valuation of a fixed flow, which indicates a lower discount rate.

5.3 Estimation

5.3.1 Unobserved heterogeneity

Estimation of the household-level adoption model can be done via maximum likelihood estimation. In the infeasible case where purchase/lease type $e \in \{\text{lease, purchase}\}$ and consumption bin $b \in \{1, ..., 5\}$ is observed, each household's contribution to the likelihood is written as:

$$\mathbb{L}_{ibe} = \prod_t [Pr^e_{ibt}]^{y_{it}} [1 - Pr^e_{ibt}]^{(1-y_{it})} \tag{17}$$

where Pr^e_{ibt} 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. We use the method of Arcidiacono and Miller (2011), treating the combination of consumption bin b and type e as permanent, unobserved heterogeneity. Each non-adopter household is one of ten possible consumption $\times$ type combinations $\{1, ..., 5\} \times \{\text{leaser, purchaser}\}$. 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:

$$\mathbb{L} = \prod_i \sum_b \sum_e w_{ibe} \prod_t [Pr^e_{ibt}]^{y_{it}} [1 - Pr^e_{ibt}]^{(1-y_{it})} \tag{18}$$

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

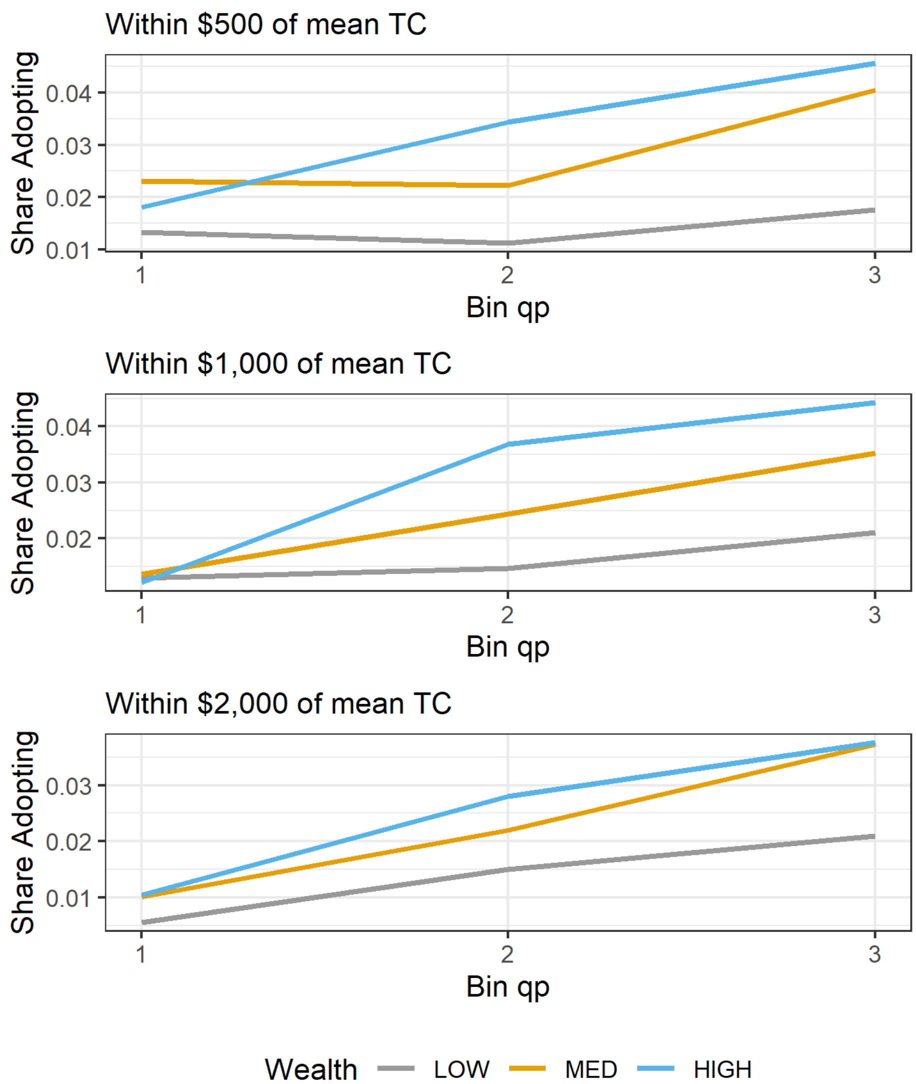

Figure 13: **Adoption rates by wealth holding total cost fixed.** Each panel shows the adoption rate across wealth bins for flow payoffs in each of three terciles along the x-axis, holding the system total cost fixed within a band around the mean. Holding up-front total cost fixed, variation in the flow payoff $q^*\bar{p}$ (labeled as qp) results from electricity rates and optimal size differences. In nearly all cases, high- and medium-wealth households adopt at a higher rate (orange and blue are above gray). As the flow payoff increases, adoption rates rise, but the rate of increase is largest for high- and medium-wealth households. This is consistent with variation in discount rates where high- and medium-wealth households have lower discount rates relative to low-wealth households. This illustrates the source of identification of discount rates by wealth.

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

$$\begin{aligned} \textstyle\sum_{e'=1}^{2} w_{ie'} &= 1 \\ \textstyle\sum_{b'=1}^{5} w_{ib'} &= 1 \\ \textstyle\sum_{i \in z} w_{ib} &= \tfrac{N_z}{5} \end{aligned} \tag{19}$$

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 19 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 quntiles). This guarantees that the moments of the consumption distribution match the empirical distribution.

The constraint in 19 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 a randomly selected bin, guaranteeing that $b^{(r)}$, the r^{th} allocation, satisfies the constraint in 19 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 $L_{ibe} = \Pi_t L_{ibet}$
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, $L_r = \Pi_i L_{ib^{(r)}}$
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-likelihod $L = \sum_z log(L_z)$

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 19 by definition.

5.3.2 Conditional Choice Probabilities

The final component of 18 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[8] to estimate the probability of adopting for household h at time t. 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 $Pr^{e'}_{ib}$ is updated in a third step, following the update of the weights. The flexible logit is specified using all interactions of the variables in X, along with time fixed effects and boundary zone fixed effects, as are used in the structural model. 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.

5.3.3 Estimation transformations

For estimation, σ is estimated as e^{σ} to preserve positive variance. The parameters of ρ are estimated with a Normal cdf transformation $\rho_i = \Phi\left(\rho + \alpha_{low} 1(\text{wealth}_i\text{=low}) + \alpha_{med} 1(\text{wealth}_i\text{=med})\right)$

6 Results

6.1 Structural Parameters

[8] A bin estimator would be feasible, but components of 7 and 15 are continuous

Table 3: Structural parameter results

Param. Grp	Parameter	Estimate	se	t	pval
σ	σ	1.790	0.004	449.408	0.000***
ρ	ρ_{high}	1.966	0.097	20.248	0.000***
	α_{med}	0.008	0.278	0.029	0.977
	α_{low}	-0.262	0.100	-2.615	0.009**
β	Wealth: lowest 1/3rd	-107.118	3.000	-35.706	0.000***
	Wealth: middle 1/3rd	-8.092	1.333	-6.072	0.000***
	β_0	87.276	1.199	72.771	0.000***
	Voter Affiliation: D	0.868	2.340	0.371	0.711
	Length of residence	-0.104	2.321	-0.045	0.964
	Child	6.851	2.560	2.676	0.007**
	Stories	-34.287	1.829	-18.750	0.000***
	Sqft (1,000's)	39.516	9.245	4.274	0.000***
	Sqft sq.	-2.727	40.572	-0.067	0.947
	Lease x Wealth: β_0	-102.320	17.887	-5.720	0.000***
	Lease x Wealth: lowest 1/3rd	77.075	6.701	11.502	0.000***
	Lease x Wealth: middle 1/3rd	33.852	15.704	2.156	0.031*
γ_{area}	γ_B	8.319	16.615	0.501	0.616
	γ_C	10.156	3.622	2.804	0.005**
	γ_D	-6.763	31.036	-0.218	0.827
$\phi_{consumption}$	ϕ_{bin1}	-4.399	2.573	-1.710	0.087.
	ϕ_{bin2}	-29.351	38.037	-0.772	0.440
	ϕ_{bin3}	-14.147	13.781	-1.027	0.304
	ϕ_{bin4}	-11.918	8.922	-1.336	0.181
$\tau_{time \times wealth}$	τ_{2014Q2}	39.972	8.818	4.533	0.000***
	τ_{2014Q3}	36.251	8.455	4.287	0.000***
	τ_{2014Q4}	-8.211	59.269	-0.139	0.889
	τ_{2015Q1}	3.192	15.194	0.210	0.834
	τ_{2015Q2}	-1.014	54.767	-0.019	0.985
	τ_{2015Q3}	-30.266	14.920	-2.029	0.042*
	τ_{2015Q4}	75.264	3.456	21.775	0.000***
	τ_{2016Q1}	51.257	6.557	7.817	0.000***
	τ_{2016Q2}	7.780	5.793	1.343	0.179
	$\tau_{2014Q2L}$	-11.792	7.247	-1.627	0.104
	$\tau_{2014Q3L}$	-14.773	5.009	-2.949	0.003**
	$\tau_{2014Q4L}$	40.047	30.811	1.300	0.194
	$\tau_{2015Q1L}$	-2.167	7.425	-0.292	0.770
	$\tau_{2015Q2L}$	30.766	15.727	1.956	0.050.
	$\tau_{2015Q3L}$	82.189	9.573	8.586	0.000***
	$\tau_{2015Q4L}$	-23.950	17.712	-1.352	0.176
	$\tau_{2016Q1L}$	-7.066	11.193	-0.631	0.528
	$\tau_{2016Q2L}$	-26.609	1.693	-15.715	0.000***
	$\tau_{2014Q2M}$	-14.933	3.486	-4.284	0.000***
	$\tau_{2014Q3M}$	-4.499	2.128	-2.114	0.034*
	$\tau_{2014Q4M}$	13.516	13.831	0.977	0.329
	$\tau_{2015Q1M}$	11.021	2.559	4.306	0.000***
	$\tau_{2015Q2M}$	16.979	10.642	1.596	0.110
	$\tau_{2015Q3M}$	71.472	9.655	7.403	0.000***
	$\tau_{2015Q4M}$	-29.040	6.212	-4.675	0.000***
	$\tau_{2016Q1M}$	-37.036	7.463	-4.963	0.000***
	$\tau_{2016Q2M}$	-30.672	6.534	-4.694	0.000***

[1] Robust std. errors from Arcidiacono and Miller (2011)

The estimated parameters are as expected. We find negative effects for low and medium wealth in the intercept, relative to high wealth (omitted), while intercept shifts for leasers show large negative values for high-wealth (Lease x Wealth: β_0) and positive shifts for leasing for medium and low wealth households. The parameter on square footage is increasing with a negative quadratic term. The positive sign for voter affiliation indicates Democratic or Green party registered households derive more utility from adopting solar, though the difference is not statistically distinguishable from zero. 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. Fixed effects 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.

The parameters of interest are ρ, the discount rate for high-wealth households, as well as α_{low} and α_{med}, the shifts for low- and medium-wealth households. Before transforming to an annual discount rate[9], the sign and significance indicates that medium wealth households have a lower discount rate, though the difference is statistically insignificant. α_{low} indicates a higher discount rate for low-wealth households, and is statistically significant.

6.2 Discount Rates

Transforming the results in Table 3 results in annual implicit discount rates of:

$$\begin{aligned} \delta_{high} &= 10.5\% \\ \delta_{med} &= 10.3\% \\ \delta_{low} &= 19.8\% \end{aligned}$$

Parameter estimates can be used to calculate θ_i using Equation 5. θ_i converts a \$1 annual flow of electricity costs avoided by installing solar into a present value, taking into account panel decline and expected electricity price increases. The ratio of θ for low-wealth households to high- or medium-wealth households quantifies the value of the flow subsidy between low- and high-/med-wealth households.

[9] $\Phi(\rho_i)^{-4} - 1$ as the time step is quarterly

Since θ_i is a function of grid electricity rate increases (ζ) and a common depreciation rate (λ), we take the weighted average of θ_i over each of the wealth bins. Weights are the probability of being in each consumption bin and type[10] w_{ibe}. We take the weighted average θ for high-wealth households, which is 50.6. The weighted mean θ for low-wealth households is 27.6, a factor of 1.8. Therefore, we find that high-wealth households, on average, value a flow of net metering benefits 1.8 times higher than low-wealth households value the exact same flow.

We calculate an equivalent $\theta_{4\%}$, which converts the flow of net metering benefits to present value using a discount rate of 4%. This reflects the approximate cost of borrowing for a government entity. At 4%, the value of $\theta_{4\%}$ is 95.22. The average θ across all wealth bins is \$42.64. That is, the present value to a government entity of providing a flow of benefits equivalent to net metering is about $\frac{95.22}{42.64} = 2.23$ times the valuation of the average household. At an average $q^*\bar{p}$ per year of \$870 (or \$217.38 per quarter period), the present value of the flow to average household is \$9,268, while the same figure for a government entity using $\theta_{4\%}$, the value is \$20,703. For scale, the average after-tax-credit cost of a system is \$9,268. The value of the benefits to the government exceeds the present value of the benefits to the household by \$11,434 for the average installation. Alternatively, one could propose a net metering policy where the flow benefits are cut in half, reducing the present value of the flow to the average household by \$4,297.50, but up-front incentives are increased by that amount, reducing the installation cost by around 1/3. An average household would be indifferent to adoption before and after this change.

Table 4: Average discount rates and implied valuation for flow benefits

Avg. Discount Rate	$\bar{\theta}$	$\bar{\theta}_{4\%}$	ratio
13.67%	42.64	95.22	2.23

[a] $\theta_{4\%}$ is value to government entity discounting at 4%

Table 5: Valuation of average flow relative to up-front total cost, full sample and adopters-only

Adopter	Average TC	Average $q^*\bar{p}$	$\bar{\bar{\theta}}$	$\bar{\theta}q^*\bar{p}$	$\bar{\theta}_{4\%}q^*\bar{p}$
All	\$9,957.93	\$217.38	42.64	\$9,268.21	\$20,702.55
Adopters Only	\$13,658.51	\$329.55	42.71	\$14,074.74	\$29,831.90

[10] θ_i does not vary with type, but ζ does vary by consumption bin and zip code

Table 6: Valuation of flow benefits by wealth bins

Wealth	Annual Discount Rate	$\bar{\theta}$	ratio
High	10.5%	50.6	1.8
Med	10.3%	51.6	1.9
Low	19.8%	27.6	1.0

7 Counterfactual Analyses

7.1 Counterfactual Overview

We explore the outcomes of two counterfactual policies. First, in order to assess the price elasticity of demand, we evaluate the effect of a 1% reduction in the total cost of installations. Second, we approximate the proposed "Net Metering 3.0" updates to California's Net Metering policy, as discussed in Section 2. We operationalize this scenario using the estimated avoided cost payout for a typical solar generation profile established in the CPUC Avoided Cost Calculator report from E3 consulting (E3, 2022), which estimates a levelized cost of energy (LCOE) of \$.062/kWh. This figure represents the levelized value of solar generation according to a typical solar generation and consumption profile. Our third scenario combines the "Net Metering 3.0" proposal combined with alternative up-front subsidies in way that results in approximately the same total number of installations under the counterfactual scenario, but results in a different distribution of adopters.

All counterfactual scenarios report the total number of 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. We construct counterfactuals such that the counterfactual price and NEM policy changes are expected to remain in place for the future. The methods presented in the previous section allow us to adjust future adoption probabilities to reflect the counterfactual, leveraging the assumption of stationarity following the end of the study period.

7.2 Counterfactual Methodology

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 attempt to use model estimates to update both $\delta_1 - \delta_0$ and $\log(Pr')$ as well.

Our strategy for calculating $\log(Pr'^{+})$ 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 rely on the flexible logit estimate of $\log(Pr^{'})$ and the model-implied *differences* in flow payoff to calculate future values of counterfactuals $\log(Pr'^{+})$. Our strategy is to leverage the stationarity of the environment to re-write future changes in the probability of adopting as an infinite series of (known) flow utility payoffs. The details can be found in Appendix C.

7.3 Counterfactual 1: 1% Reduction in Panel Cost

This counterfactual scenario reports the total predicted adoptions under a 1% reduction in the panel cost, in all time periods (consumers also expect costs in the future to also be less expensive). The purpose is straightforward – to calculate the model-predicted elasticity of demand. Table 7 shows the ratio of counterfactual to baseline adoptions under scenario 1, a 1% reduction in total costs.

Table 7: Scenario 1: 1% decrease in up-front total cost; ratio of counterfactual to baseline adoption

		1% Decrease in Up-Front Total Cost		
Wealth	Rate	Counterfactual Installations	Counterfactual Purchases	Counterfactual Leases
HIGH	10.5%	1.025	1.027	1.020
MED	10.3%	1.020	1.024	1.017
LOW	19.8%	1.010	1.015	1.006
All	–	1.019	1.023	1.014

Under this scenario, high-wealth households increase adoption by 2.5%, while medium-wealth households increase adoption by 2.0% and low-wealth households increase adoption by only 1.0%. The average response of 1.9% is in line with previous reduced form estimates of demand elasticity, especially given this is the effect of a long-lasting price reduction (rather than a single, one-time discount).

7.4 Counterfactual 2: $.0625 per kWh NEM

In the secion, we evaluate the proposed Net Metering 3.0 revisions approved by the CPUC in December 2022. Our second counterfactual examines the outcome under a revision only to the NEM rate as determined by the 2022 Avoided Cost Calculator (E3, 2022), which serves as the underlying input for the value of rooftop solar generation for the revisions. The levelized cost is calculated as the quantity-weighted average value of rooftop solar net generation. The proposed NEM revisions split the benefit of solar generation into two parts: when instantaneous consumption is less than generation, billed consumption is offset. Compensation for offset consumption takes the same form as the existing NEM incentive, and reduces the billed quantity. When consumption is less than generation, exports to the grid receive the $0.0625/kWh compensation. We assume a range of potential "splits" between solar generation that offsets consumption and solar generation that is exported and calculate results for $\{0, 30, 50, 70, 100\}$ percent exported. We further assume that optimal installation size remains fixed under the counterfactual, and apply the counterfactual export-consumption split to the baseline offset consumption. Under this assumption, a 0% export implies that 100% is used to offset billed consumption, which results in zero change under the counterfactual. For more information on the proposed NEM policy and the $.0625/kWh, see Appendix A of the proposed decision.

Table 8: Scenario 2: Reformed NEM rate; percent counterfactual adoptions relative to baseline

		Reformed NEM rate; % Exported to Grid at $.0625				
Wealth	Rate	0	30	50	70	100
HIGH	10.5%	1	0.596	0.435	0.326	0.222
MED	10.3%	1	0.634	0.476	0.364	0.252
LOW	19.8%	1	0.839	0.749	0.670	0.572
All	-	1	0.677	0.537	0.435	0.328

Table 8 shows the ratio of counterfactual to baseline adoptions in the study period and sample over the range of export-consumption splits. We focus on Column 3, the 50-50 split, where 50% of solar generation offsetting grid consumption, and 50% exported at the reformed NEM rate. High- and medium-wealth households with discount rates of 10.5% and 10.3%, respectively, show the largest drop in counterfactual adoptions by 57% and 53%. Low-wealth households, who are less attuned to the flow of benefits, drop by only 25%, though from a lower baseline.

7.5 Counterfactual 3: \$.0625 per kWh NEM with revenue recycling

Reforming NEM policy reduces the flow payoff to installing solar. This reduction in the flow payoff could be converted to other subsidies if policymakers have an interest in supporting solar installation. We evaluate a counterfactual where a fraction of the total net present value (NPV) of the reduction in flow payoffs due to net metering reform is given as an up-front subsidy. For households with discount rates greater than 4%, the conversion of a flow of benefits to an up-front payment at a 4% discount rate will results in a higher present value. Further, given results indicating heterogeneity over wealth in discount rates, it is expected that converting flow payoffs to up-front payments will mitigate the gap in adoption.

Table 9: Scenario 3: Reformed NEM rate; percent counterfactual adoptions relative to baseline. Assumes a 50-50 export-consumption split. NPV of decreased subsidy calculated at 4% and rebated per-kWh, per-kW capacity, per-installation, and a combination of per-kWh and per-installation.

		Reformed NEM rate; 50% Exported to Grid; 50% Savings Rebated			
Wealth Wealth	Rate Generated	Per-kWh/yr Per-kW capacity	Per-kW capacity Flat Per-Install	Flat Per-Install	50% kWh, 50% Install
HIGH	10.5%	1.012	1.056	0.976	0.987
MED	10.3%	0.924	0.918	0.930	0.920
LOW	19.8%	1.046	1.028	1.267	1.145
All	-	0.982	0.986	1.033	0.999

We implement this through four potential subsidy mechanisms under the \$0.0625 NEM rate. In each, we calculate the decrease in the flow payoff for every adopter in our data, and sum the net present value of that decrease at 4%, a "government" rate. This total represents the NPV of the decrease in NEM benefits from the reform. We then calculate the average subsidy on a per-kWh generated (in expectation at installation) basis, a per-kW capacity basis, a flat per-installation basis, and a mix where 50% of the subsidy is offered as per-kWh generated, and 50% is offered as a flat per-installation subsidy. We find the fraction of the total NPV that would have to be rebated in order to keep expected counterfactual installations approximately equal. For all four mechanisms, the fraction rebated is approximately 50%. Table 9 shows the counterfactual installation rates by wealth, and by subsidy mechanism.

Column 1 of Table 9 shows the distribution of adoption relative to the baseline for the first subsidy mechanism. As expected, because low-wealth households exhibit higher discount rates, the rate of adoption increases relative to the baseline under this mechanism – the flow is captured up-front, and thus is not as heavily discounted. Column 2 shows similar results. Column 3 shows the highest gradient over wealth in changes in adoption rates. Low-wealth households are more likely to be lower consumers of energy, and thus are more likely to have smaller optimal installations. A flat per-installation subsidy provides a larger relative benefit for low-wealth households, closing the baseline gap in solar adoption between low- and high-wealth households. In all cases, only 50% of the NEM savings are offered as a subsidy, but on average, total installations remain approximately constant. In every mechanism, particularly in a flat per-installation mechanism, low-wealth households increase their share of total adoptions.

8 Conclusion

This paper provides a compelling method and setting for identifying heterogeneous household discount rates. These rates are relevant both generally, and to the context of residential adoption of renewable generation. The nature of many "green" technologies is that a large up-front investment pays off over long periods of time. When the "green" technology has positive spillovers to air quality or carbon emissions, policymakers who wish to capture these spillover benefits must consider the individual or household adoption decision. The household discount rate identified here is a key part of this decision when flows payoffs last for greater than 20-25 years.

We leverage novel and plausibly exogenous variation in solar payoffs to identify the key parameters – the household discount rate – applied by households in California in the solar adoption decision. We show model-free evidence that high- and medium-wealth households are more responsive to the value of the solar flow payoff obtained by investing in solar panels. We then estimate a structural dynamic model that pins down heterogeneity in discount rates by wealth. Our results help explain the noted disparities in solar adoption rates between low- and high-wealth households.

Substantive contributions to the literature are made in methods of estimating the model with allowances for unobserved heterogeneity in prior consumption. We also contribute to the literature on counterfactual identification in Conditional Choice Probability models. In the consumption dimension of unobserved heterogeneity, we introduce a method for applying the Expectation Maximization (EM) algorithm to contexts where there is joint dependence in the unobserved heterogeneity in the sample – in our context, accounting for the fact that each of the five consumption bins must have an equal number of households in it. Finally, we leverage the stationarity assumption to note that counterfactuals can be generated as differences in the utility of adopting in the next period, and show that the recursive sum of differences in future adoption can be expressed in a closed form.

The policy applications of our results are clear and timely. As California (and many other states) reform net metering 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. We first show that demand elasticity is approximately 2%, with low-wealth households exhibiting 0.9% and high-wealth households exhibiting 2.4%. We show that a significant reduction in the flow payoff of net metering as would be inherent in an "avoided cost" net metering scheme will reduce solar adoption by 67%, but with a larger reduction for high- and medium-wealth households (78 and 75%, respectively). Combined with an "up-front" subsidy, the effect is two-fold: first, the reduction in flow payoffs closes the gap between household wealth groups and adoption rates, largely by reducing high-wealth households' likelihood of adoption. As we show, it is likely that there exists a "sweet spot" where a combination of flow payoff reductions and up-front subsidies can obtain a fixed level of adoption at *lower* cost to utilities and taxpayers, and with benefits spread equitably across wealth levels rather than concentrated among high- and medium-wealth households.

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Appendix

A Size Imputations

TO FILL IN LATER

B Sizing with Rebound

The above model also captures unobserved rebound effects if the marginal value of the extra generation is zero. As an alternative, we can allow for rebound using a demand elasticity of electricity, ε. Let:

$$\log(q) = \varepsilon \log(p) + \log\left(\frac{q_0}{(p_H)^{\varepsilon}}\right) \tag{20}$$

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. We can expect demand to increase by Δq, which is the maximum value of r such that:

$$r \leq -\varepsilon \left(\frac{p_H - p_L(r)}{p_H}\right) q_0 \tag{21}$$

in which q^* is still defined as the optimal solar generation ignoring rebound and p_L is the effective marginal electricity rate with rebound r using the discount rate used to size the installation:

$$p_L(r) = \min_{r^S} \left(\min\left(p(q_0 - q^* + r - r^S), \frac{C/25}{q'\left(K(q^* + r^S)\right)\left(\sum_{t=1}^{25} \frac{1}{(1+\delta)^t}\right)}\right)\right), \tag{22}$$

in which $r^S \leq r$ is the amount of the rebound electricity generated from increasing the installation size. 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 (21) 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 levelized marginal rate of additional solar electricity), but as the installation size increases and the levelized 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:

$$
\begin{aligned}
\Delta S^R &= \int_{p_L}^{p_H} q(p)dp - (p_H - p_L)q_0 + \int_{q_0}^{q_0+\Delta q-\Delta q^S} (p_L - p(q-q^*))dq \qquad (23) \\
&= \int_{p_L}^{p_H} p^{\varepsilon}\frac{q_0}{(p_H)^{\varepsilon}}dp - (p_H - p_L)q_0 + \int_{q_0}^{q_0+\Delta q-\Delta q^S} (p_L - p(q-q^*))dq \\
&= \left(\left(\frac{1}{1+\varepsilon}\right)\left(\frac{(p_H)^{1+\varepsilon} - (p_L)^{1+\varepsilon}}{(p_H)^{\varepsilon}}\right) - (p_H - p_L)\right) q_0 + \int_{q_0}^{q_0+\Delta q-\Delta q^S} (p_L - p(q-q^*))dq.
\end{aligned}
$$

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:

$$p_L(q_0 + \Delta q^S) - \big(TC(K(q^* + \Delta q^S)) - TC(K(q^*))\big) \qquad (24)$$

This term is the levelized value of the solar rebound minus the cost. It is equal to zero is 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.

C Detailed Counterfactual CCP Calculations

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:

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

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:

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

Note we can write:

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

and thus

$$\begin{aligned}\log(Pr') &= \Lambda^{-1}(Pr') + \log(1-Pr') \\ &= \frac{1}{\sigma}(\delta_1' - \delta_0') + \log(1-Pr'),\end{aligned} \tag{25}$$

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:

$$
\begin{aligned}
\Delta B &= B^{+} - B \\
&= \rho\left(\frac{1}{\sigma}(\delta_1' - \delta_0') + \Delta A\eta + \Delta B' + \log(1 - Pr'^{+})\right) - \rho\gamma - B \\
&= \rho\left(\frac{1}{\sigma}(\delta_1' - \delta_0') + \Delta A\eta + \rho(\log(Pr''^{+}) - \log(Pr'')) + \log(1 - Pr'^{+})\right) - \rho\gamma \\
&\quad -\rho\left(\frac{1}{\sigma}(\delta_1' - \delta_0') + \log(1 - Pr')\right) - \rho\gamma \\
&= \rho\eta\Delta A + \rho^2(\log(Pr''^{+}) - \log(Pr'')) + \rho(\log(1 - Pr'^{+}) - \log(1 - Pr')) \\
&= \rho\eta\Delta A + \rho\Delta B' + \rho(\log(1 - Pr'^{+}) - \log(1 - Pr')) \qquad (26)
\end{aligned}
$$

where $\Delta B'$ is the next-period discounted difference between counterfactual and actual $\log(Pr')$. ΔB can be rewritten using the following recursion:

$$
\begin{aligned}
\Delta B &= \rho\eta\Delta A + \rho(\log(1 - Pr'^{+}) - \log(1 - Pr')) + \rho\Delta B' \\
&= \rho\eta\Delta A + \rho^2\eta^2\Delta A + \rho\left(\log(1 - Pr'^{+}) - \log(1 - Pr')\right) \qquad (27) \\
&+ \rho^2\left(\log(1 - Pr''^{+}) - \log(1 - Pr'')\right) + \Delta B'' \\
&= \sum_{t=1}^{\infty}\rho^t\eta^t\Delta A + \sum_{s=1}^{\infty}\rho^s\left(\log\left(\frac{1 - Pr_s'^{+}}{1 - Pr_s'}\right)\right) \qquad (28)
\end{aligned}
$$

where the t subscript on A_t indicates the fact that A can change in future periods based on the evolution of the state variables that are affected by the counterfactual changes (electricity prices, solar prices, etc.).

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 $\log(Pr_s'+)$ where s is the number of periods into the future. ΔB is a recursive sum. Each recursion produces $\Delta A'$ that is equal to ΔA scaled by ρ and η, as well as a discounted difference in logged probability of *not* adopting s periods ahead.

Adoption probabilities are very small and thus we approximate: $\log\left(\frac{1-Pr_s'^{+}}{1-Pr_s'}\right) \approx 0$. This means we can write:

$$
\Delta A + \Delta B = \sum_{t=0}^{\infty}\rho^t\Delta A_t = \sum_{t=0}^{\infty}(\Delta u_t - \rho\Delta u_{t+1}) = \frac{1}{\sigma}\Delta u_t. \qquad (29)
$$

For example, if we change the variable costs such that VC is scaled by $\frac{1}{c}$ in all periods, this reduces variable costs by $(c-1)/c$ and the current-period t change in the utility of adopting is:

$$\Delta A + \Delta B = \frac{1}{\sigma}\left(\frac{c-1}{c}VC\right) \tag{30}$$

Now let us write the next period differences in the counterfactual value of adopting relative to not adopting as:

$$\frac{1}{\sigma}\left(\delta_1'^{+} - \delta_0'^{+}\right) = \frac{1}{\sigma}\left(\delta_1' - \delta_0'\right) + \overbrace{\Delta A \eta}^{\Delta A'} + \overbrace{\rho(\log(Pr''^{+}) - \log(Pr''))}^{\Delta B'}$$

Recall

$$Pr' = \frac{1}{1+\exp(-(\delta_1' - \delta_0')/\sigma)} \tag{31}$$

and so by rearranging terms, we have:

$$\begin{aligned} 1/Pr'^{+} - 1 &= \exp(-(\delta_1' - \delta_0')/\sigma))\exp(-\Delta A' - \Delta B') &(32)\\ &= (1/Pr' - 1)\exp(\Delta A' + \Delta B') &(33)\end{aligned}$$

So this gives us the change in Pr' under the counterfactual:

$$Pr'^{+} - Pr' = Pr'\left(\frac{1}{(1-Pr')\exp(-\Delta A' - \Delta B') + Pr'} - 1\right) \tag{34}$$

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

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

Using the fixed progression of VC such that $\Delta A' = \eta \Delta A$, we can write the relationship between counterfactual and observed next-period utility as

$$\frac{1}{\sigma}\left(\delta_1'^{+} - \delta_0'^{+}\right) = \frac{1}{\sigma}\left(\delta_1' - \delta_0'\right) + \overbrace{\Delta A \eta}^{\Delta A'} + \overbrace{\rho(\log(Pr''^{+}) - \log(Pr''))}^{\Delta B'}$$