Means-Tested Solar Subsidies*

Mark Colas
University of Oregon

Emmett Reynier
Stanford University

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Abstract

We study the design of income-contingent subsidies for residential solar panels. We develop sufficient statistics for evaluating the cost-effectiveness of means-tested subsidies and estimate them using remotely sensed data on solar panel installations across the US and a border-discontinuity design. Our estimates reveal that the responsiveness of installation rates to subsidies is strongly decreasing in income. Using these empirical estimates, we estimate a structural model that embeds a solar adoption decision into a dynamic consumption/savings framework with borrowing constraints. Counterfactuals reveal that switching to production-maximizing income-contingent solar subsidies leads to a nearly three-fold increase in public funds received by low-income households and a 2.4% increase in national solar production. Means-tested subsidies are justified on equity and efficiency grounds.

JEL Classification: H21, H23, Q42, Q48

Keywords: rooftop solar, subsidies, renewable energy

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1 Introduction

Subsidies for many green consumer technologies disproportionately benefit high-income households, exacerbating inequality in climate policy and potentially undermining political support for decarbonization.[1] Means-tested subsidies are an increasingly popular way to address this imbalance. A prominent example is income-based incentives for residential solar in the United States. While several states had existing subsidy programs that explicitly based eligibility on household income, the scope and impact of means-tested solar subsidies expanded substantially with two major federal initiatives: the 2022 launch of the Low-Income Communities Bonus Credit Program, which offers tax credits for solar installations in low-income communities, and the 2023 launch of the Solar for All program, which awarded 7 billion dollars to fund low-income solar programs. The Trump administration subsequently froze payments for the Solar for All program, intensifying debate over whether means-tested solar subsidies represent an effective use of public funds.[2] However, despite their expanded role and the policy debate they have generated, there is no quantitative analysis on how to design these subsidies most effectively.

This paper studies the equity and efficiency trade-offs associated with income-contingent subsidies for residential solar. We derive sufficient statistics for evaluating the cost-effectiveness of means-tested subsidies and estimate them empirically for solar panel adoption using a border-discontinuity design. We use these empirical estimates to identify parameters in our structural model and then use our structural model to solve for the efficient income-contingent subsidy schedules.[3] We conclude that there are substantial equity and efficiency gains to instituting federal means-tested subsidies for rooftop solar panels.

To motivate our reduced-form analysis, consider a government that uses income-contingent subsidies to maximize green technology adoption subject to a fiscal cost constraint. All else equal, the government will optimally provide subsidies to income groups with many *additional* households, that is, households who will be induced to adopt in response to a small subsidy increase. On the other hand, the fiscal costs of providing subsidies are increasing in the number of *non-additional* households: the households who

[1] See, e.g., Borenstein and Davis (2024), for evidence the regressive nature of many green subsidies. Carattini, Kallbekken, and Orlov (2019) find that perceived policy unfairness reduces public support for climate policies. Stokes (2020) documents how unequal benefits from climate policy have fueled political backlash in the US.

[2] The freeze was later overturned by federal courts.

[3] Our main exercise is to solve for the income-contingent subsidies for rooftop solar which maximize solar production subject to a government cost constraint. We refer to the subsidies that solve this constrained maximization problem as the "efficient" subsidies. We avoid using the term "optimal" as the planner does not aim to maximize welfare.

already choose to adopt the technology absent the subsidy increase.[4] We show analytically that the ratio of the additional over non-additional households, as measured by the partial elasticity of adoption with respect to subsidies, can be used as a sufficient statistic for the cost-effectiveness of income-targeted subsidies. Specifically, we show that if this partial elasticity is decreasing (increasing) in income, then cost-neutral increases in the progressivity of the subsidy schedule will increase (decrease) total adoption. More generally, we show that the government can increase adoption by making subsidies more progressive over intervals of the income distribution where this partial elasticity is decreasing in income and more regressive where the partial elasticity is increasing in income.

We then empirically investigate how this partial elasticity varies across income levels in the case of residential solar panels. We use the Deepsolar database (Yu et al., 2018), which applies a machine-learning framework to satellite imagery across the contiguous US to measure the total residential solar panel area in each census tract, along with state-level subsidy data. Across a wide range of specifications, including border-discontinuity regressions and specifications that allow responsiveness to subsidies to vary nonparametrically in tract-level income, we consistently find that low-income tracts have partial elasticities greater than those of high-income tracts. Tracts with the median income level have a partial elasticity 15% to 43% higher than tracts at the 90th percentile. These results are robust to a battery of alternative specifications and suggest that means-tested subsidies could increase total solar production without increasing fiscal costs.

We then turn to a quantitative model of residential solar demand to evaluate counterfactual income-contingent subsidy schemes. Our framework embeds a homeowner's decision to install rooftop solar panels into a dynamic consumption/savings framework. Installing solar panels involves an upfront monetary cost but delivers subsidies and a stream of electricity production over the life of the panel. Households face borrowing constraints and, therefore, may not be able to smooth consumption fully if they choose to purchase solar panels. The model includes household heterogeneity in solar irradiance, preferences, and prices faced by households across space, as well as a rich quantification of the current federal and state subsidy schemes for solar panels, which accounts for differences in time profiles across which subsidies are paid and the nonrefundable nature of the Federal Investment Tax Credit.

We structurally estimate the model via indirect inference by using the remotely sensed data on residential solar installations from Deepsolar, as well as data on solar irradiance, electricity prices, subsidies, and income distributions across census tracts in the US. To achieve identification, we target our partial elasticity estimates from our border discon-

[4] "Additional" and "non-additional" agents are sometimes refereed to as "marginal" and "inframarginal" agents, respectively. See, e.g., Colas, Findeisen, and Sachs (2021).

tinuity regressions, as well as additional moments on solar panel installations across the income distribution and demographic groups. We show that our sparsely parameterized model matches both installation rates and elasticities of installations with respect to subsidies across the income distribution. The model is also consistent with non-targeted quasi-experimental estimates of the responsiveness of solar installations with respect to prices and subsidies.

Our estimated structural model provides a framework that allows us to quantify the equity-efficiency consequences associated with various subsidy schemes. We first turn our attention to the current subsidy scheme for residential solar in the US. Current subsidies for residential solar are highly regressive, driven by the fact that installation rates increase strongly with household income. To understand the factors driving this regressivity, we use our model to decompose the mechanisms that create the positive correlation between income and installation rates. Our model-based decomposition reveals that borrowing constraints and the nonrefundability of the Federal Investment Tax Credit are the primary drivers of this positive relationship for low-income households. Meanwhile, differences in preferences play a larger role for high-income households.

We then use the estimated model to analyze the effects of introducing small income-contingent subsidies to the current subsidy scheme. Consistent with our reduced-form results, we find that introducing income-targeted subsidies for low-income households induces more electricity production per dollar of public funds than income-neutral subsidies. We show that the larger number of non-additional households at high income levels is the primary driver of differences in cost-effectiveness across income groups: Households who would have installed panels absent these subsidies receive over 50% of subsidies targeted at the 75th income percentile, as compared to roughly 35% of subsidies targeted at the 25th income percentile.

Next, we consider a planner who chooses income-contingent subsidies to maximize solar production without increasing fiscal costs. Despite the fact that this social objective places no weight on equity, we find that the efficient subsidies are highly progressive. The increase in progressivity associated with moving to these subsidies and the resulting increase in installation rates for low-income households lead to a much more equitable distribution of public funds. The amount of solar subsidies received by households in the bottom income quartile nearly triples, while the amount received by households in the top quartile falls by half. This scheme also increases national solar production by 2.4% at no additional fiscal cost.

We then consider a planner who maximizes utilitarian welfare subject to a net cost constraint. The welfare-maximizing schedule is slightly more progressive than the production-maximizing subsidies, as means-tested subsidies increase solar production while channeling funds towards poorer households with higher marginal utilities of income. This progressive subsidy scheme increases national solar production by 2.0%. Means-tested subsidies are justified on both equity and efficiency grounds.

We then conduct a series of robustness and sensitivity checks of our structural results. We examine how sensitive our findings are to 1) alternative assumptions on households' dynamic income process, 2) alternative household discount rates, 3) a government that maximizes environmental benefits rather than solar production, and 4) decreases in the cost of solar panels. Across all specifications, we reach the same qualitative conclusions: the efficient income-contingent subsidies are decreasing in income, and switching to means-tested subsidies leads to substantial equity and efficiency gains.

It is important to caveat that we assume a partial equilibrium framework throughout our analysis and, therefore, abstract away from endogenous changes in electricity prices or prices of solar installations.[5] Accounting for endogenous responses of electricity prices may be particularly important in states with net metering, where electricity companies may raise electricity prices in response to increased residential solar in order to recover the costs associated with providing net metering.[6] Further, the main focus of this paper is finding efficient subsidies for residential solar, holding constant total government spending on residential solar. We do not analyze whether the total amount of spending on residential solar subsidies is optimal, nor do we consider subsidies for utility-scale solar.[7]

To the best of our knowledge, ours is the first paper to quantify the efficient income-contingent subsidies for solar panels. This focus on income-contingent subsidies differentiates our paper from other papers which use structural models to analyze the effectiveness of various types of income-neutral subsidies for solar panels (e.g., Burr, 2014; De Groote and Verboven, 2019; Langer and Lemoine, 2022; Feger, Pavanini, and Radulescu, 2022; Colas and Reynier, 2024; Snashall-Woodhams, 2024; Bollinger, Gillingham, and Kirkpatrick, 2025).[8] Of these, our paper is closest to Feger, Pavanini, and Radulescu (2022) and Colas

[5]See Pless and Van Benthem (2019), for example, for evidence that suppliers of solar installations may increase prices in response to subsidy increases.

[6]See, e.g., Borenstein and Bushnell (2022).

[7]Colas and Reynier (2024) find that spending on subsidies for residential solar in the US substantially exceeds the optimal level. We also do not quantify the extent to which increases in residential solar may crowd out utility-level solar. This crowd-out of utility-level solar may be particularly relevant in states that use a combination of utility-level renewable sources and rooftop solar to meet renewable energy standards. In Appendix B.22, we solve for the income-contingent subsidy schedule that minimizes government cost subject to the constraint that total rooftop solar production is equal to the current level. The schedule is nearly identical to the production-maximizing schedule (though slightly less generous). It would not lead to crowd-out of utility-level solar as rooftop solar production is held constant.

[8]Snashall-Woodhams (2024) uses a dynamic model and data from California to solve for optimal subsidies that vary by electricity consumption type, rooftop, and location. Dorsey and Wolfson (2023) analyze differences in solar installation purchases across income and race groups and calculate differences in consumer surplus across demographic groups. Bollinger, Gillingham, and Kirkpatrick (2025) estimate a dynamic model of solar adoption and sizing where household discount rates vary by household wealth.

and Reynier (2024). Feger, Pavanini, and Radulescu (2022) analyze the equity-efficiency trade-offs associated with solar panel cost subsidies and energy tariffs by estimating a rich, dynamic model of solar panel installation and electricity usage using detailed Swiss data. They do not model savings. Instead, preference parameters that directly depend on household wealth generate differences in installation behavior across income groups.[9] Colas and Reynier (2024) use data from Deepsolar to study how subsidies for residential solar panels should optimally vary across space, with a focus on spatial variation in the environmental benefits of solar energy. They do not differentiate Households by income, nor do they model savings. In addition to our novel focus on income-continent subsidies, we contribute to this literature methodologically by 1) modeling households' dynamic consumption/savings decisions in an environment with borrowing constraints and 2) utilizing a utility function that exhibits nonzero income effects. These features allow our model to replicate two patterns in the data that play a pivotal role in determining the returns to targeted subsidy increases: 1) installation rates across the income distribution and 2) elasticities of installations with respect to subsidies across the income distribution.

We contribute to the body of research emphasizing the role of additionality (vs. non-additionality) in assessing the cost-effectiveness of subsidies for pro-environmental technologies (e.g., Chandra, Gulati, and Kandlikar, 2010; Mian and Sufi, 2012; Boomhower and Davis, 2014; Davis, Fuchs, and Gertler, 2014; Houde and Aldy, 2017; Xing, Leard, and Li, 2021).[10] We extend this literature by formally demonstrating that the ratio of additional over non-additional adopters—equivalent to the partial elasticity of adoption with respect to subsidies—acts as a sufficient statistic for evaluating the cost-effectiveness of income-contingent subsidies.[11] Our approach is generalizable and could be adapted to other green technologies, such as electric vehicles, energy-efficient appliances, and heat pumps.

More broadly, we are also related to a literature which quantifies the distributional effects of energy policy (e.g., Bento et al., 2009; Borenstein, 2012; Jacobsen, 2013; Borenstein and Davis, 2016; Fried, Novan, and Peterman, 2018; Reguant, 2019; Davis and Knittel, 2019; Holland et al., 2019; Goulder et al., 2019; Morehouse, 2021; Hahn and Metcalfe, 2021; Linn, 2022; Cahana et al., 2022; Fried, Novan, and Peterman, 2022; Dauwalter and

[9]Relatedly, Kiribrahim-Sarikaya and Qiu (2023) use data from Phoenix, Arizona, to estimate a dynamic model of solar adoption. They also do not model savings. They use the model to simulate the effects of making federal tax credits refundable and introducing subsidies targeted at lower-income groups.

[10]For instance, Boomhower and Davis (2014) considers a social planner who provides energy efficiency subsidies that must be financed through distortionary taxation. They show that the derivative of social welfare with respect to the subsidy increases with the number of additional adopters and decreases with the number of non-additional recipients.

[11]More broadly, we show that this elasticity can be used as a sufficient statistic for assessing the cost-effectiveness of targeted subsidy increases.

Harris, 2023). We contribute to this literature by quantifying the dual equity-efficiency benefits in the case of residential solar subsidies. Finally, this paper is also related to several reduced-form papers estimating the responsiveness of solar installations to subsidies in the United States, which we discuss in Section 3.4. Relative to these papers, we focus on how the responsiveness of installations varies as a function of household income.

2 Reduced-Form Analysis

2.1 Cost-Effectiveness and Means-Tested Subsidies

We begin by deriving simple, sufficient conditions for the cost-effectiveness of progressive subsidies in a general model where the government seeks to maximize the adoption of an environmentally friendly technology. While we use the language of solar panel adoption to align with our empirical analysis, the framework is broadly applicable to other technologies, such as electric vehicles or energy-efficient appliances.

Formally, individual households are associated with an income level $y \in \left[\underline{y}, \overline{y}\right]$.[12] The government has access to a system of income-contingent subsidies for solar electricity production characterized by the function s, where $s(y)$ denotes the production subsidy available for households with income y.[13] Let $K_y\left(s(y)\right)$ be a function that maps subsidies for income level y to total solar production from households of income level y. We assume that $K_y\left(\cdot\right)$ is increasing in subsidies, $s(y)$. Further, let

$$Prod[s] = \int_{\underline{y}}^{\overline{y}} K_y\left(s(y)\right) dy$$

denote the functional which maps the subsidy function s to total electricity production and let

$$Cost[s] = \int_{\underline{y}}^{\overline{y}} K_y\left(s(y)\right) s(y) dy$$

denote the functional which maps s to fiscal cost.

Assume there are initially no income-contingent subsidies, as is the case federally, such that $s(y) = \bar{s}$ for all income levels y, where $\bar{s}$ is a nonnegative constant. We are interested in the implications of small changes to the subsidy function around this income-neutral baseline. Formally, let δs denote a *variation* to the function s such that subsidies

[12] In Appendix B.1, we consider a setting with discrete household groups rather than a continuum of households differentiated by income. We show that the partial elasticity of adoption with respect to subsidies serves as a sufficient statistic for measuring the cost-effectiveness of targeted subsidy changes.

[13] For simplicity, we assume that the government only has access to these income-contingent production subsidies. In the structural model, we will include a rich model of subsidies for solar panels, including state and federal investment subsidies.

received by any income level y change to $\bar{s} + \delta s(y)$, where $\delta s(y)$ represents an arbitrary infinitesimal change to subsidies.[14] We will focus on variations that are 1) cost-neutral and 2) progressive. Cost-neutral variations are those that lead to no change in fiscal cost, and progressive variations are those that are decreasing in income, such that subsidies become more generous for low-income households and less generous for high-income households.[15]

Proposition 1 provides a simple sufficient condition for when cost-neutral progressive subsidy variations lead to increases in solar production.

Proposition 1. *Define*

$$\eta(y) \equiv \frac{\frac{\partial K_y}{\partial s(y)}}{K_y} \tag{1}$$

as the "cost-effectiveness" of a subsidy increase at income level y. If η is weakly decreasing (increasing) in income and nonconstant on a set of positive measure, then any cost-neutral progressive subsidy variation strictly increases (decreases) in total solar production.

Proof. Appendix A.1 □

Proposition 1 shows that we can use measures of η across the income distribution as sufficient statistics for when moving to progressive subsidies can increase production: if η is decreasing in income, then cost-neutral progressive subsidies variations will lead to production *increases*. If η is increasing in income, then these progressive subsidy variations lead to production *decreases*.[16]

[14] Explicitly, we consider moving from the subsidy function $s(y) = \bar{s}$ to the alternative subsidy function $\tilde{s}(y) = \bar{s} + \epsilon g(y)$, where $g(y)$ is a function in y and where we take the limit as $\epsilon \to 0$.

[15] Formally, a cost-neutral variation is any variation δs such that

$$\int_{\underline{y}}^{\overline{y}} \frac{\delta Cost}{\delta s(y)} \delta s(y)\, dy = 0,$$

where $\frac{\delta Cost}{\delta s(y)}$ is the functional derivative of $Cost[s]$ with respect to $\delta s(y)$. A progressive variation is any variation δs such that

$$(y'' - y')\left(\delta s(y'') - \delta s(y')\right) < 0$$

for $y'' \neq y'$.

[16] The condition "nonconstant on a set of positive measure" requires that the function takes at least two distinct values on a nonnegligible part of its domain. This condition excludes functions that are constant everywhere or constant almost everywhere (i.e., constant except on a measure-zero set).

In Appendix B.2, we relate the distribution of cost-effectiveness across the income distribution to the production-maximizing subsidy schedule for a budget-constrained government. We show the production-maximizing subsidy schedule $s^\star(\cdot)$ must satisfy

$$s^\star(y) = \frac{1}{\lambda} - \frac{1}{\eta^\star(y)}$$

for all income levels y, where λ is the Lagrange multiplier from the government's budget constraint and $\eta^\star(y)$ is the cost-effectiveness associated with income level y given the production-maximizing subsidy schedule. Therefore, the production-maximizing subsidy schedule will be decreasing in income if and only if $\eta^\star$ is decreasing in income.

To see why this is the case, consider first the derivative $\frac{\partial K_y}{\partial s(y)}$ in the numerator of equation (1), which we refer to as the amount of "additional production." This value indicates how much solar production will increase in response to a small increase in subsidies for a given income level. All else equal, it is more cost-effective for the government to raise subsidies for income levels where additional production is high, as subsidy increases for these households will lead to larger increases in total solar production. The denominator measures the amount of "non-additional production," the amount of production by panels installed absent that subsidy increase. If subsidies increase, households receive higher subsidies for this non-additional production, even if they do not increase solar production. Consequently, more non-additional production implies higher marginal costs for the government. Together, we can think of this ratio of additional over non-additional production as measuring the "bang for your buck" of a targeted subsidy increase since it measures the total change in solar production per dollar paid to non-additional households.

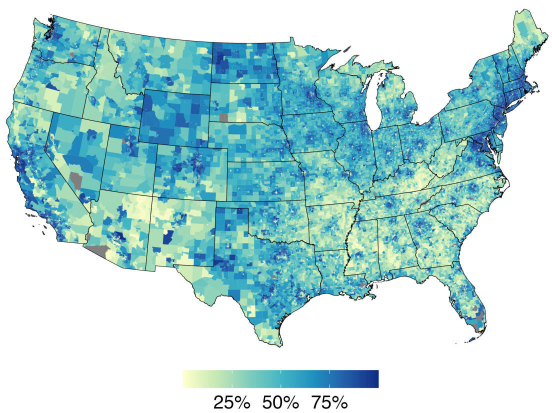
Proposition 1 establishes the benchmark case where cost-effectiveness η is monotonic over the entire income distribution. Proposition 2 generalizes this result by only requiring η to exhibit monotonicity over some interval of the income distribution.

Proposition 2. *Let $\underset{\sim}{y}$ and $\widetilde{y}$ be any income levels such that $\underline{y} \leq \underset{\sim}{y} < \widetilde{y} \leq \overline{y}$. If η is weakly decreasing (increasing) in income over any interval $\left[\underset{\sim}{y}, \widetilde{y}\right]$ and nonconstant on a set of positive measure within that interval, then any cost-neutral subsidy variation that is progressive over $\left[\underset{\sim}{y}, \widetilde{y}\right]$ and zero elsewhere strictly increases (decreases) in total solar production.*

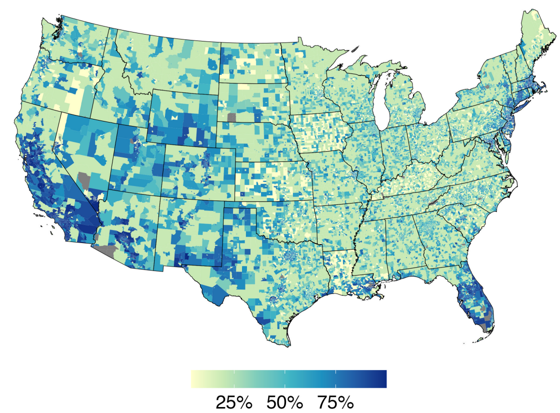
Proof. Applying the proof in Appendix A.1 to the interval $\left[\underset{\sim}{y}, \widetilde{y}\right]$ and holding subsidies constant elsewhere yields the result. □

Therefore, whenever η is monotonic over any interval of the income distribution, the government can strictly increase production by implementing appropriately designed income-contingent subsidies restricted to that interval. Such an interval is guaranteed to exist under relatively weak conditions on η; for instance, any non-constant continuous function necessarily contains such an interval.

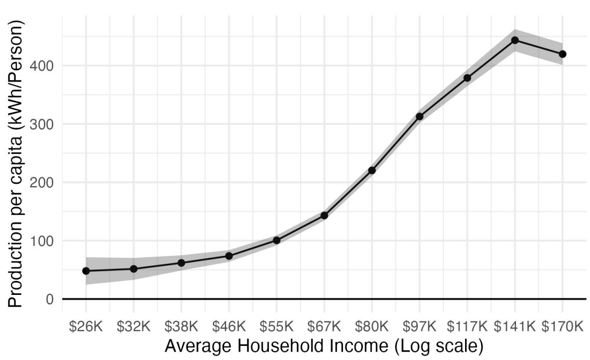
Furthermore, Proposition 2 offers a straightforward rule for designing income-contingent subsidies: subsidies should become more progressive in income ranges where $\eta'(y) < 0$, meaning cost-effectiveness decreases with income, and more regressive where $\eta'(y) > 0$, meaning cost-effectiveness increases with income. Our goal in the coming sections is to empirically estimate how η varies across the income distribution.



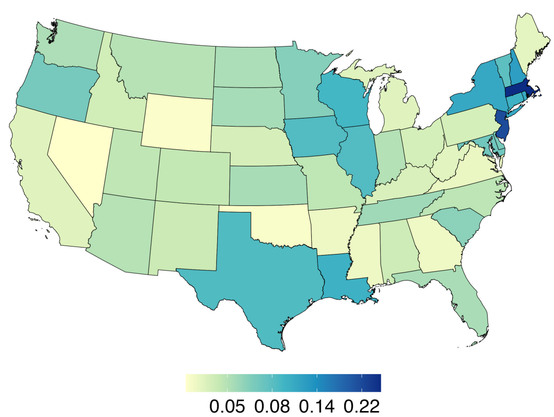
(a) Census tract income percentiles.



(b) Census tract residential solar production percentiles.



(c) Solar production per capita by tract-level income.



(d) State residential solar subsidies in \$/kWh.

Figure 1: Spatial variation in tract income, tract solar panel production, and state solar subsidies. Income comes from the 2015 5-year ACS, solar production from Deepsolar, and subsidies from Sexton et al. (2021). Panel (c) shows coefficients from regressing annual solar production per capita on 11 income bins evenly spaced in log income. Standard errors are clustered by state.

2.2 Data and Descriptive Results

We empirically estimate the cost-effectiveness of income-targeted subsidies using tract-level variation in solar production and state-level variation in subsidies. For this, we need a large sample of tract-level data on installations and income levels across the US and state-level data on solar panel subsidies.

Solar panel installations We use the Deepsolar database (Yu et al., 2018) for tract-level residential solar panel installations and total panel area across the 48 states in the contiguous US. These data result from a deep-learning model trained to detect solar panels from satellite imagery captured in 2016, providing the first comprehensive and spatially fine measurement of solar panels.[17] In addition to providing the deep-learning model output, Deepsolar attaches several other variables for each census tract collected from many sources. These include solar irradiance from NASA Surface Meteorology and Solar Energy, state-average retail electricity prices from the EIA, and average income and other demographic data from the 2015 5-year American Community Survey (ACS).[18] We calculate solar production in each census tract by multiplying total residential panel area in a tract by its average solar radiation.

Panels (a) and (b) of Figure 1 show the spatial distribution of tract-level average income and total residential solar production. Solar production is concentrated in sunny areas such as the Southwest, Florida, and California and high-subsidy states in the Northeast. Meanwhile, income is highest along the East Coast, California coast, and surrounding major cities. Panel (c) depicts the relationship between tract-level average income and solar production per capita. Solar production is strongly increasing in income: the lowest income tracts, those with average income less than 38 thousand dollars, produce around 50 kWh of residential solar electricity per capita annually. The highest income tracts, those with an average income over 117 thousand dollars, produce around 400 kWh of residential solar electricity per capita annually, eight times higher than the lowest income tracts.

Solar subsidies We use measures of state-level solar panel subsidy generosity calculated by Sexton et al. (2021) using 2017 data from the Database of State Incentives for Renewables and Efficiency (DSIRE).[19] They calculate the total amount of subsidies that an average-sized installation in each state is eligible for and convert it into a per-kWh

[17] Alternatives rely on self-reported data (e.g., Open Solar Project) or do not cover the entire US (e.g., Tracking the Sun).

[18] Notably, we use population density, percent with a college degree, percent owner-occupied homes. Percent voting Democrat in the 2016 election comes from townhall.com.

[19] While several states currently have income-contingent subsidy programs in place, the majority of these programs were introduced after 2016, and therefore the solar installations we observe in our data would not have been eligible for these subsidies.

measure of subsidy generosity. These generosity measures account for federal and state investment tax credits, state production credits, property and sales tax rebates, Solar Renewable Energy Certificates, and other state-level subsidies.[20] We will refer to these measures as the "generosity" of subsidies in each state, which we use in the reduced-form estimation of how responsiveness to subsidies varies across income groups. We disaggregate into several different types of subsidies in the formal quantitative model that follows.

As we discuss further below, one potential concern is that this subsidy data is from 2017, but many of the solar installations are from prior to 2017. We assess the robustness of our reduced-form results with respect to the subsidy measure in Appendix B.8, where we utilize a "historically-adjusted" subsidy generosity measure from Sexton et al. (2021).

Panel (d) of Figure 1 shows the spatial distribution of state subsidies. Generally speaking, subsidies are most generous in the Northeast. Massachusetts has the highest subsidies in the country, at 28 cents per kWh. Meanwhile, several states that do not offer any subsidies in addition to the federal incentives have subsidies under 4 cents per kWh.

Border Discontinuities Our main empirical strategy is to use border-discontinuity regressions to estimate how the responsiveness of solar production compares across tracts with varying average income levels. To motivate this strategy, we present descriptive evidence on how solar production levels in low- and high-income tracts change as we cross the border from a state with less generous subsidies to a state with more generous subsidies.

We define a tract's location relative to the nearest border as the positive distance to the border for tracts on the side of the border with more generous subsidies and the negative distance to the border for tracts on the side with less generous subsidies. We then categorize tracts into 10-mile-wide bins based on this location relative to the border, and regress log solar production per capita on border fixed effects, fixed effects for these location bins, and controls for population density.[21] We run these regressions separately for high- and low-income tracts, where tracts are categorized as "high-income" if their average income is in the top quartile of tract-level income and are labeled as "low-income" otherwise. We then plot the estimated location-bin fixed effects, which show conditional average production levels for low- and high-income tracts in narrow bandwidths around state borders.

Ideally, we would like to compare discontinuities in these average production levels at state borders to learn about how the responsiveness of solar production to subsidies

[20] Unlike Sexton et al. (2021), we do not consider net metering to be a subsidy in our analysis as the government does not pay for it.

[21] This follows the approach used by Bayer, Ferreira, and McMillan (2007) to visualize how house prices respond to changes in school quality around school district borders.

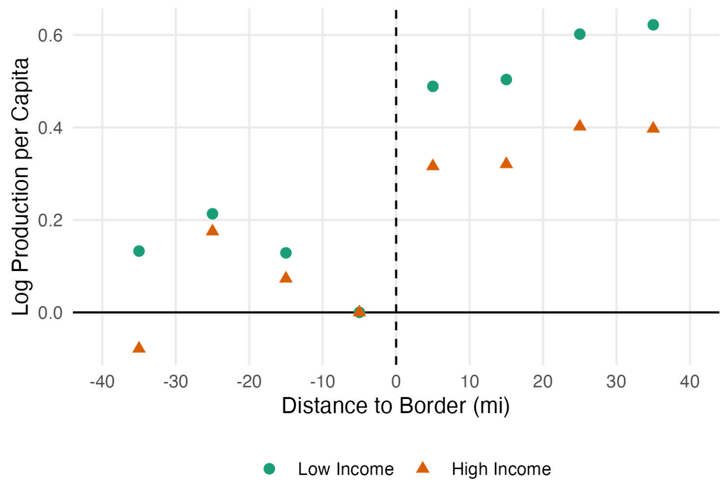


Figure 2: Border Discontinuities in Log Production per Capita. The graph plots estimated location-bin fixed effects from a regression log production per capita in high-income tracts (orange triangles) and low-income tracts (green circles) on border fixed effects, location-bin fixed effects, and controls for population density. Positive values on the X-axis represent households on the side of the border with more generous subsidies, and negative values on the X-axis indicate the side of the border with less generous subsidies. Observations are reweighted such that the total sum of weights around each state border is equal to the total population of all tracts in that border region. We do not include confidence intervals in this figure since the magnitude of the change in subsidies going from the less to the more generous side of the state border varies considerably. Therefore, the confidence intervals would conflate sampling uncertainty with heterogeneity in treatment intensity, making it difficult to interpret them as measures of statistical precision.

varies across income groups. As we show in Appendix B.4, one issue is that high-income tracts are more likely to be located in the Northeast, where the differences in subsidies across state borders tend to be large. In contrast, lower-income tracts are more likely to be located in the South, where subsidy levels are relatively similar across states. As a result, a regression run with only high-income tracts places greater weight on state borders where subsidy differences are large, while a regression run with only low-income tracts places greater weight on state borders where subsidy differences are small. To make the weighting of state borders consistent across the two regressions, we reweight observations such that a given state border receives the same weight in both the regression with only low-income tracts and in the regression with only high-income tracts.[22]

Figure 2 plots the estimated location-bin fixed effects for high-income and low-income tracts. Positive values on the X-axis represent tracts on the side of the border with more generous subsidies, and negative values on the X-axis represent tracts on the side with

[22]We reweight observations in each of the two regressions such that the sum of weights around each state border is equal to the total population of *all* tracts in that border region. Formally, let Pop_ℓ denote the population of a given tract ℓ, let $\overline{Pop}_\theta$ denote the total population in all tracts in the region around a given border θ, and let $\overline{Pop^I}_\theta$ denote the total population tracts of income group I around a given border θ. In our regression for tracts of income level I, we weight tract ℓ in border region θ by $\overline{Pop}_\theta \frac{Pop_\ell}{\overline{Pop^I}_\theta}$. We show the graphs without reweighting in Appendix B.4.

less generous subsidies.[23] We can see that log production rates for both groups increase sharply as we move to the side with more generous subsidies and that the increase in production is larger for low-income tracts: production rates increase by roughly 50% in low-income tracts compared to roughly 30% in high-income tracts. We show that household demographic characteristics do not exhibit discontinuities at state borders in Section 2.4 and Appendix B.7, suggesting that differences in demographics do not drive the observed discontinuities in production rates. These descriptive results suggest that production rates in low-income tracts may be more responsive to increases in subsidies than production rates in high-income tracts.

2.3 Empirical Strategy

We can rewrite our measure of cost-effectiveness in equation (1) as a partial elasticity,

$$\eta(y) \equiv \frac{\frac{\partial K_y}{\partial s_y}}{K_y} = \frac{\partial \log K_y}{\partial s_y}. \tag{2}$$

If these partial elasticities are decreasing in income, then means-tested subsidies can increase solar production at no additional fiscal cost. Our reduced-form strategy is to estimate how these empirical partial elasticities vary across income levels using tract-level data on solar installations outlined above.

Concretely, we estimate various forms of the regression

$$\log K_\ell = \beta(Y_\ell) s_\ell + x_\ell' \boldsymbol{\gamma} + \varepsilon_\ell, \tag{3}$$

where K_ℓ is total solar production in census tract ℓ, Y_ℓ is average income in tract ℓ, s_ℓ is the generosity of subsidies available in tract ℓ, and x_ℓ is a vector of controls. The object of interest, $\beta(Y_\ell)$, gives the empirical partial elasticity of solar capacity with respect to subsidies for tracts with average income Y_ℓ. In practice, we will use several methods to parameterize how $\beta(\cdot)$ varies as a function of income.

Before discussing the parameterization of $\beta(\cdot)$, it is important to highlight that we use tract-level, not household-level, data on solar production. We therefore estimate the partial elasticity of tract-level solar production as a function of tract-level average income level, not the partial elasticity of production as a function of household income.[24] Census

[23]The regressions omit the location-bin fixed effect for the location bin nearest to the border on the less generous subsidy side. Therefore, we can interpret these estimated location bin fixed effects as the conditional average of log production rates in a given location bin relative to this omitted bin.

[24]In Appendix B.3, we show that the tract-level partial elasticity that we estimate is equal to the production-weighted average of the household-level partial elasticity within the tract. Note that some policies, such as the Low-Income Communities Bonus Credit Program, base eligibility on local average

tracts are small geographic areas designed such that the population within each tract is relatively homogeneous in terms of demographic and economic characteristics.[25] In our structural analysis, we model a distribution of household income within each tract and account for the fact that tract-level elasticities differ from household-level elasticities.

Border Discontinuity Regressions Our first method to parameterize $\beta(\cdot)$ is to assume the partial elasticity of solar production is linear in log income and utilize a border-discontinuity approach.[26] Formally, let θ denote the nearest state border to a given tract and let Loc_ℓ denote the location of the tract relative to this border, again defined as the positive distance to the border for tracts on the side of the border with more generous subsidies and the negative distance to the border for tracts on the side with less generous subsidies.[27] Further, let the variable $\hat{Y}_\ell$ denote "de-medianed" income, calculated as tract-level income less the median income level across all tracts. Limiting our sample to tracts within 40 miles of state borders, we run regressions of the following form:

$$\log K_\ell = \beta_0^{\text{Dis}} s_\ell + \beta_1^{\text{Dis}} s_\ell \times \log \hat{Y}_\ell + x_\ell' \boldsymbol{\gamma}^{\text{Dis}} + g_\theta\left(\text{Loc}_\ell\right) + \varepsilon_\ell^{\text{Dis}}. \tag{4}$$

The term $g_\theta\left(\text{Loc}_\ell\right)$ is a border-specific smooth, flexible function in a tract's location relative to the border and controls for unobservables which may affect solar production rates. In practice, we specify these functions as border-specific polynomials which vary from degree 0, in which case $g_\theta(\cdot)$ is simply a border fixed-effect, to polynomials of degree 5.

The parameters of interest are β_0^{Dis}, which gives the empirical partial elasticity of solar production for tracts at the median income level, and β_1^{Dis}, which dictates how this partial elasticity varies with tract-level income. A value of $\beta_1^{\text{Dis}} < 0$ implies that the partial elasticity of solar production with respect to subsidies is decreasing in income, and therefore, means-tested subsidies can increase solar production without increasing fiscal cost.

Nonlinear Specifications Given that the border-discontinuity approach is quite demanding of the data, we cannot reliably estimate border-discontinuity models where the

income rather than individual household income. In this case, the partial elasticity as a function of local average income would be the relevant elasticity.

[25] https://perma.cc/VPL7-9G9F

[26] Hughes and Podolefsky (2015) and Colas and Reynier (2024) also use border-discontinuity approaches to estimate the effects of subsidies on solar panel installations. Neither paper estimates how the responsiveness of installations with respect to subsidies varies across income groups.

[27] Which of the two sides is normalized as the positive side does not affect any of the results as we always use border-specific polynomials. In Appendix B.4, we visualize the discontinuities in subsidy generosity and installation rates at state borders. In Figure 3, we show that household demographics do not exhibit discontinuities at state borders.

partial elasticity of solar production varies flexibly with income. [28] Instead, we consider an alternative strategy in which we expand our sample to all tracts, including those not around state borders, and estimate two specifications that allow for flexible non-linearities in this empirical partial elasticity.

The first of these specifications divides tracts into "bins" based on their average income level and estimates separate coefficients for each bin. Letting $\mathbb{1}(\ell \in \text{Bin}_b)$ denote that tract ℓ falls within income bin b, we estimate

$$\log K_\ell = \beta_0^{\text{Bin}} s_\ell + \sum_{b \neq b_0} \beta_b^{\text{Bin}} s_\ell \times \mathbb{1}(\ell \in \text{Bin}_b) + x_\ell' \boldsymbol{\gamma}^{\text{Bin}} + \varepsilon_\ell^{\text{Bin}}. \tag{5}$$

Thus, β_0^{Bin} gives the empirical partial elasticity associated with base income bin b_0, and the β_b^{Bin} coefficients tell us how partial elasticity in income bin b differs from that of the base income bin. In practice, we will set the base income bin as the bin corresponding to the median tract-level income level such that β_0^{Bin} gives the partial elasticity at this median income level.

Next, we estimate a model that allows for heterogeneity in the partial elasticities with cubic B-splines,

$$\log K_\ell = \sum_{h=1}^{H} \beta_h^{\text{Spl}} s_\ell \times B_h(Y_\ell) + x_\ell' \boldsymbol{\gamma}^{\text{Spl}} + \varepsilon_\ell^{\text{Spl}}, \tag{6}$$

where $B_1(Y)$ to $B_H(Y)$ are standard basis functions for a cubic B-spline degree H. This specification balances allowing for arbitrary non-linearities while estimating relatively few parameters. The estimated partial elasticity for a given income level Y is a weighted average over the H spline coefficients, where the weights are given by the basis functions $B_h(Y)$.

Controls All regressions include tract-level controls for income, electricity prices (and their interaction with income), solar irradiance, population density (linear and quadratic terms), the share of college-educated individuals, homeownership rates, and the county-level Democratic vote share in the 2016 presidential election. The border-discontinuity regressions include the border-specific polynomials introduced above, while the nonlinear specifications include census region or census division fixed effects.[29]

[28] These discontinuity regressions rely on within-border variation in subsidies, and thus, identification of a non-linear effect of subsidies requires within-border variation in subsidies within narrow bins in income. Since we only have tract-level income available, there is insufficient variation in subsidies across all income bins.

[29] Since we use state-level variation in subsidies, we cannot use more spatially refined fixed effects.

2.4 Reduced-Form Results

Border-Discontinuity Regressions Table 1 reports parameter estimates from equation (4), the border discontinuity regression with partial elasticity linear in log income. Each column corresponds to a different specification. Specifications vary the bandwidth around state borders (either 40 or 80 miles from state borders) and the degree of the polynomials in location relative to the state border (polynomials of degree 0, 3, and 5).[30]

Column (3) contains our preferred specification, with a 40-mile bandwidth and 3rd-degree border distance polynomials. The estimates imply that a one cent per kWh increase in subsidies is associated with a 4.3% increase in solar production for a tract at the median income level and that this elasticity is decreasing in tract-level income. The same one cent per kWh subsidy increase is associated with only a 3.4% increase in solar production per capita for a tract at the 90th percentile of the income distribution. In other words, the empirical partial elasticity of solar production with respect to subsidies for tracts at the median income level is 28.0 percent higher than the partial elasticity for tracts at the 90th percentile income level. The estimates in column (4), where we use an 80-mile bandwidth, are similar, implying that the partial elasticity at the median income level exceeds that at the 90th percentile by 27.7 percent.

The first two columns of Table 1 show results when we include polynomials of degree 0 in location relative to state borders, equivalent to including border fixed effects. These specifications result in elasticities that have a similar slope with respect to income but are slightly higher in levels than our main specification—a one cent per kWh increase in subsidies increases solar production by 6.0 to 6.5 percent for a tract at the median income. These partial elasticities for the median income tracts are 15.3 to 18.7 percent higher than those of tracts at the 90th income percentile.

Finally, columns (5) and (6) of Table 1 use fifth-degree border polynomials and again find similar results. In these specifications, the partial elasticity of solar production with respect to subsidies is 38.1 to 43.5 percent higher for tracts at the median income compared to those at the 90th percentile. Taken together, we find that the partial elasticity of solar production is strongly decreasing in tract-level income.

One threat to identification is that household preferences for solar panels may be discontinuous at state borders. This discontinuity could occur if, for example, households with a stronger preference for solar panels tended to locate on the side of the border with more generous subsidies. We investigate this type of sorting in Figure 3, where we look for discontinuities in household demographic characteristics around state borders. Specifically, we categorize tracts into 20-mile-wide bins based on their location relative to

[30] Appendix B.8 shows results for various other bandwidths and border-specific-polynomial degrees. The results are similar except for the smallest bandwidths.

Table 1: Effect of Subsidies on Log Production per Capita

Border Polynomial Deg.	0		3		5	
Bandwidth (mi)	40 mi	80 mi	40 mi	80 mi	40 mi	80 mi
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Subsidy	6.04***	6.53***	4.31**	4.74**	3.57*	4.02**
	(0.949)	(1.08)	(2.01)	(1.93)	(2.11)	(1.95)
Subsidy × Log Income	-1.50**	-1.92**	-1.76***	-1.92**	-2.02***	-2.07***
	(0.704)	(0.913)	(0.428)	(0.845)	(0.450)	(0.681)
Fit statistics						
Observations	20,187	30,410	20,187	30,410	20,187	30,410
R^2	0.48	0.49	0.55	0.55	0.55	0.56

Clustered (State) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Estimates of coefficients from Equation (4). Sample is limited to tracts within either 40 or 80 miles bandwidths to state borders. All regressions include controls for tract-level income, electricity prices, electricity prices interacted with income, solar irradiance, population density and population density squared, a battery of tract-level demographic measures, and border-specific polynomials in location relative to border.

the border and regress various demographics on border fixed effects and fixed effects for these location bins. Figure 3 plots these estimated location-bin fixed effects for average household income, the percent of individuals with a college degree, and percent of voters in the county who voted Democrat in the 2016 presidential election. There is no discontinuity in these characteristics as we cross to the side of the border with more generous subsidies. Appendix B.7 replicates this exercise with many more demographic variables, none of which demonstrate discontinuities at the border. These results suggest that household sorting is unlikely to bias our estimates.

Beyond subsidies, some states implement other programs designed to encourage solar installations, such as net metering, state-sponsored financing programs for solar installations, or incentives for builders to incorporate solar panels into newly built structures. These alternative policies may represent a threat to identification, as they could lead to discontinuities in solar installation rates at state borders. In Appendix B.8, we address this by rerunning the border discontinuity regressions with additional controls for these other state-level programs aimed at increasing solar installations that are not included in our subsidy measures. Our results remain robust even with the inclusion of these additional controls.

Note that we can only use tracts with positive solar production when estimating re-

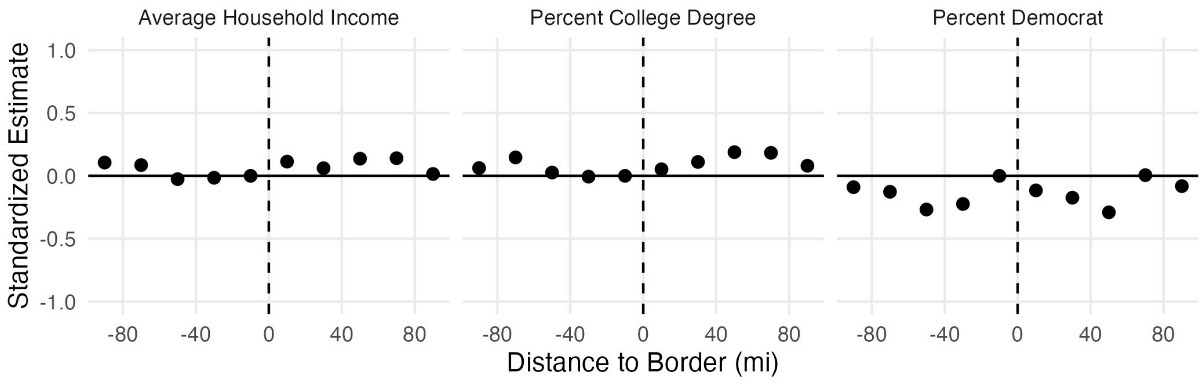


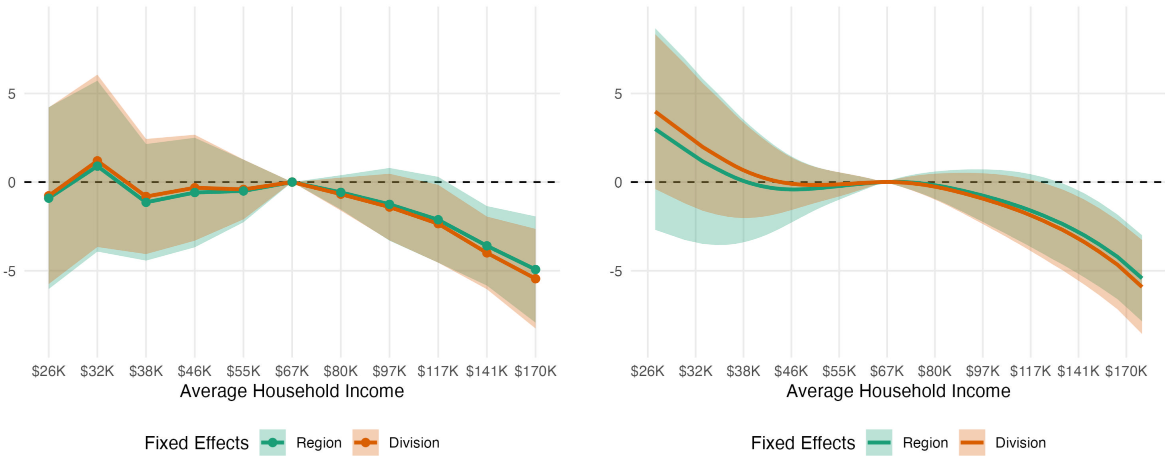
Figure 3: Border Discontinuities in Demographics and Household Income. Each graph plots estimated location-bin fixed effects from a regression of the variable in question on border fixed effects and location-bin fixed effects. Estimates are rescaled by the standard deviation of the respective variables. Positive values on the X-axis represent households on the side of the border with more generous subsidies, and negative values on the X-axis indicate the side of the border with less generous subsidies.

gressions with $\log K_\ell$ as the outcome. About a quarter of all tracts have zero production in the Deepsolar data.[31] In Appendix B.9, we explore how our focus on tracts with positive production affects our conclusions on cost-effectiveness. Empirically, we estimate border discontinuity models to assess the impact of subsidies on the likelihood of a tract having any installations, a relationship we term the "extensive margin" elasticity.[32] We show that 1) this extensive margin elasticity is small in magnitude, and 2) like our baseline partial elasticity estimates, the extensive margin elasticity is decreasing in income. The results suggest that restricting our sample to tracts with positive solar production in the baseline regressions is unlikely to change our main conclusions and would likely only strengthen them.

Another potential issue is we run our regressions using subsidy data from 2017 despite the fact that many of the installations in our data occurred before 2017. To understand how our use of 2017 subsidies might influence our main conclusions, we conduct a robustness exercise using the "historically-adjusted" subsidy generosity measure from Sexton et al. (2021). This measure is calculated by first determining the net present value of subsidies a household in a given state would receive for an installation in each year from 2000 to 2017, based on the subsidy levels available in that year. They then take the weighted average of the subsidy values across, weighted by the number of installations each year. We rerun our main regressions using this alternative subsidy measure in Table A3. The results are qualitatively similar to our baseline results.

[31] Slightly more, about 30%, of tracts within either 40 or 80 miles of a border have zero solar production in the Deepsolar data.

[32] Our approach is in the spirit of the "hurdle" approach of Gillingham and Tsvetanov (2019).



(a) Partial elasticity using income bins.

(b) Partial elasticity using cubic B-splines over income.

Figure 4: Partial elasticity of solar production across the tract-level income distribution. Panel (a) estimates a separate partial elasticity for 11 income bins, while panel (b) uses cubic B-splines. Both present estimates relative to a tract at the median income. We estimate the partial elasticity to be 7.81 for the median income bin on the left and 7.36 for the median income using splines on the right when using census division fixed effects. The green line in each figure shows estimates from a regression that includes region-fixed effects, and the orange line shows estimates from a regression with division-fixed effects. All regressions include the control variables listed in the text. We cluster standard errors by state. Cubic B-splines have 7 knots evenly spaced based on population-weighted income.

Nonlinear Specifications Figure 4 demonstrates results from two approaches that allow the partial elasticity to vary non-linearly with income—using bins in log income and cubic B-splines over income levels—across specifications with either census region or division fixed effects.[33] Figure 4a shows estimates of the β_b^{Bin} from equation (5), where we divide tracts into 11 income "bins" based on their income level. The orange line shows estimates of β_b^{Bin} across income bins from a regression that uses census region fixed effects, and the green line shows estimates from a regression with census division fixed effects. Recall that β_b^{Bin} measures the partial elasticity in income bin b relative to the partial elasticity in tracts with the median income level. We obtain estimates of β_0^{Bin}, the parameter which gives the partial elasticity in tracts with the median income level of 6.0 in the regression with region fixed effects and 7.8 in the regression with division fixed effects.

In both specifications, the partial elasticity of production is relatively similar for tracts with income levels below the median income but drops steeply for tracts above the median income. Using the specification with region fixed effects, a tract at the 90th percentile of income (contained by the $117K income bin) has a partial elasticity of 3.9—implying that the partial elasticity for a tract at the median income is 54 percent higher than a tract at

[33]These models use data from all census tracts and include controls for tract-level income, electricity prices, electricity prices interacted with income, solar irradiance, population density and population density squared, and a battery of tract-level demographic measures.

the 90th percentile. Similarly, the estimates from the regression with division fixed effects imply that the partial elasticity is 43 percent higher for a tract at the median income than a tract at the 90th percentile.

Figure 4b shows results where we use cubic B-splines to estimate partial elasticities as a smooth and continuous function of income while still allowing for arbitrary nonlinearities. To maintain comparability to the bin specification, we normalize the estimated partial elasticities relative to that of the median income. Again, the results from these specifications are similar to those of our other specifications. We estimate that a one-cent increase in subsidies leads to a 5.6 or 7.4 percent increase in solar production using region or division fixed effects, respectively. Meanwhile, a tract at the 90th percentile only increases solar production by 4.0 or 5.5 percent in response to the same one-cent subsidy increase. Thus, a median tract has a partial elasticity that is 33.5 to 39.2 percent higher than a tract at the 90th income percentile. Unlike when we use bins, the spline specification suggests that the partial elasticity may be considerably higher for the lowest-income tracts, though this increase is not statistically significant.

Regardless of the specification, we consistently find that the partial elasticity of residential solar production per capita decreases with income, with the steepest drop above median income. Our results suggest that this partial elasticity may further increase in locations with below-median income relative to those with median income; however, this increase is not consistent across specifications and is not statistically significant.

Robustness In Appendix B.8, we examine the robustness of our reduced-form results to alternative outcomes (total production, total panels, panels per capita, installations, installations per capita), alternative bandwidths for border-discontinuity regressions, alternative controls, excluding states without net-metering, using a Poisson model, and alternative means of estimating heterogeneity in the partial elasticity by income level. The results remain qualitatively the same in each case: the partial elasticity of solar production is decreasing in tract-level income. These results strongly suggest that the cost-effectiveness of residential solar subsidies is decreasing in household income and, thus, that a decrease in subsidies for high-income households and an increase in subsidies for low-income households could achieve increased residential solar production at the same fiscal cost.

3 Quantitative Model and Estimation

Our reduced-form results suggest that employing means-tested subsidies may allow policymakers to increase solar production without increasing fiscal costs. That analysis does not allow us to determine the magnitude of the benefits of introducing federal means-tested subsidies nor the efficient schedule of means-tested subsidies. Here, we construct and structurally estimate a partial equilibrium model of solar panel demand with borrowing constraints. Homeowners in the model make a once-and-for-all decision whether to install solar panels, considering the lifetime costs and benefits. Homeowners face borrowing constraints, meaning low-income homeowners may not install panels despite the long-run benefits.[34] We use the estimated model to evaluate the equity and efficiency consequences of introducing various income-contingent subsidy schemes and to quantify the efficient subsidy schedule.

3.1 Model

Homeowners are indexed by i, and time is indexed by $t = 1, ...T$, which in our empirical setting will be years. In $t = 1$, homeowners choose whether to install solar panels, considering the lifetime costs and benefits of installation.[35] Let $m_i \in \{0, 1\}$ indicate whether or not a homeowner installs solar panels and let N_i be the number of solar panels homeowner i installs conditional on installation.

Each homeowner has access to solar panel technology that can produce a stream of solar energy of $\{A_{it}\}_{t=1}^{T}$ over time, where A_{it} represents the amount of electricity each panel installed by homeowner i will produce in year t. This measure of solar production captures both differences in sunlight at their residence and depreciation of solar panels over time.

Budget Constraint Homeowners who install panels pay an upfront installation cost but receive value from the electricity that the panels produce over time. Let the function $p_j^{\text{Ins}}(N_i)$ denote the monetary cost of installing N_i panels and let p_j denote the price of electricity, where j indexes the state in which a homeowner lives.[36] The total market value of electricity produced by homeowner i in period t is therefore equal to $m_i N_i A_{it} p_j$. We can think of this as both the value of reducing the amount of electricity a homeowner needs to purchase from the grid and the value of selling solar electricity back to the grid.

[34] Renters do not typically install solar panels. We therefore only model the installation decision of homeowners and assume households who are not homeowners do not install solar panels.

[35] Burr (2014) use an optimal stopping model where households decide whether to install each period, exiting the market if they do choose to install. Gillingham and Tsvetanov (2019) presents evidence that households in most states do not treat installation as an install or wait decision.

[36] We assume that electricity can be purchased and sold back to the grid at this same price. For homeowners in the 39 states with net metering, homeowners receive the retail price of electricity for the electricity they sell back to the grid. In states without net metering, there may be different prices for electricity purchased by the homeowner and electricity sold by the homeowner. It would be straightforward to limit our estimation sample to states with net metering. Ito (2014) finds that consumers respond to average, rather than marginal, electricity prices.

Homeowners also receive subsidies for installing solar panels and for the electricity they produce. Let $s_i^{\text{Upfront}}(\cdot)$ denote the *upfront* subsidy homeowner i would receive at the time of installation and let $s_i^{\text{Flow}}(\cdot)$ denote the *flow* subsidy the homeowner i would receive each year over the life of the panel. When we take the model to the data, we will consider investment tax credits and sales tax rebates as upfront subsidies. We allow upfront subsidies to depend on the cost of the installation, $p_j^{\text{Ins}}(N_i)$, to reflect that investment tax credits and sales tax rebates depend on the cost of installation. We also allow upfront subsidies to depend on a homeowner's federal income tax burden to reflect that the federal investment tax credit is a nonrefundable tax credit, meaning that the amount a household receives cannot exceed the tax burden that they would otherwise owe.[37] Empirically, we categorize property tax rebates, renewable energy credits, and production tax credits as flow subsidies. We allow flow subsidies to depend on installation costs to reflect that property tax rebates often depend on the cost of installation and on A_{it} to reflect that renewable energy credits and production tax credits depend on the amount of electricity produced.

The homeowner's budget constraint in year $t = 1$ is given by

$$\begin{aligned} c_{i1} + a_{i2} + m_i p_j^{\text{Ins}}(N_i) = y_i - \tau(y_i) + (1+r)\, a_{i1} + \\ m_i \left(N_i A_{it} p_j + s_i^{\text{Upfront}}\left(p_j^{\text{Ins}}(N_i), \tau(y_i)\right) + s_i^{\text{Flow}}\left(p_j^{\text{Ins}}(N_i), A_{it}\right) \right), \end{aligned} \tag{7}$$

where c_{i1} is consumption of the numeraire good in period $t = 1$, a_{i2} is the amount the homeowner saves for the following period, y_i is household income, $\tau(y_i)$ is federal income tax burden (not including federal solar credits), a_{i1} is initial assets, and r is the real interest rate. Due to data limitations, we assume that income for each household is constant over time. We consider a version of the model with a stochastic income process in Section 5.1.

After the first period, homeowners continue to make consumption-savings decisions and receive electricity and flow subsidies from installed solar panels. Additionally, while federal tax credits are nonrefundable, excess credits can be carried over to the following years. We can write the homeowner's budget constraint for $t > 1$ as

$$\begin{aligned} c_{it} + a_{it+1} = y_i - \tau(y_i) + (1+r)\, a_{it} + \\ m_i \left(N_i A_{it} p_j + s_i^{\text{Flow}}\left(p_j^{\text{Ins}}(N_i), A_{it}\right) + s_{it}^{\text{Carry}} \right), \end{aligned} \tag{8}$$

where s_{it}^{Carry} gives the value of any federal tax credits that have been carried over from previous years.

[37] Kiribrahim-Sarikaya and Qiu (2023) uses data from Arizona to analyze the effects of the nonrefundable nature of the federal income tax credits on solar installation rates across the income distribution.

Homeowners face a borrowing constraint in each period. We write this as

$$a_{it+1} \geq \bar{a}_i, \tag{9}$$

where $\bar{a}_i$ is the minimum level of assets homeowner i must maintain. Specifically, we follow Braxton et al. (2024) and parameterize the minimum asset level as a linear function of household income:

$$\bar{a}_i = \alpha_1 + \alpha_2 y_i$$

where α_1 and α_2 are parameters. We use the values of α_1 and α_2 from Braxton et al. (2024), who estimate these parameters using data from the Survey of Consumer Finances.[38]

It is important to highlight that we abstract away from changes in subsidies and prices over time. We can therefore view our model as capturing the forward-looking installation behavior for homeowners who expect subsidies and prices to remain at their current levels.[39] Furthermore, our model differs from those in De Groote and Verboven (2019), Langer and Lemoine (2022), and Feger, Pavanini, and Radulescu (2022), by treating the installation decision as a one-time event, with homeowners permitted to install panels only in the beginning of the model. Incorporating a dynamic installation decision into the model would significantly increase the computational burden of estimating the model and solving for the optimal policy. As a result, our model is not well suited to analyze how dynamic subsidy paths will affect the timing of installations. Instead, the main goal of our model is capturing differences in installation behavior across the income distribution for homeowners facing a given set of subsidies.

Utility Homeowners' lifetime utility is given by

$$\sum_{t=1}^{T} \beta^{t-1} \frac{(c_{it})^{1-\gamma}}{1-\gamma} + m_i \phi_i,$$

where $\beta = \frac{1}{1+r}$ is the homeowner discount rate, γ is a preference parameter, and ϕ_i gives the nonpecuniary benefit of a solar installation for homeowner i, reflecting inconvenience costs or other individual preferences for installing solar panels. We specify ϕ_i as

[38]They estimate $\alpha_2 = -0.204$, implying that a 1 dollar increase in income is associated with a 20 cent increase in borrowing limit. It would also be possible to allow the borrowing limit to vary by state and whether or not the homeowner has installed solar panels to better reflect the availability of financing programs for solar panel installations.

[39]Hughes and Podolefsky (2015) and Anderson, Kellogg, and Sallee (2013) find that consumers do not correctly forecast the extent to which prices change over time and expect future prices to be similar to current prices. In Section 5.4, we re-calculate efficient subsidies under the assumption that installation prices drop to 50% of their current levels.

$$\phi_i = \phi_0 + \phi_{\text{Coll}} X_\ell^{\text{Coll}} + \phi_{\text{Pol}} X_\ell^{\text{Pol}} + \sigma\epsilon_i,$$

where X_ℓ^{Coll} is the fraction of individuals with a college education in the census tract in which the homeowner lives, X_ℓ^{Pol} is the fraction of voters in the county who voted Democrat in the 2016 presidential election and ϵ_i is a logit preference draw with scaling parameter σ. Let $\bar{\phi}_i = \phi_i - \sigma\epsilon_i$ denote the portion of non-pecuniary utility that does not contain an idiosyncratic component.

Installation Probabilities Previous research has found that the number of panels per installation does not strongly correlate with rooftop solar subsidies.[40] We therefore abstract away from the intensive margin decision and parameterize N_i as a reduced-form function of homeowner income and tract-level characteristics. We estimate the parameters of this reduced-form function jointly with the other structural parameters using indirect inference. We provide additional details in Appendix B.11.

Each homeowner makes a discrete choice over whether to install solar panels and then makes consumption-savings decisions. Given that ϵ_i has a logit distribution, the probability homeowner i installs solar panels is given by

$$P_i = \frac{\exp\left(\frac{1}{\sigma}\sum_{t=1}^{T}\beta^{t-1}\frac{\left(c_{it}^{m=1}\right)^{1-\gamma}}{1-\gamma} + \bar{\phi}_i\right)}{\exp\left(\frac{1}{\sigma}\sum_{t=1}^{T}\beta^{t-1}\frac{\left(c_{it}^{m=1}\right)^{1-\gamma}}{1-\gamma} + \bar{\phi}_i\right) + \exp\left(\frac{1}{\sigma}\sum_{t=1}^{T}\beta^{t-1}\frac{\left(c_{it}^{m=0}\right)^{1-\gamma}}{1-\gamma}\right)},$$

where $c_{it}^{m=1}$ and $c_{it}^{m=0}$ give the homeowner's optimal consumption level in period t conditional on installing and not installing solar panels, respectively.

The parameter γ plays a crucial role in our analysis as it dictates how the elasticity of installations varies across income levels. To see this, note that partial elasticity of installation with respect to upfront subsidies s^{Upfront} is given by

$$\frac{\partial \log P_i}{\partial s^{\text{Upfront}}} = \frac{\left(c_{i1}^{m=1}\right)^{-\gamma}}{\sigma}\left(1 - P_i\right), \tag{10}$$

where $c_{i1}^{m=1}$ gives the homeowner's optimal consumption choice in period 1 conditional on installing panels. We provide a derivation of equation (10) in Appendix B.10. Homeowners with high income and asset levels will generally have higher values of $c_{i1}^{m=1}$. If γ is large, homeowners with high income and asset levels will be less responsive in their installation

[40] Colas and Reynier (2024) find that installation size is not sensitive to monetary incentives, but the probability of installations is highly responsive to monetary incentives. They conclude that accounting for the extensive margin installation decision is much more important than the intensive margin decision of the number of panels to install.

decisions, all else equal.[41] This lower responsiveness is because a larger value for γ means the marginal utility of consumption decreases more rapidly as consumption levels increase.

Additionally, a higher installation probability P_i decreases responsiveness to subsidies. This decrease reflects that homeowners with a higher P_i are more likely to be inframarginal—their installation decision is unaffected by a marginal subsidy change. Finally, the parameter σ determines the overall level of the partial elasticity of installations with respect to subsidies. A larger value of σ, representing stronger idiosyncratic preferences for solar installations across all homeowners, implies that homeowners will be less responsive to subsidies in their installation decision.

3.2 Data

For structural estimation, we combine the data on subsidies, electricity prices, and residential solar installations described in Section 3.2 with income and homeownership data from the ACS and solar irradiance data from Google Project Sunroof. Here, we give an overview of the main data sources that we do not use in our reduced-form analysis. We provide additional details on the data we use for structural estimation in Appendix B.11.

Solar Potential We use data from Google Project Sunroof (GPS) to construct the solar potential for panels installed by each homeowner. GPS applies a machine-learning framework to satellite imagery and provides measures of solar production capacity per panel at the tract level, accounting for local weather conditions, rooftop sizes, and shading. We assume a homeowner's yearly solar potential for newly installed panels, A_{i1}, is equal to the mean household solar potential in the GPS data for the homeowner's tract. We assume solar panel efficacy depreciates by a constant rate of 0.5% each year before fully depreciating after 20 years.[42]

Installation Prices We assume installation prices are given by the function $p_j^{\text{Ins}}(N_i) = p_j^{0,\text{Ins}} + N_i p_j^{1,\text{Ins}}$, where $p_j^{0,\text{Ins}}$ is a fixed cost and $p_j^{1,\text{Ins}}$ is a per-panel cost. We take estimates of $p_j^{0,\text{Ins}}$ and $p_j^{1,\text{Ins}}$ from Colas and Reynier (2024), who estimate these pricing functions using data from Tracking the Sun, a project collecting data on solar panel installations. As Tracking the Sun does not cover all states within the US, they assume that pricing functions are common within each Census region.

[41] To see this, note that if $\gamma = 0$, the partial elasticity of installation across homeowners will not depend on $c_{i1}^{m=1}$, and variation across homeowners will only be due to differences in installation probability P_i.

[42] Jordan and Kurtz (2013) find a median degradation rate of 0.5% in their review of the literature on depreciation rates of solar panels.

Income and Initial Assets Simulating our model requires the household income distribution for homeowners across the United States. For this, we construct tract-level income distributions for homeowners by combining 1) tract-level data on average household income, Gini coefficient, and number of households from the ACS, and 2) household-level data on homeownership and income from the ACS. We describe this procedure in detail in Appendix B.12.

An additional empirical issue is that we do not observe initial assets, a_{i1}. To deal with this, we use estimates of the joint distribution of income and wealth from Jäntti, Sierminska, and Van Kerm (2015), who estimate a parametric distribution of income and wealth in the US using data from the Survey of Consumer Finances.[43] Using their estimates, we calculate the distribution of initial assets conditional on a household's income level. Further details of this procedure are in Appendix B.13. We then integrate over each household's conditional distribution of the initial assets when simulating model outcomes.

3.3 Estimation

Our primary strategy is to estimate the model by indirect inference, where we target regression coefficients from our reduced-form results and moments describing the distribution of installations across income and demographic groups. We first compute a set of "auxiliary models" that describe installation behavior in the data. Then, given a vector of structural parameters, we simulate the structural model and calculate the auxiliary models with simulated data. We repeat this procedure for different values of structural parameters and search for the parameters such that the auxiliary models computed from the model match those from the data.

Formally, let $\bar{\beta}$ denote the vector of auxiliary model parameters we estimate in the data and let $\hat{\beta}(\Theta)$ denote the same auxiliary model parameters computed from the structural model given an arbitrary vector of structural parameters denoted by Θ. The estimated vector of structural parameters is given by

$$\hat{\Theta} = \text{argmin}_{\Theta} \left\{ \left(\hat{\beta}(\Theta) - \bar{\beta} \right)' W \left(\hat{\beta}(\Theta) - \bar{\beta} \right) \right\},$$

where W is a weighting matrix.

We use the following auxiliary models[44]:

AM 1: Border discontinuity regression coefficients from estimation of equation

[43] They also provide estimates for four other OECD countries.

[44] We show the full set of auxiliary model parameters we use in Table A10 in Appendix B.15. We weight by the inverse of the variance of each moment. We then increase the weights on AM 1 as these moments are particularly important for the optimal subsidies.

(4). Specifically, we regress tract-level log production on subsidies and subsidies interacted with log average income for tracts within 40 miles of a border with 3rd degree polynomials in distance from each border, and the same controls as column 3 of Table 1.

AM 2: Coefficients from regressions of tract-level installations per capita on tract-level average income.

AM 3: Installations per capita by income quintile.

AM 4: Coefficients from regressions of tract-level installations per capita on tract-level demographics.

AM 5: Coefficients from a regression of tract-level average number of panels per installation on tract-level characteristics.

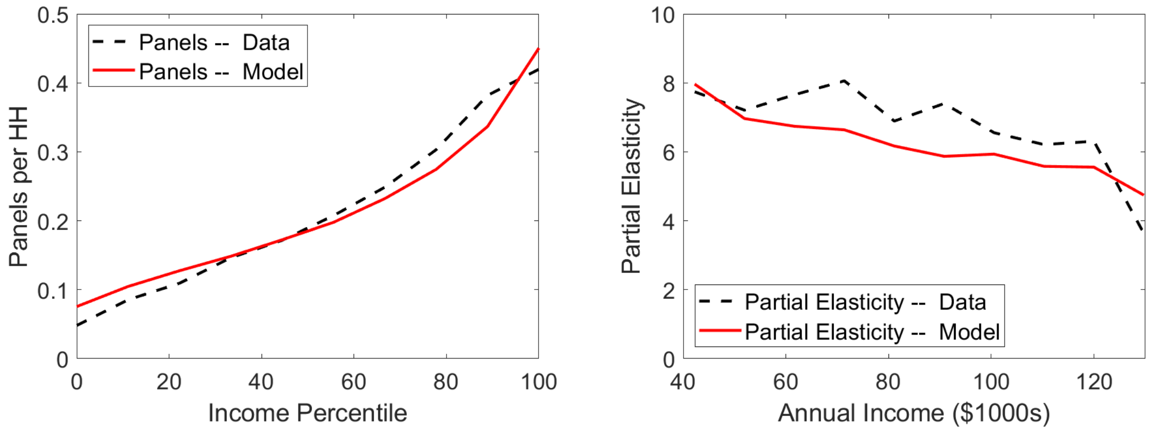
The parameters are well-identified. As previously noted, the parameter σ dictates the overall partial elasticity of installations with respect to subsidies across all homeowners, while γ dictates how these elasticities vary with household income and assets. "AM 1" and "AM 2" help to identify these two parameters. "AM 1" describes how the elasticity of installations with respect to subsidies varies by income, and "AM 2" describes how installations vary with income. The parameters ϕ_0, ϕ_{Coll}, and ϕ_{Pol}, which determine the nonpecuniary benefits of installations, are largely identified by "AM 4", which describes how installations vary with tract characteristics. Finally, "AM 5" helps to pin down the parameters that determine how the size of installations varies by demographic group.

3.4 Model Fit

We present the full set of estimated parameters in Appendix B.14. The estimated model fits both targeted and untargeted moments well. We give an overview of model fit here and leave additional results in Appendix B.15.

Targeted Moments Figure 5 plots panels per household (including non-homeowners) across percentiles of tract-level income in the model and data. The red line shows the panels per household in the data, while the black dashed line shows the simulated panels from the estimated model. The model does an excellent job of matching differences in the number of solar panels per household across the entire income distribution.

As discussed in Section 2, variation in the partial elasticity of solar production across the income distribution is critical for determining the cost-effectiveness of subsidies by income level. To assess the model fit in this dimension, we estimate the relationship



(a) Panels: Income

(b) Partial Elasticity

Figure 5: Panel (a) shows panels per household across percentiles of tract-level income in the model and data. The red line shows the panels per household in the data, while the black dashed line shows the simulated panels from the estimated model. Panel (b) shows partial elasticities across income levels in the model and data. These are estimated using the same set of controls as Figure 4 with census division fixed effects.

between log tract-level installations and subsidy generosity across income groups in the model and the data. We again divide tracts into income bins based on the average income level in each census tract. Let $\mathbb{1}(\ell \in \text{Bin}_b)$ denote that tract j falls within income bin b. Using both actual data and simulated data from the model, we run regressions of the form

$$\log K_\ell = \sum_{b=1} \beta_b^{\text{Fit}} s_\ell \times \mathbb{1}(\ell \in \text{Bin}_b) + x_\ell' \gamma^{\text{Fit}} + \varepsilon_\ell^{\text{Fit}}, \tag{11}$$

where K_ℓ is the total solar production in tract j, s_ℓ denotes the subsidy generosity measure from Sexton et al. (2021) which we used in our reduced-form analysis, and b indexes income groups. We use the same controls as in Figure 4, with census division fixed effects. The β_b^{Fit} parameters, therefore, measure the partial elasticity of solar production with respect to subsidies for households income bin b. Figure 5b plots the estimates of these parameters for the model and the data. The model fits the empirical partial elasticity of installations with respect to subsidies across income levels well.

Untargeted Moments We also compare simulated results from the model to data not targeted in estimation to further assess model validity. The 2015 Residential Energy Consumption Survey (RECS) has income and solar installation status data for 5,700 households across the United States, along with data on other energy-related goods and behaviors. Appendix Figure A11 shows the percent of households with solar panels by income quartile from our model simulations and the RECS data.[45] The fit is reasonably

[45]Income in RECS data is presented in income categories. We combine categories such that the bins in the figure roughly correspond to income quartiles in 2015.

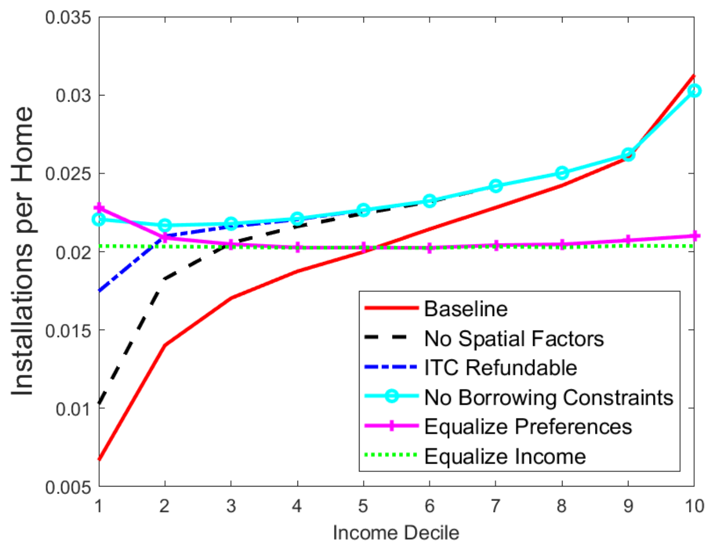


Figure 6: Model-Based Decomposition. The graph shows the average number of installations per homeowner across deciles of household income over various model specifications. See text for details on each specification.

good, though our model does predict lower installation rates for high-income levels than in the RECS data.

Comparison to Existing Literature Several other studies use diverse methods and empirical applications to credibly estimate the effect of subsidies on household demand for solar panels (Hughes and Podolefsky, 2015; Crago and Chernyakhovskiy, 2017; Gillingham and Tsvetanov, 2019; Colas and Reynier, 2024). We use our estimated model to reproduce results from those studies, the details of which are in Appendix B.16. For each of these four studies, our replication is consistent with the results of the respective study.

4 Counterfactuals

4.1 Why are Installations Increasing in Income?

Current subsidies for residential solar panels in the US are highly regressive, as installation rates are strongly increasing in household income (Borenstein and Davis, 2024). As our first counterfactual, we use our estimated model to understand the mechanisms driving this positive correlation between income and installation rates under the current subsidy scheme.

Five main mechanisms in our model collectively generate a relationship between household income and installations per homeowner. First, high-income households tend to live in states with more generous subsidies and higher electricity prices.[46] Second, the Federal Investment Tax Credit is nonrefundable, and therefore, low-income households may not be able to take full advantage of this tax credit because their tax burden is too low. Third, households face borrowing constraints, and therefore, low-income households may not be able to afford solar panels despite the long-run monetary benefits. Fourth, high-income households may have stronger preferences for installations.[47] Finally, differences in income and assets imply different marginal utilities of consumption.

We perform a model-based decomposition to understand the role played by each of these features in generating the positive relationship between household income and installations. Specifically, we remove each of these features one by one and re-simulate the model. All changes to the model specification are cumulative. Recall that we only consider homeowners in our analysis. Therefore, we plot the relationship between income and installations per homeowner rather than household.[48]

The results are displayed in Figure 6. The solid red line shows the baseline case. Roughly 0.6 percent of homeowners in the bottom income decile install panels compared to over 3 percent of homeowners in the top decile. We begin our decomposition by removing all spatial factors and assuming all subsidies, prices, and levels of solar irradiance are drawn randomly from their respective unconditional distributions. This removal leads to a slight increase in installations for poorer households, as states with lower income levels tend to have less generous subsidies and lower electricity prices.

The nonrefundable nature of the Federal Investment Tax Credit may play an important role in explaining low installation rates for low-income households. We next simulate a version of the model in which we additionally assume that the Federal Investment Tax Credit pays in full in the year of installation. This change leads to a large increase in installations for lower income levels but no change in installations for households with higher income, who already have a large enough tax burden to receive the full credit in the year of installation.

Next, we simulate a version of the model in which households additionally do not face a borrowing constraint and can borrow freely against future income. This change leads to a large increase in installations for poorer households but no change for higher-income households, who both face less stringent borrowing constraints and are less likely to need

[46]The tract-level correlation between average income and electricity prices is 0.18. The correlations between average income and property taxes, production subsidies, and cost subsidies are 0.11, 0.10, and 0.06, respectively.

[47]The correlation between income and tract-level college-educated share and democrat share capture these differences in preferences.

[48]We show the same graph with installations per household, rather than homeowner, in Appendix B.18. Homeownership rates are strongly increasing in household income. Therefore, the installation rates per household, including non-homeowners, increase more strongly in income than those shown here.

to borrow to finance solar panels compared to lower-income households. We next remove the correlation between household income and preferences by setting X_ℓ^{Coll} and X_ℓ^{Pol} to the median values in the data. This equalization lowers installation rates for high-income households. Finally, we remove the role of income directly by setting all household income levels to the national mean. This fully removes the relationship between income and installations.

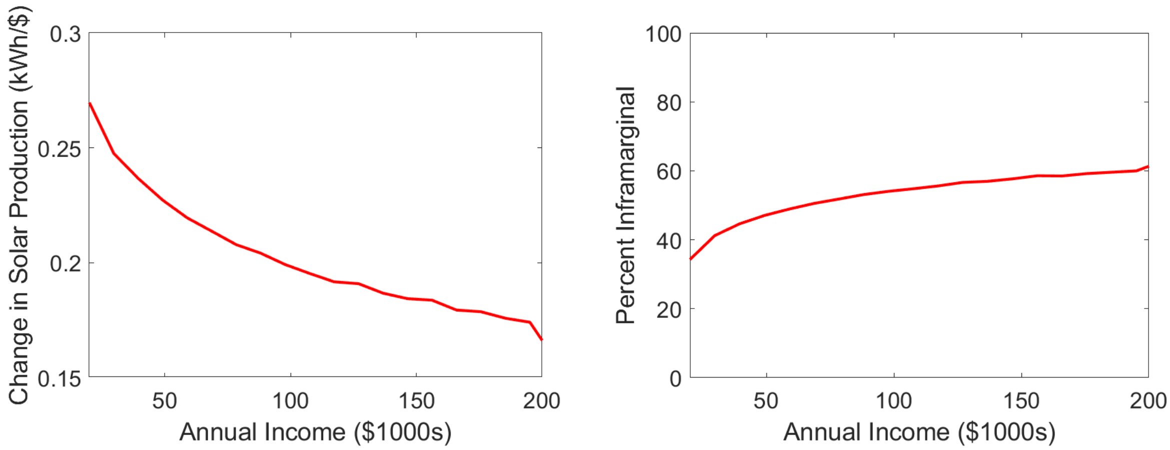
In summary, this decomposition suggests that borrowing constraints and the non-refundability of the Federal Investment Tax Credit play major roles in generating the positive relationship between installations and income for lower-income households, while preferences play a larger role for higher-income households.

4.2 Introducing Income-Contingent Subsidies

We now analyze the cost-effectiveness of introducing small income-contingent subsidies to the current subsidy scheme. Specifically, we calculate the additional solar capacity per dollar of public funds associated with income-contingent subsidies. To calculate this, we divide households into 20 income groups. We then simulate installations 1) given the current system of subsidies and 2) where we also offer small, targeted subsidies for households of a given income group. We calculate the additional solar capacity per dollar for that income group as the increase in solar capacity divided by the increase in fiscal cost. We repeat the process for all income groups. We assume these income-contingent subsidies are upfront subsidies: they are paid in full at the time of installation.

The results are presented in Panel (a) of Figure 7. Solar capacity per dollar of public funds is decreasing in household income. Introducing subsidies targeted at households with an income of $40,000 leads to an increase of 0.24 kWh of solar electricity per additional dollar of subsidies. On the other hand, subsidies targeted at high-income households are two-thirds as cost-effective: subsidies targeted at households with income over $200,000 lead to 0.16 kWh of solar electricity per dollar.

As highlighted in Section 2, a key determinant of the cost-effectiveness of introducing income-contingent subsidies is the number of non-additional households relative to additional households. To illustrate how this relationship varies across the income distribution, we calculate the percent of targeted subsidies for each income group received by households who choose to install panels absent the subsidy increase. Panel (b) of Figure 7 shows the results. The percentage of non-additional households is strongly increasing in income. For households with an income of $40,000, 45% of targeted subsidy funds go to households who would already install solar panels absent the targeted subsidies. The percent of non-additional households is over twice this for high-income households: over



(a) Additional production per dollar

(b) Percent of installations non-additional

Figure 7: Cost-effectiveness of introducing income-contingent subsidies to the current subsidy scheme. Panel (a) shows the change in solar capacity per dollar of additional fiscal cost associated with introducing income-contingent subsidies to each income group. Panel (b) shows the percent of income-contingent subsidy funds received by non-additional households.

60% subsidies for households with income over $200,000 are received by households who would already install panels absent the subsidy increase.

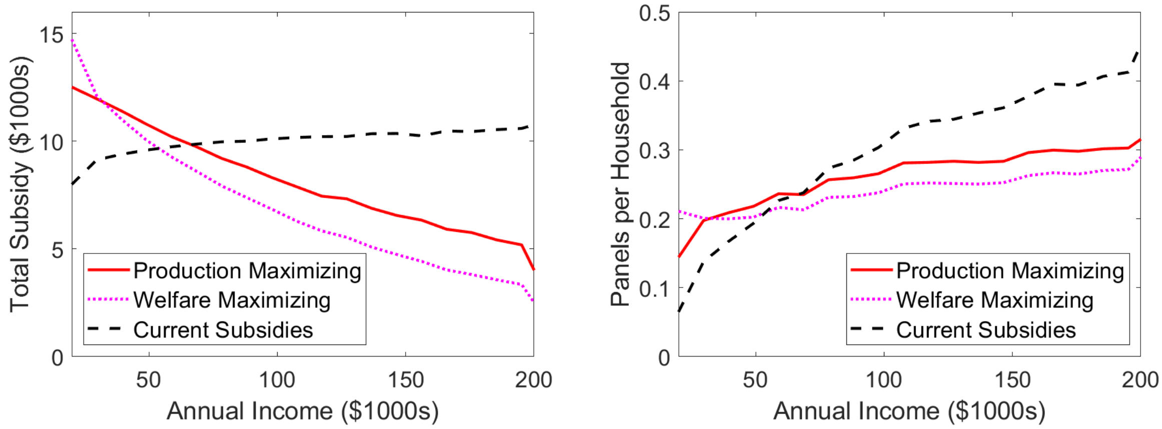
4.3 Production-Maximizing Subsidies

Next, we consider a federal government that chooses a national income-contingent subsidy schedule to maximize total solar production subject to the constraint that total government spending must be no greater than spending under current subsidies. We hold all other state and federal subsidies constant and again assume that the government pays income-contingent subsidies upfront.[49] Note that since this objective does not account for household utility, we have removed the equity rationale for means-tested subsidies as there is no motive for the government to redistribute from rich to poor households. In Appendix B.19, we formalize the government's problem and derive its first-order conditions. To solve for the production-maximizing subsidies, we numerically calculate the system of income-contingent subsidies that satisfy these first-order conditions.

The results are displayed in Table 2 and in Figure 8. Figure 8a presents the production-maximizing subsidies (solid red line) and the current subsidies (black dotted line) as a function of income. Specifically, each line shows the average present discounted value of subsidies a household of a given income level would receive conditional on installing solar panels.[50] Moving to the production-maximizing subsidies involves increasing subsidies

[49]We compare the efficacy of upfront subsidies to flow subsidies in Section ??. We do not evaluate the optimality of the overall level of subsidies. Colas and Reynier (2024) find that subsidy levels are suboptimally high in nearly all US states.

[50]Current subsidies are increasing in income for two main reasons. First, because the Federal Investment Tax Credit is nonrefundable, households with low income tax burdens cannot receive the full value of an



(a) Average Subsidy

(b) Panels per Household

Figure 8: The figure on the left shows the average present discounted value of subsidies received for an installation across income levels under various subsidy schemes. The figure on the right shows the average panels per household across income levels under these same subsidy schemes.

for low-income households and decreasing subsidies for high-income households. Under the production-maximizing schedule, households in the first income quartile receive over $12,000 in subsidies for an installation. In contrast, households in the top income quartile receive less than $7,000. Figure 8b shows simulated installations across the income distribution under both subsidy schemes. Installations increase by over 100% for households in the first income quartile while installations of households in the top income quartile decrease by roughly 25%.

As shown in Panel III of Table 2, these changes in subsidies and the profile of installations lead to a much more equitable distribution of public funds. Switching from the current subsidy schedule to the production-maximizing subsidy schedule nearly triples the amount of solar subsidies received by households in the bottom income quartile, from 7.7% of total subsidies to 22.2%. On the other hand, funds received by households in the top income quartile drop by half, from 45.1% to 21.6% of total subsidy payments.

Panel IV shows the relative total solar production under the production-maximizing subsidies. These subsidies increase total solar production by 2.4% relative to current subsidies without raising fiscal costs. Achieving this same 2.4% increase with income-neutral subsidies would require a universal upfront subsidy of $270 per installation—roughly 4% of the average Federal Investment Tax Credit—and would increase fiscal costs by 4.8%. Thus, adopting the production-maximizing schedule could yield meaningful gains in solar production while delivering substantial cost savings relative to income-neutral subsidies.

upfront subsidy. Second, many subsidies pay a fraction of the cost of installation, and higher-income households tend to install larger, and therefore more expensive, solar panel systems.

	(1) Baseline	(2) Prod Max	(3) Utility Max
I. Production per Household			
Income Q1	20.3	42.9	61.7
Income Q2	50.1	65.1	63.6
Income Q3	77.9	77.6	70.6
Income Q4	120.2	92.6	83.4
Overall	68.8	70.4	70.2
II. Subsidy Generosity ($1000s)			
Income Q1	8.1	12.3	14.4
Income Q2	9.3	11.5	11.3
Income Q3	9.8	9.8	8.7
Income Q4	10.4	6.3	4.7
III. % of Public Funds Received			
Income Q1	7.1%	20.6%	33.5%
Income Q2	18.4%	28.5%	27.4%
Income Q3	29.0%	28.7%	23.7%
Income Q4	45.5%	22.2%	15.3%
IV. Relative Production	100.0	102.4	102.0

Table 2: Panel I shows the average annual solar capacity in kWh per household in each income quartile. Panel II shows the average present discounted value of subsidies a household from each income quartile would receive for a solar installation. Panel III shows the percentage of solar subsidies received by each income quartile. We measure these subsidies as the present value of all state and federal subsidies received by households in a given income quartile as a fraction of the total amount received across all households. Panel IV shows total solar production. We scale total production under the baseline simulation to 100.

4.4 Welfare-Maximizing Subsidies

We now solve for the schedule of income-contingent subsidies that maximizes the sum of all households' lifetime utility subject to the constraint that net costs, which we define as total fiscal costs less environmental benefits, must not exceed the current level. To calculate environmental benefits, we estimate NERC-region-level marginal damages of electricity production during daytime hours using the estimation strategy and data from Holland et al. (2020). Our estimates measure the environmental damages of greenhouse gases and pollutants that fossil-fuel power plans would otherwise emit. We provide additional details in Appendix B.17. We formalize the maximization problem and present the first-order conditions in Appendix B.23.

The results are displayed in Column 3 of Table 2 and in the magenta dotted lines of Figure 8. The utility-maximizing subsidies are strongly decreasing in income, as the decreasing marginal utility of income gives the government an incentive to redistribute resources from higher-income households to lower-income households. Households in the first quartile of the income distribution receive 14.4 thousand dollars on average for a solar installation, while households in the top income quartile receive less than 5 thousand dollars. Switching to this welfare-maximizing subsidy scheme leads to a 2.0% increase in solar production.

5 Robustness and Additional Results

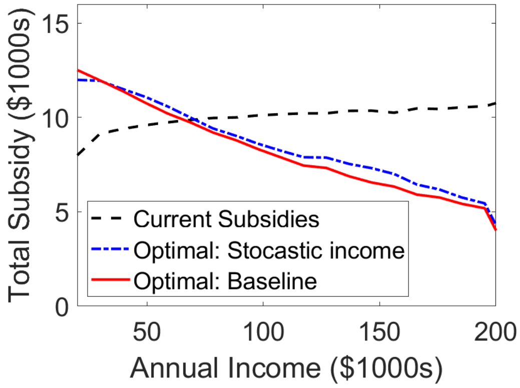
5.1 Stochastic Income

In this section, we consider a version of our model in which household income follows a linear Gaussian process with both persistent and transitory shocks, a common way of modeling stochastic earning processes in the macro and labor literature (see, e.g., Storesletten, Telmer, and Yaron, 2004; Meghir and Pistaferri, 2004; Guvenen, 2009; Heathcote, Storesletten, and Violante, 2010; Krueger, Mitman, and Perri, 2016; Guvenen et al., 2021). We first give an overview of the model before showing how stochastic income affects our main results—additional model details and results are in Appendix B.24.

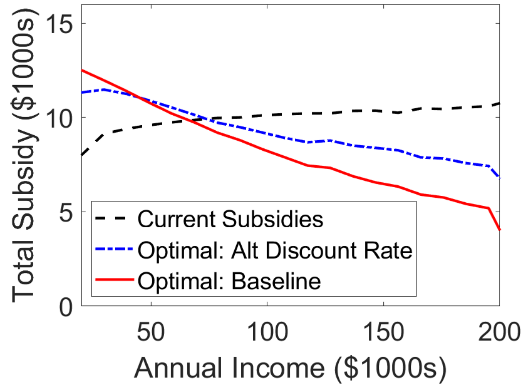
Model Let z_{it} denote the persistent component of household i's income. We assume this follows an AR(1) process as

$$z_{it} = \rho z_{it-1} + \eta_{it},$$

where ρ is a parameter that dictates the persistence of income, and η_{it} is a persistent income shock drawn from a normal distribution with mean zero and variance σ_η^2.



(a) Stochastic Income



(b) Alternative Discount Rate

Figure 9: The figure on the left shows the average subsides under the current subsidy scheme, with the production-maximizing subsidy scheme in a model with a stochastic income process and the production-maximizing subsidy scheme in the baseline model. The figure on the right shows the average subsides under the current subsidy scheme, the production-maximizing subsidy scheme in a model an alternative household discount rate, and the production-maximizing subsidy scheme in the baseline model. For each alternative specification, we re-estimate the model and re-solve for the production-maximizing subsidies.

Log household earnings in year t are given by

$$\log y_{it} = z_{it} + \varepsilon_{it},$$

where ε_{it} is a normally distributed transitory shock with mean zero and variance σ_ε^2. As is standard, we assume households know the distributions of ε_{it} and η_{it} but only learn the values of the two shocks in year t. Households make installation, consumption, and savings decisions to maximize lifetime expected utility by integrating over the distribution of future shocks.

We calibrate the parameters ρ, σ_ε^2 and σ_η^2 using the estimates from Storesletten, Telmer, and Yaron (2004), who estimate these parameters using earnings data from the Panel Study of Income Dynamics. We then re-estimate the remaining parameters using the indirect inference procedure described in Section 3.3.

Results The production-maximizing subsidy schedules in the model with stochastic income is displayed in Figure 9a. The production-maximizing subsidy schedules are very similar to that in the baseline model.

5.2 Alternative Household Discount Rate

In our baseline model, we assumed that households' discount rate was $\beta = \frac{1}{1+r}$, where r is the market interest rate.[51] However, De Groote and Verboven (2019) show that households heavily discount the future monetary benefits associated with solar panel installations.

[51] We follow Sexton et al. (2021) and set $r = .05$ in our baseline model.

Here, we re-estimate the model with stochastic income and re-calculate optimal subsidies when households use a discount rate of $\beta = 0.85$, based on the results from De Groote and Verboven (2019). Figure 9b shows the optimal subsidies under this alternative discount rate, which remain strongly decreasing in income.

5.3 Maximizing Environmental Benefit

Our main results have focused on a government that maximizes residential solar production subject to a fiscal cost constraint. However, a large literature highlights that the environmental benefits of solar panels vary dramatically depending on where the solar panels are installed.[52] Therefore, the subsides which maximize solar production are not necessarily the best for the environment.

In Appendix B.20, we solve for the income-contingent subsidy schedule that maximizes environmental benefits. As in Section 4.4, we calculate environmental benefits of solar panels by estimating NERC-region-level marginal damages of electricity production during daytime hours using the estimation strategy and data from Holland et al. (2020). We provide additional details in Appendix B.17. The benefit-maximizing schedule is very similar to the production-maximizing schedule and leads to a 2.4% increase in environmental benefits of residential solar nationally.

5.4 Lower Installation Prices

The cost of residential solar installations has decreased substantial over the past two decades (Barbose et al., 2023). To understand how efficient income-contingent subsidy schedules would adjust if installation prices were significantly lower than current levels, we calculate the production-maximizing subsidies assuming a 50% reduction in installation costs in Appendix B.21. The production-maximizing subsidies with lower installation prices are still strongly decreasing in income.

6 Conclusion

We study the design of income-contingent subsidies for residential solar panels. We show reduced-form evidence that the partial-elasticity of solar production with respect to subsidies is decreasing in income, suggesting that means-tested subsidies could induce greater

[52] See e.g. Siler-Evans et al. (2013), Graff Zivin, Kotchen, and Mansur (2014), Holland et al. (2016), Millstein et al. (2017), Callaway, Fowlie, and McCormick (2018), Holland et al. (2020), Brown and O'Sullivan (2020), Lamp and Samano (2023) Borenstein and Bushnell (2022), Sexton et al. (2021), and Colas and Reynier (2024).

solar production per dollar of public funds compared to income-neutral subsidies. Simulations from a quantitative model reveal that optimally set income-contingent subsidies lead to a much more equitable distribution of public funds and an increase in residential solar production. Therefore, means-tested solar subsidies are justified on both equity and cost-efficiency grounds.

More generally, means-tested subsidies for environmentally friendly technologies are often promoted for their equity benefits. However, our results show that, in addition to these equity benefits, targeting green subsidies at low-income families can also yield substantial efficiency gains by addressing two market imperfections that would otherwise lead to underinvestment in these technologies: 1) credit constraints due to incomplete financial markets, and 2) environmental benefits that households do not internalize in private adoption decisions.

Future work could extend the empirical exercise here to other green products, such as energy-efficient appliances or electric vehicles. Similar to solar panels, these technologies potentially offer long-term financial benefits but require substantial upfront costs that may place them out of reach of credit-constrained households. It would also be interesting to consider a government that can offer financing programs for green products in addition to means-tested subsidies. These financing programs would alleviate borrowing constraints for low-income households, which would change the benefits of providing income-contingent subsidies to those households. We leave these questions for future research.

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A Theoretical Appendix

A.1 Proof of Proposition 1

Consider a variation of s denoted by δs. We are interested in subsidy variations that are cost-neutral, such that

$$dCost = \int_{\underline{y}}^{\overline{y}} \frac{\delta Cost}{\delta s\left(y\right)} \delta s\left(y\right) dy = \int_{\underline{y}}^{\overline{y}} \delta s\left(y\right) \left(\frac{\partial K_y}{\partial s(y)} \bar{s} + K_y(\bar{s}) \right) dy = 0 \tag{12}$$

and that are progressive, meaning that

$$\left(y'' - y'\right)\left(\delta s(y'') - \delta s(y')\right) < 0 \tag{13}$$

for $y'' \neq y'$. The total change in production associated with the variation δs is equal to

$$dProd = \int_{\underline{y}}^{\overline{y}} \frac{\partial K_y}{\partial s(y)} \delta s\left(y\right) dy.$$

We can think of the change in cost associated with δs as the costs from additional households, who each receive $\bar{s}$, plus the costs from non-additional households, who each receive an additional $\delta s(y)$. Explicitly, we can rewrite $dCost$ as the current subsidy level times the change in production multiplied by a constant:

$$dCost = \bar{s} \times dProd + A, \tag{14}$$

where we define

$$\int_{\underline{y}}^{\overline{y}} \delta s\left(y\right) K_y(\bar{s}) dy \equiv A.$$

Intuitively, A gives the change in cost associated with non-additional households, while $\bar{s} \times dProd$ gives the change in cost associated with additional households. The change in production will be large relative to cost when the cost to non-additional households, given by A, is small, all else equal. We can rewrite A in terms of cost-effectiveness as

$$A = \int_{\underline{y}}^{\overline{y}} \delta s\left(y\right) \frac{\partial K_y}{\partial s(y)} \eta^{-1}(y) dy.$$

Since δs is decreasing in income, and since δs is a cost-neutral variation, there must exist some "cutoff" income level $\tilde{y}$ such that $\delta s(y) \geq 0$ for $y \leq \tilde{y}$ and $\delta s(y) \leq 0$ for $y > \tilde{y}$. We can rewrite A as an integral over households with income below $\tilde{y}$ (who receive subsidy increases), plus an integral over households with income above $\tilde{y}$ (who receive subsidy reductions):

$$A = \int_{\underline{y}}^{\tilde{y}} \delta s\left(y\right) \frac{\partial K_y}{\partial s(y)} \eta^{-1}(y) dy + \int_{\tilde{y}}^{\overline{y}} \delta s\left(y\right) \frac{\partial K_y}{\partial s(y)} \eta^{-1}(y) dy. \tag{15}$$

Let $\eta(\tilde{y})$ denote the cost-effectiveness associated with this cutoff income level $\tilde{y}$.

We now consider two cases. First, we consider the case in which η is decreasing in income. Second, we consider the case in which η is increasing in income.

Case 1: η Decreasing In Income Assume η is weakly decreasing in income. Thus, it must be the case that $\eta^{-1}(y) \leq \eta^{-1}(\tilde{y})$ for $y \leq \tilde{y}$ and $\eta^{-1}(y) \geq \eta^{-1}(\tilde{y})$ for $y > \tilde{y}$ with at least one of these two inequalities holding strictly. As $\delta s\left(y\right) \geq 0$ for $y \leq \tilde{y}$, it must be that

$$\int_{\underline{y}}^{\tilde{y}} \delta s\left(y\right) \frac{\partial K_y}{\partial s(y)} \eta^{-1}(y) dy \leq \int_{\underline{y}}^{\tilde{y}} \delta s\left(y\right) \frac{\partial K_y}{\partial s(y)} \eta^{-1}(\tilde{y}) dy. \tag{16}$$

Further, since $\delta s\left(y\right) < 0$ for $y > \tilde{y}$, we know that

$$\int_{\tilde{y}}^{\overline{y}} \delta s\left(y\right) \frac{\partial K_y}{\partial s(y)} \eta^{-1}(y) dy \leq \int_{\tilde{y}}^{\overline{y}} \delta s\left(y\right) \frac{\partial K_y}{\partial s(y)} \eta^{-1}(\tilde{y}) dy. \tag{17}$$

At least one of the above inequalities must hold strictly, because either $\eta^{-1}(y) > \eta^{-1}(\tilde{y})$ for $y \leq \tilde{y}$ or $\eta^{-1}(y) < \eta^{-1}(\tilde{y})$ for $y > \tilde{y}$.

Using these inequalities in equations (16) and (17), we can rewrite equation (15) as

$$\begin{aligned} A = \int_{\underline{y}}^{\tilde{y}} \delta s\left(y\right) \frac{\partial K_y}{\partial s(y)} \eta^{-1}(y) dy + \int_{\tilde{y}}^{\overline{y}} \delta s\left(y\right) \frac{\partial K_y}{\partial s(y)} \eta^{-1}(y) dy < \\ \int_{\underline{y}}^{\tilde{y}} \delta s\left(y\right) \frac{\partial K_y}{\partial s(y)} \eta^{-1}(\tilde{y}) dy + \int_{\tilde{y}}^{\overline{y}} \delta s\left(y\right) \frac{\partial K_y}{\partial s(y)} \eta^{-1}(\tilde{y}) dy. \end{aligned} \tag{18}$$

We can rewrite this inequality as

$$A < \eta^{-1}(\tilde{y}) \left(\int_{\underline{y}}^{\overline{y}} \delta s\left(y\right) \frac{\partial K_y}{\partial s(y)} dy \right) = \eta^{-1}(\tilde{y}) \times dProd.$$

Adding $\bar{s} \times dProd$, and noting the cost-neutrality constraint, yields

$$\underbrace{\bar{s} \times dProd + A}_{=dCost=0} < \left(\bar{s} + \eta^{-1}(\tilde{y})\right) dProd.$$

Finally, dividing both sides by $(\bar{s}+\eta^{-1}(\tilde{y}))>0$ yields

$$dProd > 0.$$

Case 2: η Increasing In Income Assume η is weakly increasing in income. Thus, it must be the case that $\eta^{-1}(y) \geq \eta^{-1}(\tilde{y})$ for $y \leq \tilde{y}$ and $\eta^{-1}(y) \leq \eta^{-1}(\tilde{y})$ for $y > \tilde{y}$ with one of these two inequalities holding strictly. Following the logic from the Case 1, we can then show that

$$A = \int_{\underline{y}}^{\tilde{y}} \delta s\left(y\right) \frac{\partial K_y}{\partial s(y)} \eta^{-1}(y) dy + \int_{\tilde{y}}^{\overline{y}} \delta s\left(y\right) \frac{\partial K_y}{\partial s(y)} \eta^{-1}(y) dy > \\ \int_{\underline{y}}^{\tilde{y}} \delta s\left(y\right) \frac{\partial K_y}{\partial s(y)} \eta^{-1}(\tilde{y}) dy + \int_{\tilde{y}}^{\overline{y}} \delta s\left(y\right) \frac{\partial K_y}{\partial s(y)} \eta^{-1}(\tilde{y}) dy. \quad (19)$$

Following the same algebriac steps as the previous case yields

$$\underbrace{\bar{s} \times dProd + A}_{=sCost=0} > \left(\bar{s}+\eta^{-1}(\tilde{y})\right) dProd$$

which implies that $dProd < 0$ since $(\bar{s}+\eta^{-1}(\tilde{y}))>0$.

B Online Appendix

B.1 Cost-Effectiveness with Discrete Household Groups

Suppose we can divide households into a finite number of discrete groups indexed by i. These groups may represent, for example, geographic regions, income brackets, or marital statuses. Let K_i denote the total level of technology adoption by all households in group i. We assume the government has access to a system of group-specific subsidies, with each group i receiving a per-unit subsidy s_i. We are interested in how changes in this system affect both total government cost, $\sum_i K_i s_i$, and total adoption, $\sum_i K_i$. We assume that adoption decisions are independent across groups: that is, changes in the subsidy for group i'' do not affect adoption in group i', for all $i' \neq i''$. Formally,

$$\frac{\partial K_{i'}}{\partial s_{i''}} = 0 \quad \text{for } i' \neq i''.$$

Assume initially that subsidies are equal for two groups, i' and i'', i.e., $s_{i'} = s_{i''}$. Now, suppose the government introduces a small, adoption-neutral policy deviation: it raises the subsidy for group i' while lowering it for group i'' in a manner that keeps total adoption unchanged. The government can achieve this by setting

$$ds_{i'} = \frac{ds}{\partial K_{i'}/\partial s_{i'}} \tag{20}$$

$$ds_{i''} = -\frac{ds}{\partial K_{i''}/\partial s_{i''}}, \tag{21}$$

where $ds_{i'}$ and $ds_{i''}$ are the subsidy changes for groups i' and i'', respectively, and ds is an arbitrary small positive constant.[53]

The net change in total subsidies gives the cost of implementing these changes. This leads to the following result:

Proposition 3. *Consider the adoption-neutral subsidy deviation that increases the subsidy rate for group i' and decreases it for group i''. This deviation reduces total cost relative to a uniform subsidy if and only if*

$$CI_{i'} > CI_{i''}, \tag{22}$$

[53]To see this, note that increasing $s_{i'}$ alone by $ds_{i'} = \frac{ds}{\partial K_{i'}/\partial s_{i'}}$ would raise total adoption by ds, while decreasing $s_{i''}$ by $ds_{i''} = -\frac{ds}{\partial K_{i''}/\partial s_{i''}}$ would lower adoption by exactly ds. The two effects thus cancel out.

where the cost-effectiveness *for group i, denoted CI_i, is defined as*

$$CI_i \equiv \frac{\partial K_i / \partial s_i}{K_i}. \tag{23}$$

Proof. The total change in cost associated with this deviation is:

$$d\text{Cost} = ds \left(\frac{K_{i'}}{\partial K_{i'} / \partial s_{i'}} - \frac{K_{i''}}{\partial K_{i''} / \partial s_{i''}} \right).$$

This change is negative (i.e., cost-saving) if and only if:

$$\frac{K_{i'}}{\partial K_{i'} / \partial s_{i'}} < \frac{K_{i''}}{\partial K_{i''} / \partial s_{i''}}.$$

Inverting both sides yields:

$$CI_{i'} > CI_{i''}.$$

□

Note that CI_i is equal to the partial elasticity of adoption with respect to the subsidy for group i, i.e., $CI_i = \frac{\partial \log K_i}{\partial s_i}$. Therefore, the government can use this partial elasticity as a sufficient statistic to guide targeted subsidies. This provides a simple rule for cost-efficient policy design: reallocate subsidies toward groups with higher values of this elasticity.

As noted in the introduction, many papers have emphasized the importance of distinguishing between additional and non-additional households when evaluating the cost-effectiveness of green subsidies. However, to the best of our knowledge, we are the first to formally show that the ratio of additional to non-additional households—equal to the partial elasticity of adoption with respect to subsidies—can be used as a sufficient statistic for the cost-effectiveness of targeted subsidy changes.

B.2 Production-Maximizing Subsidy Schedule in General Model

Consider a government which chooses a subsidy schedule to maximize total solar production subject to an exogenously set budget constraint. Specifically, the government chooses a subsidy function s to maximize

$$\int_{\underline{y}}^{\overline{y}} K_y\left(s(y)\right) dy$$

subject to the constraint that

$$\int_{\underline{y}}^{\overline{y}} K_y\left(s(y)\right) s(y) dy \leq C$$

where C is the maximum fiscal cost. We can write the government's program as the Lagrangian:

$$\max \int_{\underline{y}}^{\overline{y}} K_y\left(s(y)\right) dy - \lambda \left(\int_{\underline{y}}^{\overline{y}} K_y\left(s(y)\right) s(y) dy - C \right),$$

where λ is the Lagrange multiplier.

The optimal subsidy function must satisfy the government's first order conditions. This implies

$$\frac{\partial K_y}{\partial s(y)}\left(s^\star\left(y\right)\right) - \lambda \left(\frac{\partial K_y}{\partial s(y)}\left(s^\star\left(y\right)\right) \times s^\star\left(y\right) - K_y\left(s^\star\left(y\right)\right) \right) = 0$$

for all income levels y, where $\frac{\partial K_y}{\partial s(y)}\left(s^\star\left(y\right)\right)$ is the derivative of K_y with respect to subsidies evaluated at the optimal subsidy level $s^\star\left(y\right)$. Dividing both sides by $\lambda K_y\left(s^\star\left(y\right)\right)$ yields

$$\eta^\star(y) \left(\frac{1}{\lambda} - s^\star\left(y\right) \right) - 1 = 0,$$

where $\eta^\star(y) \equiv \frac{\frac{\partial K_y}{\partial s(y)}\left(s^\star(y)\right)}{K_y\left(s^\star(y)\right)}$ is the cost-effectiveness of a subsidy increase targeted at income level y given the production-maximizing subsidy schedule.

Rearranging the above equation yields

$$s^\star\left(y\right) = \frac{1}{\lambda} - \frac{1}{\eta^\star(y)}.$$

Therefore, if $\eta^\star$ is decreasing in income, then $s^\star$ must also decrease in income.

B.3 Tract-Level Elasticities

Let i index household types and let $k_i\left(s\right)$ denote production by household type i as a function of subsidies s. Total solar production in tract ℓ is given by

$$K_\ell = \int k_i\left(s\right) df_\ell\left(i\right)$$

where $f_\ell\left(i\right)$ is the density of household type i in tract ℓ.

We are interested in the partial elasticity of K_ℓ with respect to subsidies s. This is given by

$$\eta_\ell \equiv \frac{\frac{\partial K_\ell}{\partial s}}{K_\ell} = \frac{\int \frac{\partial k_i}{\partial s} df_\ell(i)}{K_\ell}. \tag{24}$$

Letting $\eta_i \equiv \frac{\frac{\partial k_i}{\partial s}}{k_i}$ denote the household-level partial elasticity of solar production with respect to subsidies, we can rewrite (24) as

$$\eta_\ell = \frac{\int k_i \eta_i df_\ell(i)}{\int k_i df_\ell(i)}.$$

Therefore, the tract-level elasticity, η_ℓ, is equal to the production-weighted average partial elasticity of all households in the tract.

B.4 Non-Reweighted Border Discontinuities in Subsidy Generosity and Log Production per Capita

We present border discontinuity graphs for subsidy generosity and log production per capita without reweighting observations, unlike our main specification. As before, we define a tract's border distance as positive on the more generous side and negative on the less generous side. Figure A1 shows these distances, with tracts binned in 10-mile intervals. We regress each outcome on border and bin fixed effects, separately for high- and low-income tracts, controlling for a quadratic in population density.

Figure A2a plots bin fixed effects from regressions on subsidy generosity. Subsidies rise sharply on the more generous side, especially for high-income tracts, who tend to lie near borders with larger subsidy gaps. The same figure also shows estimates for log production per capita.

Together, the plots show that moving from a less to a more generous state is linked to larger increases in both subsidies and production for high-income tracts. The reweighting used in Section 2.2 ensures consistent comparison across income groups.

B.5 Full Coefficient Tables

Table A1 reports all coefficients for the specifications in Table 1.

B.6 Linear specification without border discontinuities

Here, we estimate the specification where the partial elasticity of solar production with respect to subsidies varies linearly in log income using all census tracts. The first two columns of Table A2 show the results. The second column, with division fixed effects, suggests that a 1 cent per KWh increase in subsidies leads to a nearly 6.5 percent increase

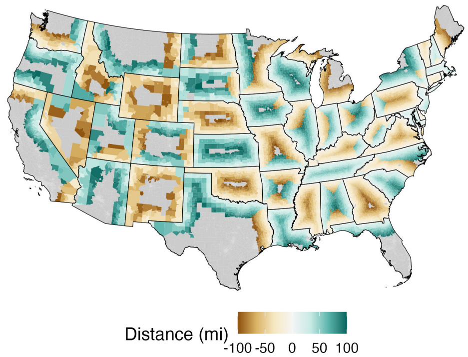
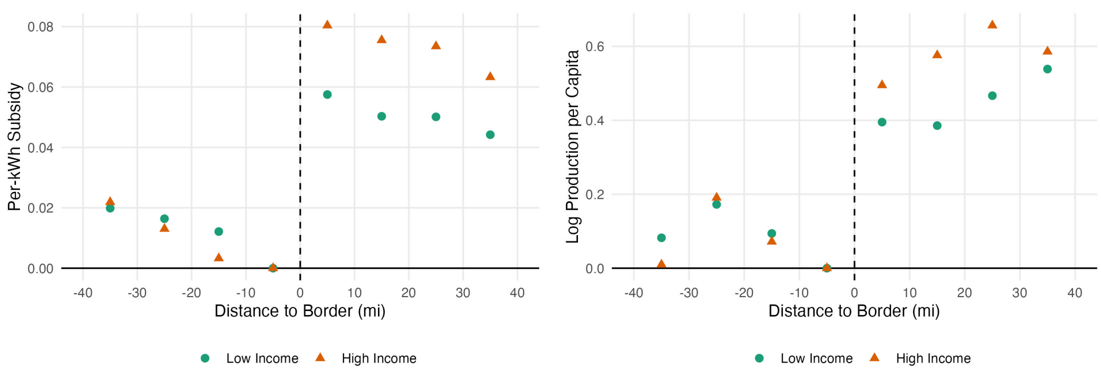


Figure A1: Distances to nearest border by census tract. Distances are positive on the side of the state border with more generous subsidies, while distances are negative on the less generous side. Tracts further than 100 miles are in gray.



(a) Subsidy Generosity (b) Log Production Per Capita (non-reweighted)

Figure A2: Border Discontinuities in Subsidy Generosity and Log Production per Capita without Reweighting. The graph plots estimated location-bin fixed effects from a regression of subsidy generosity (Panel (a)) or log production per capita (Panel (b)) separately for high-income (orange triangles) tracts and low-income (green circles) tracts on border fixed effects, location-bin fixed effects, and a quadratic in population density. Positive values on the X-axis represent households on the side of the border with more generous subsidies, and negative values on the X-axis indicate the side of the border with less generous subsidies.

Table A1: Effect of Subsidies on Log Production per Capita

Border Polynomial Deg.	0		3		5	
Bandwidth	40 mi	80 mi	40 mi	80 mi	40 mi	80 mi
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Constant	-3.40*	-4.13***	-4.53***	-2.53*	-3.53***	-3.33***
	(1.96)	(1.53)	(1.19)	(1.28)	(1.09)	(1.14)
Subsidy	6.04***	6.53***	4.31**	4.74**	3.57*	4.02**
	(0.949)	(1.08)	(2.01)	(1.93)	(2.11)	(1.95)
Log Income	-0.323	-0.371	-0.173	-0.239	-0.226	-0.274
	(0.228)	(0.252)	(0.172)	(0.249)	(0.177)	(0.208)
Elec. Price	-39.4	-43.9	-0.077	-16.8	-12.9	-16.9
	(27.1)	(31.3)	(26.1)	(34.5)	(25.2)	(25.9)
Solar Irradiance	1.26***	1.37***	0.988***	0.728***	0.844***	0.771***
	(0.415)	(0.326)	(0.245)	(0.207)	(0.237)	(0.223)
Percent College	0.877***	1.02***	0.965***	1.10***	0.954***	1.05***
	(0.175)	(0.157)	(0.164)	(0.140)	(0.167)	(0.136)
Percent Owner	0.329	0.267	0.222	0.170	0.212	0.116
	(0.346)	(0.259)	(0.333)	(0.250)	(0.337)	(0.247)
Percent Democrat	0.334	0.543*	0.213	0.444*	0.234	0.373
	(0.370)	(0.273)	(0.391)	(0.251)	(0.376)	(0.258)
Population Density	-5.23***	-5.27***	-5.57***	-5.43***	-5.65***	-5.64***
	(0.449)	(0.440)	(0.496)	(0.452)	(0.496)	(0.449)
Population Density sq	2.17***	2.15***	2.33***	2.26***	2.36***	2.33***
	(0.257)	(0.242)	(0.286)	(0.253)	(0.277)	(0.245)
Subsidy × Log Income	-1.50**	-1.92**	-1.76***	-1.92**	-2.02***	-2.07***
	(0.704)	(0.913)	(0.428)	(0.845)	(0.450)	(0.681)
Elec. Price × Log Income	3.96	4.59	2.68	3.32	3.52**	3.99**
	(2.52)	(2.82)	(1.66)	(2.55)	(1.68)	(1.98)
Fit statistics						
Observations	20,187	30,410	20,187	30,410	20,187	30,410
R^2	0.48	0.49	0.55	0.55	0.55	0.56

Clustered (State) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Estimates of coefficients from Equation (4). Sample is limited to tracts within either 40 or 80 miles bandwidths to state borders. All regressions include border-specific polynomials in location relative to border.

in solar production per capita. The following two columns of Table A2 have estimates of equation (3), where we specify that cost-effectiveness is linear in log income. We have again "de-medianed" log income by subtracting the median log income level from our log income variable. Using estimates from column 4, a 1 cent per-kWh increase in subsidies is associated with a 7.3% increase in solar production per capita for a tract at the median income level, and, consistent with our border discontinuity result, is decreasing in income. The same 1 cent per-kWh subsidy increase is associated with only a 5.1'% increase in solar production per capita for a tract at the 90th percentile of income distribution. The empirical partial elasticity of solar production with respect to subsidies for tracts at the median income level is 44 percent higher than the partial elasticity for tracts at the 90th percentile income level—somewhat larger than our border discontinuity result.

B.7 Smoothness of demographics across state borders

Figure A3 replicates those of Figure 3. We divide census tracts into 20-mile-wide bins relative to their distance from the closest state border. Then, we regress the demographic variable in question on border fixed effects and fixed effects for each distance bin. We control for a quadratic in population density. The demographics are rescaled by their respective standard deviation in order to make their units comparable. None of the demographics exhibit a discontinuity moving across the state border.

B.8 Robustness

Border Discontinuity Bandwith and Polynomial Degree In our main specification, we use a border discontinuity with a bandwidth of 40 miles, with border fixed effects interacted with 3rd degree polynomials in distance from the border. Figure A4 shows estimates using bandwidths between 20 and 100 miles and polynomials ranging from degree 0 (just border fixed effects) to 5. The results are similar for all but the smallest bandwidths.

Historically Adjusted subsidies Table A3 replicates Table 1 using the historically adjusted measure of subsidies from Sexton et al. (2021). The results are slightly weaker than our main results, but the weight of the evidence still implies that cost-effectiveness is decreasing with income. For the specifications with statistically significant coefficients, the partial elasticity of solar production with respect to subsidies is 18 to 31% lower for tracts at the 90th income percentile relative to tracts at the median income. These values fall within the range of those from our main specification in Table 1.

Table A2: Effect of Subsidies on Log Production per Capita

Model:	(1)	(2)	(3)	(4)
Variables				
Subsidy	4.67***	6.28***	5.51***	7.34***
	(1.49)	(1.22)	(1.70)	(1.33)
Log Income	-0.250	-0.405	-0.208	-0.356
	(0.443)	(0.435)	(0.342)	(0.350)
Population Density	-5.46***	-5.47***	-5.50***	-5.52***
	(0.522)	(0.416)	(0.528)	(0.433)
Population Density sq	2.30***	2.32***	2.32***	2.34***
	(0.374)	(0.325)	(0.373)	(0.330)
Percent College	0.384	0.463*	0.430	0.511*
	(0.297)	(0.258)	(0.293)	(0.260)
Percent Owner	0.441	0.470	0.460	0.489
	(0.334)	(0.330)	(0.340)	(0.337)
Percent Democrat	0.983***	0.790***	0.951***	0.750**
	(0.256)	(0.278)	(0.258)	(0.282)
Elec. Price	-58.0	-71.9**	-76.7**	-93.9***
	(39.4)	(34.3)	(33.7)	(25.8)
Solar Irradiance	1.44***	1.52***	1.45***	1.53***
	(0.256)	(0.304)	(0.259)	(0.304)
Elec. Price × Log Income	6.20*	7.18**	7.87***	9.12***
	(3.49)	(3.21)	(2.91)	(2.39)
Subsidy × Log Income			-3.69***	-4.23***
			(1.19)	(1.02)
Fixed-effects				
Region	Yes		Yes	
Division		Yes		Yes
Fit statistics				
Observations	49,010	49,010	49,010	49,010
R^2	0.57	0.58	0.57	0.58
Within R^2	0.35	0.34	0.35	0.34

Clustered (State) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

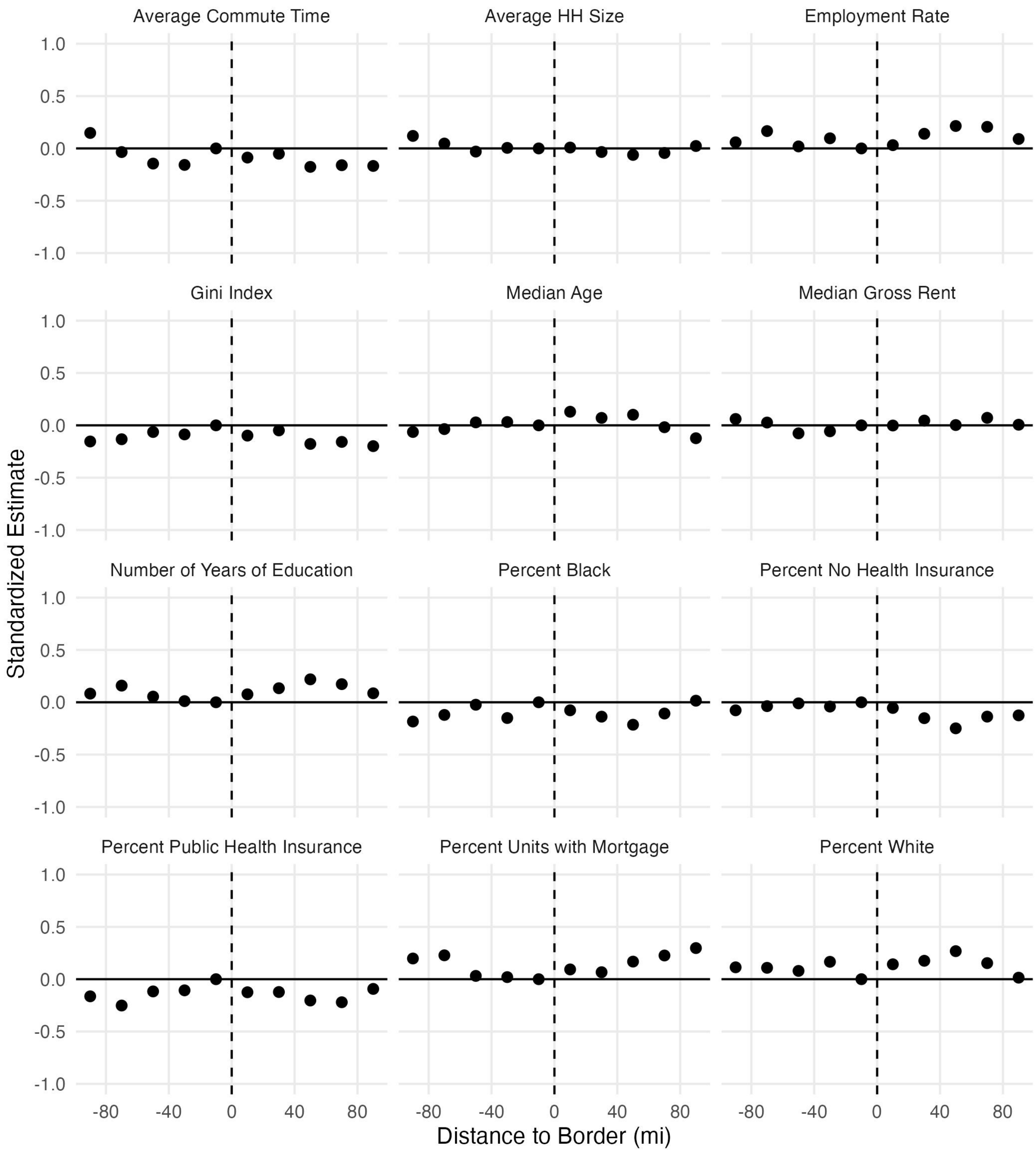


Figure A3: Smoothness of demographic variables across state borders. We divide tracts into 20 mile wide bins in distance from the border and regress the demographic variable on border fixed effects and fixed effects for the distance bins. All demographic variables are normalized by their standard deviation, thus the Y-axis represents the difference in the demographic variable relative to the closest bin (on the less-generous side of the border) in standard deviations.

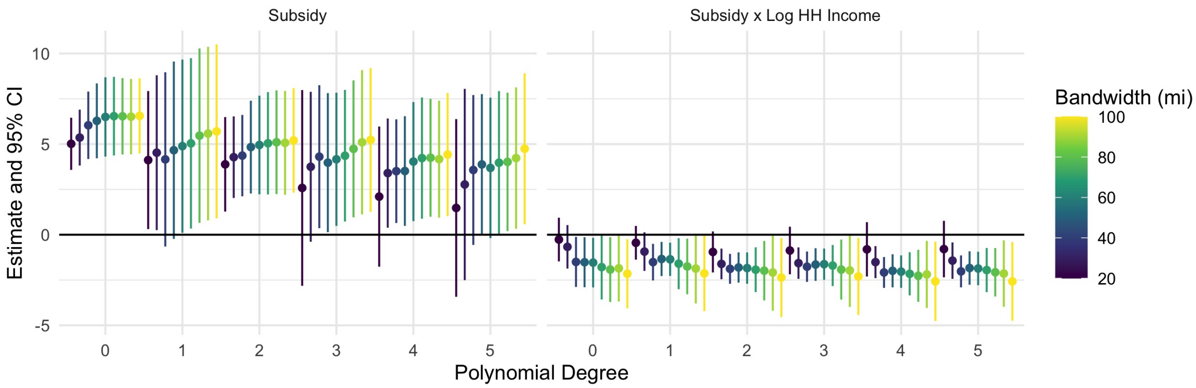


Figure A4: Robustness of border discontinuity estimates to different bandwidths and polynomial degrees.

Table A3: Effect of Historical Subsidies on Log Production per Capita

Border Polynomial Deg.	0		3		5	
Bandwidth (mi)	40 mi	80 mi	40 mi	80 mi	40 mi	80 mi
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Hist. Subsidy	4.87***	4.05*	3.41*	4.49***	3.94**	3.45**
	(0.827)	(2.02)	(1.97)	(0.866)	(1.82)	(1.69)
Hist. Subsidy × Log Income	0.113	-1.16***	-1.43***	-0.167	-1.32	-1.54**
	(0.783)	(0.432)	(0.421)	(0.942)	(0.879)	(0.705)
Fit statistics						
Observations	20,187	20,187	20,187	30,410	30,410	30,410
R^2	0.48	0.55	0.56	0.48	0.55	0.45

Clustered (State) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Estimates of coefficients from Equation (4) using historically adjusted subsidies. Sample is limited to tracts within either 40 or 80 miles bandwidths to state borders. All regressions include controls for tract-level income, electricity prices, electricity prices interacted with income, solar irradiance, population density and population density squared, a battery of tract-level demographic measures, and border-specific polynomials in location relative to border.

Controls for Other State Solar Policies A threat to identification in our border discontinuity models is a change in other policies across state borders that affects household solar installation decisions. We gather data on other state-level policies related to solar panels from DSIRE that are not monetary subsidies. We then count the number of programs in each state split into three categories: financing, access rules, and building incentives.[54] In addition to using the counts of policies, we also run models using indicators for the presence of these policies.

Tables A4 and A5 replicate Table 1 adding controls for counts of DSIRE policies and for indicators for the presence of DSIRE policies. The results are similar to our main models. The coefficient on the interaction between subsidies and log income remains very stable across all of the DSIRE specifications. The coefficient on subsidies—reflecting the partial elasticity of installations with respect to subsidies for a tract with median log income—does increase in some specifications. However, these partial elasticities are never statistically significantly different at the 5 percent level from that of our baseline model without DSIRE controls.

Net Metering One concern might be that the availability of a net-metering policy significantly changes the financial incentives to install solar panels. In 2017, all but six states had net-metering policies in place.[55] Table A6 replicates Table 1 restricted to only states that had net metering in 2017. These results are qualitatively similar to our main specification, generally becoming marginally stronger.

Alternative Controls and Fixed Effects for Nonlinear Specifications Our main results include demographic controls and census division fixed effects. Figures A5 shows robustness to alternative fixed effects and omitting the demographic controls. We show just the income spline specification for simplicity, but results are similar across different means of allowing the marginal effect of subsidies to vary by income level. Adding controls and more refined fixed effects makes our results marginally stronger.

Alternative Outcomes We derive cost-effectiveness using production per capita as the outcome of interest. Here, we explore robustness to different outcome variables that we could have also used to derive cost-effectiveness—counts of residential solar installations and residential solar panels. Table A7 shows results for the same specifications as Table 1, but with log panels per capita as the outcome. Figure A6 shows the robustness of

[54] Financing are policies with labels of "Loan Program" and "PACE Financing" in DSIRE, access are solar policies with labels of "Solar/Wind Access Policy" and "Solar/Wind Permitting Standards", and building incentives are policies with the label of "Building Energy Codes" and "Green Building Incentives"

[55] Non-net metering states are Alabama, Idaho, South Dakota, Tennessee, Texas, and Vermont.

Table A4: Effect of Subsidies on Log Production per Capita with DSIRE count controls

Border Polynomial Deg.	0		3		5	
Bandwidth (mi)	40 mi	80 mi	40 mi	80 mi	40 mi	80 mi
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Subsidy	7.52***	6.35***	7.85***	8.28***	7.03***	7.78***
	(1.39)	(2.30)	(2.53)	(1.51)	(2.30)	(2.44)
Subsidy × Log Income	-1.44*	-1.82***	-2.07***	-1.89**	-1.94**	-2.11***
	(0.717)	(0.425)	(0.449)	(0.926)	(0.847)	(0.681)
Count DSIRE financing	0.262***	0.126	0.207	0.252***	0.216*	0.225
	(0.065)	(0.130)	(0.147)	(0.070)	(0.112)	(0.138)
Count DSIRE access	0.062	-0.088	-0.185*	-9.65×10^{-5}	-0.042	-0.080
	(0.088)	(0.111)	(0.107)	(0.093)	(0.109)	(0.113)
Count DSIRE building	-0.074	-0.091	-0.212	-0.017	-0.025	-0.262
	(0.127)	(0.218)	(0.142)	(0.132)	(0.253)	(0.166)
Fit statistics						
Observations	20,187	20,187	20,187	30,410	30,410	30,410
R^2	0.49	0.55	0.56	0.49	0.55	0.56

Clustered (State) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Estimates of coefficients from Equation (4) adding DSIRE count controls. Sample is limited to tracts within either 40 or 80 miles bandwidths to state borders. All regressions include controls for tract-level income, electricity prices, electricity prices interacted with income, solar irradiance, population density and population density squared, a battery of tract-level demographic measures, and border-specific polynomials in location relative to border.

Figure A5: Cost-effectiveness using production for different controls and fixed effects.

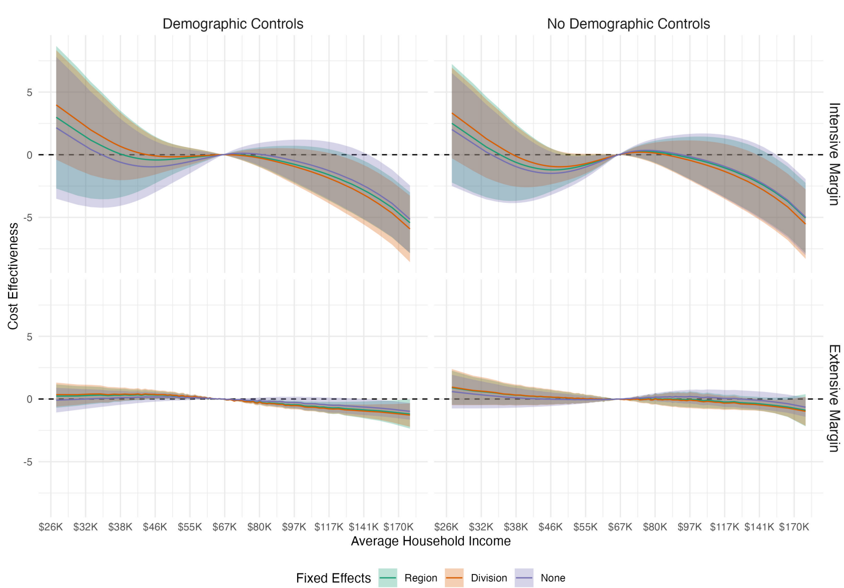


Table A5: Effect of Subsidies on Log Production per Capita with DSIRE indicator controls

Border Polynomial Deg.	0		3		5	
Bandwidth (mi)	40 mi	80 mi	40 mi	80 mi	40 mi	80 mi
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Subsidy	6.99***	6.78***	7.98***	8.06***	7.67***	9.07***
	(1.51)	(2.15)	(2.55)	(1.65)	(2.13)	(2.26)
Subsidy $\times$ Log Income	-1.42*	-1.83***	-2.08***	-1.90*	-1.96**	-2.09***
	(0.760)	(0.423)	(0.448)	(0.948)	(0.841)	(0.674)
Has DSIRE financing	0.301***	0.231	0.314	0.351***	0.411**	0.409*
	(0.092)	(0.194)	(0.195)	(0.101)	(0.193)	(0.219)
Has DSIRE access	0.097	-0.125	-0.189	-0.089	-0.155	-0.224
	(0.127)	(0.136)	(0.167)	(0.131)	(0.138)	(0.153)
Has DSIRE building	-0.049	-0.257	-0.482*	0.012	-0.095	-0.473*
	(0.196)	(0.238)	(0.246)	(0.201)	(0.248)	(0.257)
Fit statistics						
Observations	20,187	20,187	20,187	30,410	30,410	30,410
R^2	0.49	0.55	0.57	0.49	0.55	0.56

Clustered (State) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Estimates of coefficients from Equation (4) adding DSIRE indicator controls. Sample is limited to tracts within either 40 or 80 miles bandwidths to state borders. All regressions include controls for tract-level income, electricity prices, electricity prices interacted with income, solar irradiance, population density and population density squared, a battery of tract-level demographic measures, and border-specific polynomials in location relative to border.

Table A6: Effect of Subsidies on Log Production per Capita, Net Metering States Only

Border Polynomial Deg.	0		3		5	
Bandwidth (mi)	40 mi	80 mi	40 mi	80 mi	40 mi	80 mi
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Subsidy	6.14***	4.30**	3.62*	6.62***	4.81**	3.98**
	(0.970)	(2.01)	(2.13)	(1.11)	(1.94)	(1.96)
Subsidy × Log Income	-1.74**	-1.93***	-2.27***	-2.23**	-2.30**	-2.35***
	(0.744)	(0.441)	(0.437)	(0.963)	(0.854)	(0.675)
Fit statistics						
Observations	18,722	18,722	18,722	27,507	27,507	27,507
R^2	0.49	0.56	0.56	0.50	0.56	0.58

Clustered (State) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Estimates of coefficients from Equation (4) restricted to net metering states. Sample is limited to tracts within either 40 or 80 miles bandwidths to state borders. All regressions include controls for tract-level income, electricity prices, electricity prices interacted with income, solar irradiance, population density and population density squared, a battery of tract-level demographic measures, and border-specific polynomials in location relative to border.

these border discontinuity results for these alternative outcomes across all bandwidths and polynomial degrees. Figures A7 and A8 demonstrate that the partial elasticity of subsidies with respect to either of these alternative outcomes is also decreasing in income when we use the nonlinear specifications and all census tracts.

Alternative Models Since installations are a count variable, we estimate a Poisson model limiting to tracts that only have positive installations. Figure A9 shows results using evenly spaced bins by log income. Our results are qualitatively unchanged.

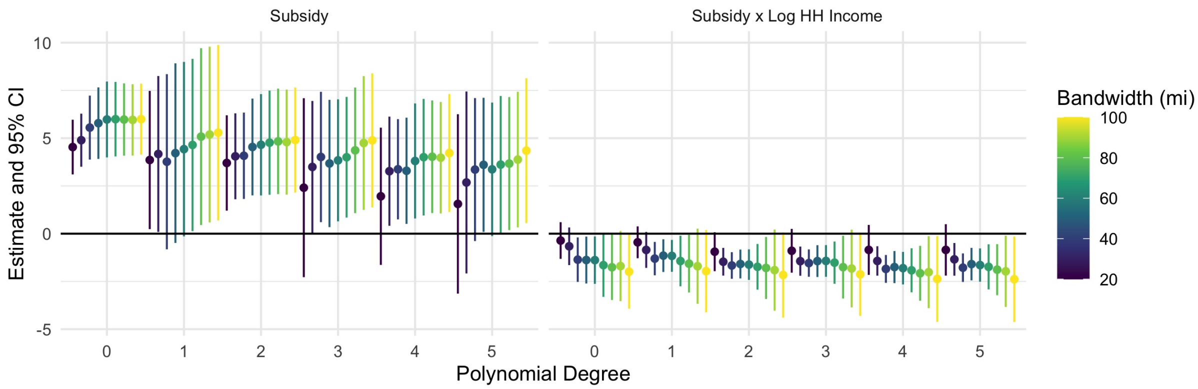
B.9 Estimating Cost-Effectiveness with Zero Production Tracts

Our main specification only includes tracts with positive solar production since it requires taking the log of production as the outcome variable. However, about a quarter of all census tracts have no residential solar installations in the Deepsolar data, representing about 21 percent of the US population. Here, we explore whether our focus on tracts with positive production affects our conclusions on cost-effectiveness.

Consider a model where the expected solar production in a given tract is equal to the probability the tract has positive solar production multiplied by the solar production con-

Figure A6: Robustness of border discontinuity model to alternative outcomes

(a) Log installations per capita



(b) Log panels per capita

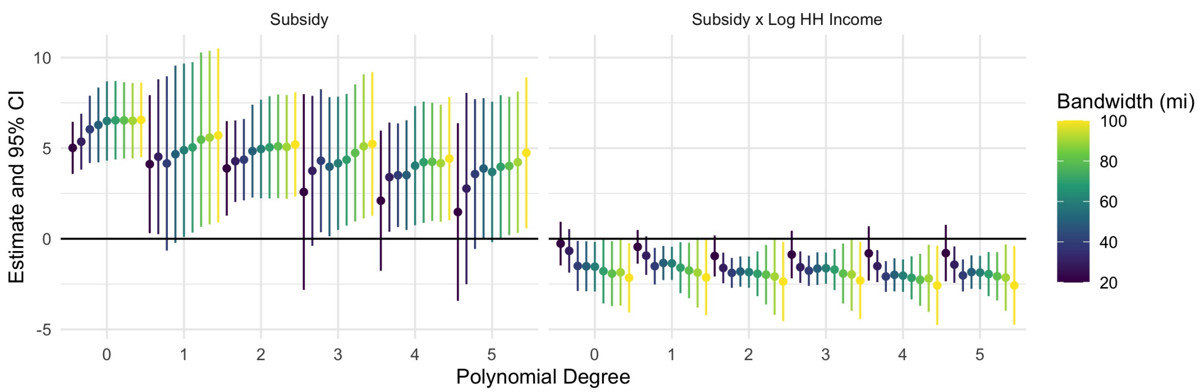
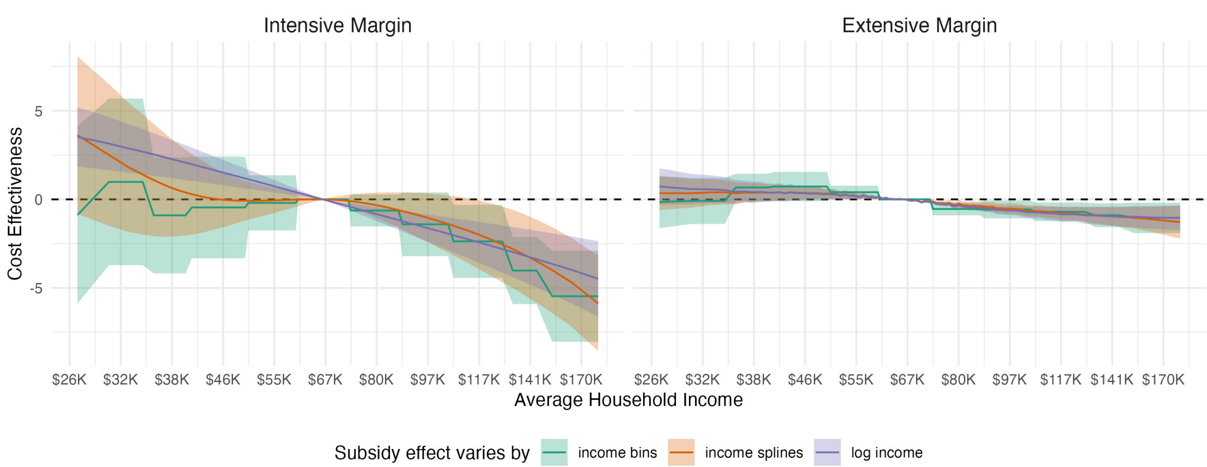


Figure A7: Installations per capita measure of cost-effectiveness.



Colors show the results for different manners of allowing the marginal effect of subsidies to vary across income levels, all of which are estimated relative to median income: income bins are 11 bins evenly spaced in log income, income deciles are based on national income distribution, splines are cubic b-splines with 7 knots evenly spaced based on population weighted income, and log income. Demographic, price, and solar controls and division fixed effects included in all regressions. Standard errors are clustered by state.

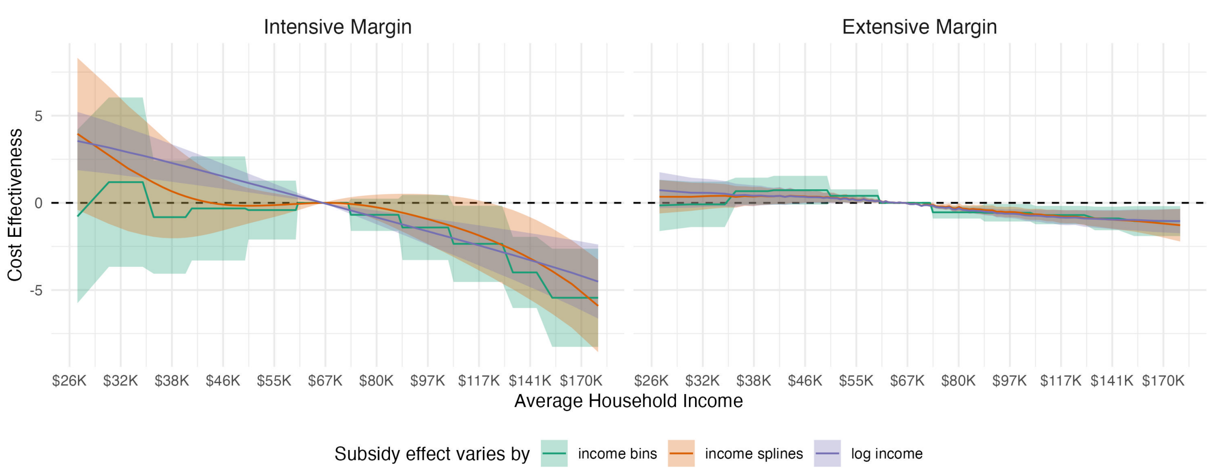
Table A7: Effect of Subsidies on Log Panels per Capita

Border Polynomial Deg.	0		3		5	
Bandwidth (mi)	40 mi	80 mi	40 mi	80 mi	40 mi	80 mi
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Subsidy	6.04***	6.53***	4.31**	4.74**	3.57*	4.02**
	(0.949)	(1.07)	(2.01)	(1.93)	(2.11)	(1.95)
Subsidy × Log Income	-1.50**	-1.92**	-1.76***	-1.92**	-2.02***	-2.07***
	(0.703)	(0.912)	(0.428)	(0.845)	(0.450)	(0.681)
Fit statistics						
Observations	20,187	30,410	20,187	30,410	20,187	30,410
R^2	0.48	0.48	0.54	0.54	0.39	0.55

Clustered (State) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

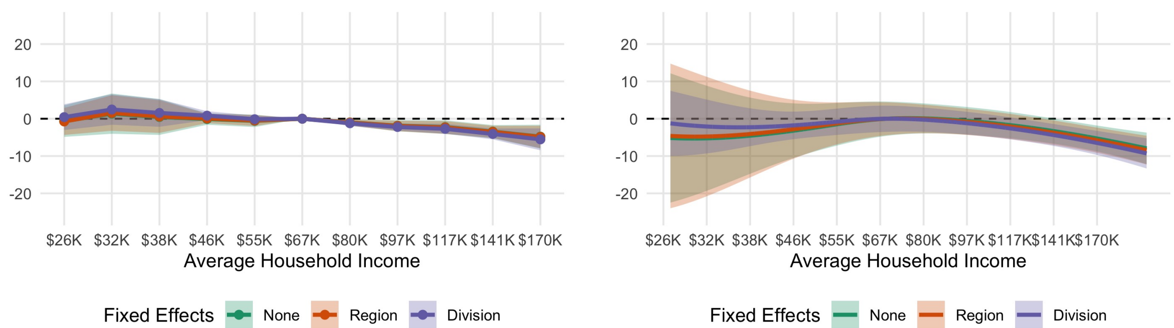
Estimates of coefficients from Equation (4). Sample is limited to tracts within either 40 or 80 miles bandwidths to state borders. All regressions include controls for tract-level income, electricity prices, electricity prices interacted with income, solar irradiance, population density and population density squared, a battery of tract-level demographic measures, counts of other state-level solar policies, and border-specific polynomials in location relative to border.

Figure A8: Panels per capita measure of cost-effectiveness.



Colors show the results for different manners of allowing the marginal effect of subsidies to vary across income levels, all of which are estimated relative to median income: income bins are 11 bins evenly spaced in log income, income deciles are based on national income distribution, splines are cubic b-splines with 7 knots evenly spaced based on population weighted income, and log income. Demographic, price, and solar controls and division fixed effects included in all regressions. Standard errors are clustered by state.

Figure A9: Installations modelled with a Poisson regression.



(a) Installations as outcome, bins in log income.

(b) Installations as outcome, splines over income.

ditional on having positive production. Concretely, let P_ℓ denote the probability a tract ℓ has strictly positive solar panels, and let $\hat{K}_\ell$ denote the tract's solar production conditional on having a strictly positive number of solar panels. Expected solar production in tract ℓ is therefore given by $\bar{K}_\ell = P_\ell \hat{K}_\ell$. The partial elasticity of expected solar production with respect to subsidies is then given by

$$\frac{\partial \log \bar{K}_\ell}{\partial s_\ell} = \underbrace{\frac{\partial \log \tilde{K}_\ell}{\partial s_\ell}}_{\text{Intensive Margin}} + \underbrace{\frac{\partial P_\ell}{\partial s_\ell}\frac{1}{P_\ell}}_{\text{Extensive Margin}} .$$

Therefore, the partial elasticity of solar production is given by the sum of 1) the partial elasticity of solar production conditional on positive production ("Intensive Margin") and 2) the partial elasticity of the probability of having positive installations ("Extensive Margin"). Note that the intensive margin is what we estimate in our baseline regressions.

We first examine how the term $\frac{\partial P_\ell}{\partial s_\ell}$ varies across the income distribution. Again limiting our sample to tracts within 40 miles of state borders, we run linear probability regressions of the following form:

$$\mathbb{I}(K_\ell > 0) = \beta_0^{\text{Ext}} s_\ell + \beta_1^{\text{Ext}} s_\ell \times \log \hat{Y}_\ell + x_\ell' \gamma^{\text{Ext}} + g_\theta^{\text{Ext}}(\text{Loc}_\ell) + \varepsilon_\ell^{\text{Ext}}, \tag{25}$$

where $\mathbb{I}(K_\ell > 0)$ indicates that there is positive solar production in tract ℓ, Y_ℓ is "de-medianed" average income in tract ℓ, s_ℓ is the generosity of subsidies available in tract ℓ, and x_ℓ is a vector of controls. As before, we specify the $g_\theta^{\text{Ext}}(\text{Loc}_\ell)$ functions as border-specific polynomials.

Table A8 reports parameter estimates from (25). Each column corresponds to a different specification, which vary in the degree of the polynomials in location relative to the state border. Across all specifications, our estimates suggest that $\frac{\partial P_\ell}{\partial s_\ell}$ is decreasing in income and small in magnitude compared to our baseline partial elasticity estimates using tracts with positive production.

Table A8: Effect of Subsidies on Pr of Any Installations

Border Polynomial Deg.	0		3		5	
Bandwidth (mi)	40 mi	80 mi	40 mi	80 mi	40 mi	80 mi
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Subsidy	0.880***	1.02***	1.34***	1.33***	1.46***	1.32***
	(0.155)	(0.170)	(0.273)	(0.249)	(0.219)	(0.251)
Subsidy × Log Income	-0.821***	-0.978***	-0.671***	-0.864***	-0.677***	-0.842***
	(0.236)	(0.253)	(0.193)	(0.228)	(0.195)	(0.224)
Fit statistics						
Observations	29,308	44,209	29,308	44,209	29,308	44,209
R^2	0.17	0.15	-189.9	0.17	-71.8	0.18

Clustered (State) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Estimates of coefficients from Equation (4). Sample is limited to tracts within either 40 or 80 miles bandwidths to state borders. All regressions include controls for tract-level income, electricity prices, electricity prices interacted with income, solar irradiance, population density and population density squared, a battery of tract-level demographic measures, counts of other state-level solar policies, and border-specific polynomials in location relative to border.

Similarly, the "Extensive Margin" panels of Figures A5, A7, and A8 show results for various alternative specifications using an indicator for positive solar production as the outcome. In each case, the results again suggest that $\frac{\partial P_\ell}{\partial s_\ell}$ is decreasing in income and small in magnitude relative to our main results.

Next we examine how $\frac{1}{P_\ell}$ varies across the income distribution. Let $P_{\hat{y}}$ denote the fraction of tracts with positive solar production in income quintile $\hat{y}$. Figure A10 plots $\frac{1}{P_{\hat{y}}}$ over income quintiles. $\frac{1}{P_{\hat{y}}}$ is decreasing in income quintile, ranging from 1.6 in the first income quintile to 1.15 in the top quintile.

Taken together, these results show that the extensive margin is small relative to the intensive margin partial elasticity, and that the extensive margin partial elasticity is decreasing in income. This suggests that the partial elasticity of expected production, accounting for tracts with zero production, is more strongly decreasing in income than our baseline partial elasticity conditional on positive production.

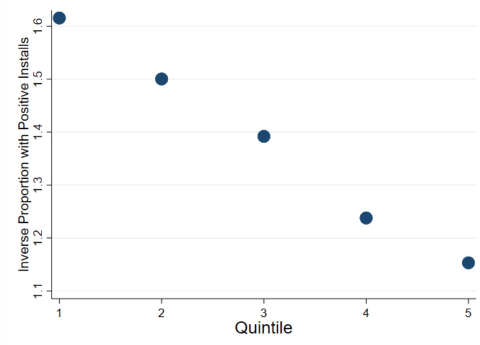


Figure A10: Inverse of proportion of tracts with positive solar production over income quintiles.

B.10 Derivation of Partial Elasticity of Installation with Respect to Subsidies

The household value function conditional on installing solar panels is given by the Lagrangian

$$V_i^{m=1} = \max_{c_i, a_i} \sum_{t=1}^{T} \beta^{t-1} \frac{(c_{it})^{1-\gamma}}{1-\gamma} + \phi_i - \sum_{t=1}^{T} \mu_t g_t (a_{it}) - \sum_{t=1}^{T} \lambda_t h_t (c_{it}, a_{it}, a_{it+1})$$

where c_i and a_i are the vectors of household consumption levels and asset levels in all periods, $g_t(a_{it})$ denotes the borrowing inequality constraint in period t, and $h_t(c_{it}, a_{it}, a_{it+1})$ denotes the budget equality constraint in period t.

Let $\bar{V}_i^{m=1} = V_i^{m=1} - \sigma\epsilon_i$ denote household i's value of installing panels less the idiosyncratic preference draw. Note that $\bar{V}_i^{m=1}$ is implicitly a function of subsidies. We can then write the probability of installation as

$$\log P_i = \left(\frac{1}{\sigma}\bar{V}_i^{m=1}\right) - \log\left(\exp\left(\frac{1}{\sigma}\bar{V}_i^{m=1}\right) + \exp\left(\frac{1}{\sigma}\sum_{t=1}^{T}\beta^{t-1}\frac{\left(c_{it}^{m=0}\right)^{1-\gamma}}{1-\gamma}\right)\right).$$

Taking the derivative of $\log P_i$ with respect to s^{Upfront} yields

$$\frac{\partial \log P_i}{\partial s^{\text{Upfront}}} = \frac{1}{\sigma}\frac{\partial \bar{V}_i^{m=1}}{\partial s^{\text{Upfront}}}(1 - P_i). \tag{26}$$

Using the notation from above, the first year's borrowing equality constraint is

$$h_t (c_{i1}, a_{i1}, a_{i2}) = c_{i1} + a_{i2} + m_i p_j^{\text{Ins}}(N_i)$$
$$-\Big(y_i - \tau(y_i) + (1+r) a_{i1} + m_i \left(N_i A_{it} p_j + s_i^{\text{Upfront}}\left(p_j^{\text{Ins}}(N_i), \tau(y_i)\right) + s_i^{\text{Flow}}\left(p_j^{\text{Ins}}(N_i), A_{it}\right)\right)\Big).$$

Therefore, the first-order condition of the Lagrangian with respect to c_1 yields

$$\left(c_{i1}^{m=1}\right)^{-\gamma} = \lambda_1. \tag{27}$$

Further, by the envelope theorem, we know what

$$\frac{\partial \bar{V}_i^{m=1}}{\partial s^{\text{Upfront}}} = \frac{\partial V_i^{m=1}}{\partial s^{\text{Upfront}}} = \lambda_1. \tag{28}$$

Combining equations (26), (27), and (28) yields

$$\frac{\partial \log P}{\partial s^{\text{Upfront}}} = \frac{\left(c_{i1}^{m=1}\right)^{-\gamma}}{\sigma} \left(1 - P_i\right).$$

B.11 Additional Data and Estimation Details

Interest and Discount Rates We follow Sexton et al. (2021) and set a real interest rate of 5% and assume panels have a life of 20 years. We also set $T = 20$. We assume a household discount rate of $\beta = \frac{1}{1+r}$.

De Groote and Verboven (2019) estimate a discount factor by estimating responses of residential solar demand to the introduction of a generous subsidy for future solar production in Belgium. They find that households' implicit real interest rate in evaluating future benefits greatly exceeds the real market interest rate. We calculate optimal subsidies using a discount rate based on De Groote and Verboven (2019) in Section 5.2.

Installation Size We parameterize the number of panels conditional on installation as $N_i = \kappa X_i$, where κ is a vector of parameters to be estimated and X_i is a vector including a constant term, household income, and tract-level college and democrat share. We estimate the vector of parameters κ jointly with the other structural parameters.

Federal Income Taxes For the federal income tax function $\tau\left(y_i\right)$, we utilize the functional form used by Heathcote, Storesletten, and Violante (2017), which has been shown to effectively replicate many features of the US income tax code.[56] The functional form for the total tax burden is given by

$$\tau\left(y_i\right) = y_i - \lambda y_i^{1-\tau},$$

where τ is a parameter that dictates the progressivity of the tax schedule, and λ is a parameter that dictates the overall level of taxes. We use the values of τ and λ estimated

[56] See e.g. Guner, Kaygusuz, and Ventura (2014).

by Guner, Kaygusuz, and Ventura (2014), who estimate these parameters using microdata from the IRS. We use their estimates for all married households.

Subsidies We use data on subsidies Sexton et al. (2021), which are assembled from data from the Database of State Incentives for Renewables & Efficiency (DSIRE). We assume that upfront subsidies are given by the sum of subsidies from state and federal investment tax credits and sales tax rebates. We assume that flow subsidies are given by the sum of solar renewable energy certificates, other production-based subsidies, and property tax rebates.

Formally, let s^{Fed} denote the portion of the Federal Investment Tax Credit that is refundable in year 1. This refundable portion equals the minimum of the household's tax burden and 30% of the cost of installation. We can write this as

$$s^{\text{Fed}} = \max\left\{0, \min\left\{0.3p_j^{\text{Ins}}\left(N_i\right), \tau\left(y_i\right)\right\}\right\}.$$

Let s_j^{Cost} denote state cost-based subsidies—subsidies which pay a fraction of the cost of installation, let SalesTaxRebate_j be a dummy variable indicating state j offers a sales tax exemption, and let SalesTaxRate_j denote the average sales tax in state j. We can write

$$s_i^{\text{Upfront}} = p_j^{\text{Ins}}\left(N_i\right) \times \left(s_j^{\text{Cost}} + \text{SalesTaxRebate}_j \times \text{SalesTaxRate}_j\right) + s^{\text{Fed}}. \tag{29}$$

Let s_j^{Kwh} denote the production-based subsidies, subsidies which pay per kWh of electricity produced, let PropTaxRebate_j be a dummy variable indicating state j offers a property tax exemption, and let PropTaxRate_j denote the average property tax rate in state j. Flow subsidies are given by

$$s_{it}^{\text{Flow}} = \left(1-\delta\right)^{t-1} p_j^{\text{Ins}}\left(N_i\right) \times \text{PropTaxRebate}_j \times \text{PropTaxRate}_j + s_j^{\text{Kwh}} N_i A_{it}$$

where δ is the depreciation rate of solar panels.

B.12 Construction of Tract-Level Income Distributions

We construct tract-level income distributions for homeowners in two steps. First, we assume tract-level income follows a log-normal distribution and use average income and Gini coefficients to match each tract's mean and variance.[57] This yields the unconditional income distribution for each tract.

[57]See Battistin, Blundell, and Lewbel (2009).

Second, using 2015 ACS household data, we estimate the probability of homeownership as a function of income with state-specific linear splines:

$$\text{Own}_i = f_s(y_i) + \varepsilon_i,$$

where knots are at \$10k–\$200k. We use these estimates to compute the income-homeownership joint distribution. Multiplying this with the unconditional tract income distributions gives tract-level income distributions for homeowners.

B.13 Conditional Distribution of Initial Assets

We discretize the initial asset distribution into $N = 20$ mass points ranging from the minimum asset level, $\bar{a}$, to $\bar{a}+1,000,000$. Our goal is to assign each household's probability distribution over these asset bins.

As in Sklar (1959), we can express the joint cumulative distribution function (CDF) of assets a and income y as

$$F(a, y) = C\left(F_a(a), F_y(y)\right)$$

where C is a copula, and F_a (F_y) is the CDF of assets (income). in our setting, $F_y(y)$ is equal to the national CDF of income given the tract-level income distributions we describe in Appendix B.12.

For F_a we use the parametric distribution of assets estimated by Jäntti, Sierminska, and Van Kerm (2015). For C we use the Plackett copula (Plackett, 1965). For both the parameteric asset distribution F_a and the Plackett copula C, we use estimates from Jäntti, Sierminska, and Van Kerm (2015), who estimate these parameters jointly using data from the Survey of Consumer Finances.

B.14 Parameter Estimates

Table A9 shows the estimates of the structural parameters with bootstrapped standard errors.

B.15 Additional Model Fit

Table A10 presents the fit for targeted moments. The model overpredicts the relationship between college share and installations and underpredicts the relationship between average tract income and percent democrat but fits relatively well overall.

		Estimate	Standard Error
Dispersion of Idiosyncratic Utility	σ	1.75	0.04
Curvature of Utility	γ	0.42	0.02
Nonpecuniary Value of Installations			
Constant	ϕ_0	-6.39	0.17
Percent College	ϕ_{Coll}	2.88	0.11
Percent Democrat	ϕ_{Pol}	-1.61	0.19
Size of Installation Parameters			
Constant	κ_0	15.45	0.05
Percent College	κ_{Coll}	-2.28	0.32
Percent Democrat	κ_{Pol}	-5.43	0.16
Demeaned Log Income	κ_{Inc}	0.96	0.16

Table A9: Parameter estimates. Bootstrap standard errors in parenthesis.

Moment	Data	Simulation
I. Regression of log panels on subsidies, with interactions		
Coeff. on subsidies	5.33	5.42
Coeff. on subsidies $\times$ log income	-1.92	-1.94
II. Panels per capita on demeaned log income		
Coeff. on income	0.25	0.24
Constant	0.21	0.21
III. Avg. panels per capita by income quintile		
Quintile 1	0.07	0.09
Quintile 2	0.13	0.14
Quintile 3	0.19	0.19
Quintile 4	0.28	0.25
Quintile 5	0.40	0.39
IV. Avg. installation size regression		
Constant	15.73	15.72
Coeff. on college education	-2.21	-2.19
Coeff. on Democrat	-5.57	-5.59
Coeff. on income	0.64	0.73
V. Panels per capita on college education		
Coeff. on college education	0.17	0.50
Constant	0.22	0.21
VI. Panels per capita on Democrat share		
Coeff. on Democrat	0.06	0.01
Constant	0.22	0.22

Table A10: Model fit of targeted moments. The column “Data” gives the value of the moment in the data, while “Simulated” gives the moment calculated in the estimated model.

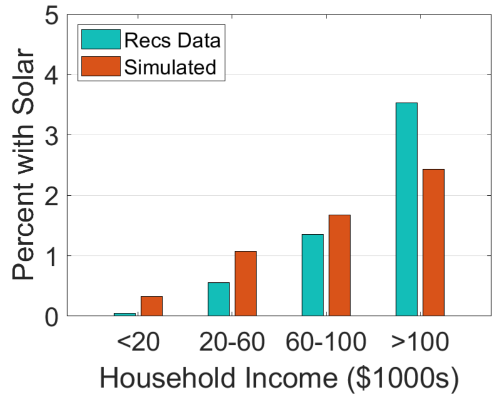


Figure A11: Untargeted Moments: Comparison to RECS installation rates. The bars show the percent of households in each income bin who have solar panels in the RECS microdata and the model simulation. RECS has income data in 8 income categories. We combine categories such that the bins in the figure roughly correspond to income quartiles in 2015.

Figure A11 compares the simulated installations across the income distribution to the distribution in RECS microdata, which is not targeted in estimation.

B.16 Comparison to Existing Literature

We further assess model validity by replicating natural experiments from design-based studies of solar adoption.

Colas and Reynier (2024) find that a \$1,000 subsidy increase raises installations by 9%; our model predicts 9.2%. Hughes and Podolefsky (2015) find a 10% increase from a \$470 rebate in California; our simulation yields 4.0%. Crago and Chernyakhovskiy (2017) estimate that a \$1/W rebate increases installations by 47% in the Northeast; we find a 40% increase. Gillingham and Tsvetanov (2019) estimate a price elasticity of -0.65 in Connecticut; our model gives -0.66.

B.17 Estimation of Marginal Damages of Electricity Production by NERC Region

Let D_{It} denote total environmental damages from electricity production for all plants located within interconnection I in a given hour t. Our estimating equation is given by

$$D_{It} = \sum_{R \in \mathbf{R}_I} \beta_R Load_{Rt} + \alpha_{mh} + \varepsilon_t,$$

where R indexes NERC regions, $\mathbf{R}_I$ is the set of NERC regions in interconnection I, $Load_{Rt}$ is total load in region R in hour t, and α_{mh} are month-by-hour fixed effects. We restrict our sample to 8 AM to 6 PM so that we only measure the marginal damages

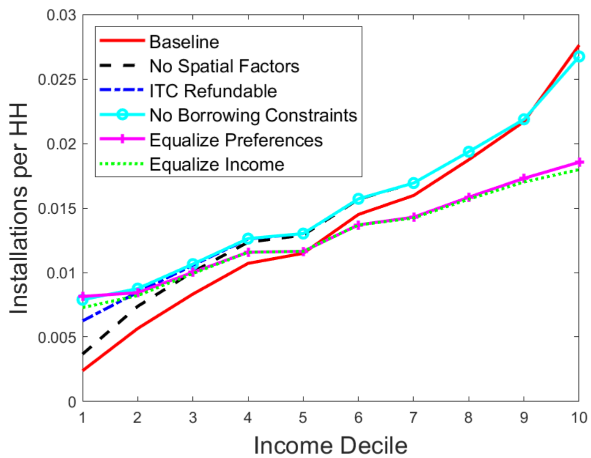


Figure A12: Model-Based Decomposition: All Households. The graph shows the average number of installations per household, including non-homeowners, across deciles of household income over various model specifications. See text for details on each specification.

associated with daytime energy production. The β_R's are the coefficients of interest and measure the marginal damages associated with additional electricity load in region R.

We use data assembled by Holland et al. (2020), who use data on individual power plant production and emissions levels from 2010-2017 from the EPA's Continuous Emissions Monitoring System. Damages are measured as the sum of environmental damages from CO2 and local pollutant emissions. To measure damages associated with CO2 emissions, the authors assume a social cost of carbon valued at \$35.56 per metric ton of CO2 in 2010, which grows at 3 percent annually. To measure environmental damages associated with the emissions of local pollutants, the authors use the AP3 integrated assessment model, which calculates the damages associated with individual pollutants at the plant level.

B.18 Additional Decomposition Results

Figure A12 repeats the decomposition exercise from Section 4.1 but displays installations per household rather than installations per homeowner.

B.19 Production-Maximizing Optimality Conditions

Let I denote the set of all households, let $P_{i|a}$ denote the probability household i installs panels conditional on having initial assets a, and let $Pr_i\left(a\right)$ denote the probability household i has initial asset level a. The government's problem is to maximize solar production

$$\int_{i\in I}\int Pr_i(a)P_{i|a}N_iA_i\,da\,di \quad \text{s.t.} \quad \int_{i\in I}\int Pr_i(a)P_{i|a}s_i\,da\,di \leq C,$$

where C is the exogenously-set government budget, and s_i is the present discounted value of subsidies received by household i conditional on installing solar panels. We can write the government's problem as the Lagrangian:

$$\max \int_{i\in I} \int Pr_i\left(a\right) P_{i|a} N_i A_i dadi - \lambda \left(\int_{i\in I} \int Pr_i\left(a\right) P_{i|a} s_i dadi - C \right),$$

where λ is the government's Lagrange multiplier. Let $s^{\text{Inc}}\left(\hat{y}\right)$ denote the income-contingent subsidy for households with income level $\hat{y}$. Taking the first-order condition with respect to $s^{\text{Inc}}\left(\hat{y}\right)$ yields

$$\int_{i\in I(\hat{y})} \int Pr_i\left(a\right) \frac{\partial P_{i|a}}{\partial s^{\text{Inc}}\left(\hat{y}\right)} N_i A_i dadi - \\ \lambda \left(\int_{i\in I(\hat{y})} \int Pr_i\left(a\right) \frac{\partial P_{i|a}}{\partial s^{\text{Inc}}\left(\hat{y}\right)} s_i dadi + \int_{i\in I(\hat{y})} \int Pr_i\left(a\right) P_{i|a} dadi \right)$$

where $I\left(\hat{y}\right)$ is the set of households with income level $\hat{y}$.

Let $M\left(\hat{y}\right) = \int_{i\in I(\hat{y})} \int Pr_i\left(a\right) P_{i|a} dadi$ denote the total number installations by households with income level $\hat{y}$. We can then rewrite the government's optimality condition as

$$\frac{\partial M\left(\hat{y}\right)}{\partial s^{\text{Inc}}\left(\hat{y}\right)} \times \left(\bar{s}\left(\hat{y}\right) - \frac{1}{\lambda} \overline{NA}\left(\hat{y}\right) \right) + M\left(\hat{y}\right) = 0.$$

The term $\frac{\partial M(\hat{y})}{\partial s^{\text{Inc}}(\hat{y})}$ gives the derivative of installations of households with income level $(\hat{y})$. These marginal installations increase government costs, as these households now receive subsidies. This marginal cost is captured by $\bar{s}\left(\hat{y}\right)$, which gives the average subsidy received across all marginal households. This is formally given by

$$\bar{s}\left(\hat{y}\right) = \frac{\int_{i\in I} \int Pr_i\left(a\right) \frac{\partial P_{i|a}}{\partial s^{\text{Inc}}(\hat{y})} s_i dadi}{\int_{i\in I} \int Pr_i\left(a\right) \frac{\partial P_{i|a}}{\partial s^{\text{Inc}}(\hat{y})} dadi}.$$

These marginal households are also associated with additional solar production. This is captured by the term $\overline{NA}\left(\hat{y}\right)$, which gives the average solar output per installation for these marginal households. This term is formally given by

$$\overline{NA}\left(\hat{y}\right) = \frac{\int_{i\in I} \int Pr_i\left(a\right) \frac{\partial P_{i|a}}{\partial s^{\text{Inc}}(\hat{y})} N_i A_i dadi}{\int_{i\in I} \int Pr_i\left(a\right) \frac{\partial P_{i|a}}{\partial s^{\text{Inc}}(\hat{y})} dadi}.$$

Finally, households at income level $\hat{y}$ who already choose to install panels given the current levels of subsidies would receive additional subsidies if the government increased $s^{\text{Inc}}\left(\hat{y}\right)$.

The additional government cost associated with more generous subsidies for these infra-marginal households is captured by the term $M(\hat{y})$.

B.20 Environmental-Benefit-Maximizing Subsidies

Optimality Conditions Let B_i denote the environmental benefits associated with one kWh of solar electricity produced by household i. Let I denote the set of all households, let $P_{i|a}$ denote the probability household i installs panels conditional on having initial assets a, and let $Pr_i(a)$ denote the probability household i has initial asset level a. The government's problem is to maximize environmental benefits,

$$\max_{Pr_i(a)} \int_{i\in I} \int Pr_i(a) P_{i|a} N_i A_i B_i \, da \, di \quad \text{s.t.} \quad \int_{i\in I} \int Pr_i(a) P_{i|a} s_i \, da \, di \leq C,$$

where C is the exogenously set government budget, and s_i is the present discount value of subsidies received by household i conditional on installing solar panels.

Similar to Appendix B.19, we can then write government's optimality condition as

$$\frac{\partial M(\hat{y})}{\partial s^{\text{Inc}}(\hat{y})} \times \left(\bar{s}(\hat{y}) - \frac{1}{\lambda} \overline{NAB}(\hat{y}) \right) + M(\hat{y}) = 0$$

where the terms $\frac{\partial M(\hat{y})}{\partial s^{\text{Inc}}(\hat{y})}$, $M(\hat{y})$, and $\bar{s}(\hat{y})$ are defined as in the previous section.

These marginal households are also associated with additional environmental benefits. This is captured by the term $\overline{NAB}(\hat{y})$, which gives the average environmental benefits per installation for these marginal households. This term is formally given by

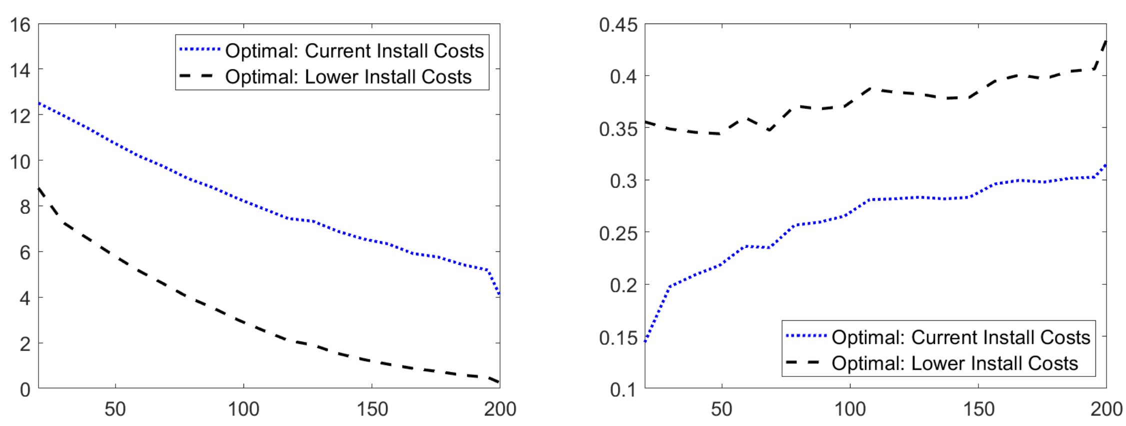
$$\overline{NAB}(\hat{y}) = \frac{\int_{i\in I} \int Pr_i(a) \frac{\partial P_{i|a}}{\partial s^{\text{Inc}}(\hat{y})} N_i A_i B_i da di}{\int_{i\in I} \int Pr_i(a) \frac{\partial P_{i|a}}{\partial s^{\text{Inc}}(\hat{y})} da di}.$$

Results To measure B_i, the marginal benefits associated with one kWh of solar electricity produced by household i, we estimate NERC-region level marginal damages of electricity production using data from Holland et al. (2020). We describe this estimation procedure in Appendix B.17.

Table A11 shows the results. The optimal subsidy schemes, distribution of installations, production levels, and environmental benefits are very similar for the production-maximizing and environmental-benefit-maximizing subsidy schemes.

	(1) Baseline	(2) Prod Max	(3) Benefit Max
I. Production per HH			
Income Q1	22.1	46.1	44.0
Income Q2	50.4	64.3	64.2
Income Q3	77.0	76.5	77.8
Income Q4	119.0	91.5	92.0
Overall	68.7	70.4	70.4
II. Subsidy Generosity ($1000s)			
Income Q1	8.1	12.4	12.2
Income Q2	9.3	11.5	11.5
Income Q3	9.8	9.8	10.0
Income Q4	10.4	6.2	6.2
III. Relative Production	100.0	102.4	102.4
IV. Relative Benefits	100.0	102.4	102.4

Table A11: Environmental-Benefit-Maximizing Subsidies. Panel I shows the average yearly solar capacity in kWh per household in each income quartile. Panel II shows the average subsidy a household from each income quartile would receive for a solar installation. Panel III shows the total solar production. We scale total production under the baseline simulation to 100. Panel IV shows the total environmental benefits of solar panels. We scale the environmental benefits under the baseline simulation to 100.



(a) Average Subsidy (b) Panels per Household

Figure A13: The figure on the left shows the average present discounted value of subsidies received for an installation across income levels under various subsidy schemes. The figure on the right shows the average panels per household across income levels under these same subsidy schemes.

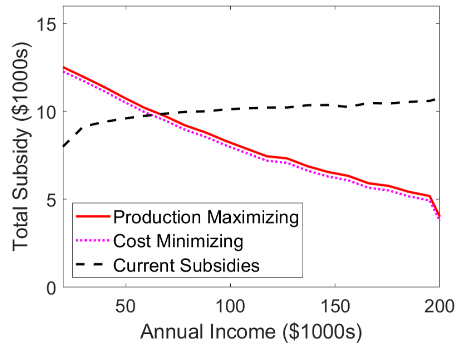


Figure A14: Average Subsidy. This figure shows the average present discounted value of subsidies received for an installation across income levels under production-maximizing, cost-minimizing and current subsidy schemes

B.21 Lower Installation Prices

Figure A13a shows the production-maximizing subsidy schedule given current installation prices (dotted blue line), and production-maximizing subsidy schedule given that installation prices are 50% of current prices (black dashed line). The production-maximizing subsidies with lower installation prices are still strongly decreasing in income but are lower than optimal subsidies given current prices. Figure A13b shows panels per households given current installation costs and the corresponding production-maximizing subsidies (dotted blue line), and panels per households given 50% of current installation costs and the corresponding production-maximizing subsidies (black dashed line). Decreasing installation costs leads to an increase in installation rates across the board, but especially for low income households.

B.22 Cost-Minimizing Subsidies

Figure A14 shows the average present discounted value of subsidies received for an installation across income levels under production-maximizing, cost-minimizing and current subsidy schemes. The cost-minimizing subsidy schedule is very similar to the production-maximizing schedule.

B.23 Welfare-Maximizing Subsidies

Let B_i denote the environmental benefits associated with one kWh of solar electricity produced by household i and let $V_{i|a}$ denote the lifetime utility of household i conditional on having initial assets a. The government's problem is to maximize

$$\underbrace{\int_{i\in I}\int Pr_i(a)P_{i|a}V_{i|a}\,da\,di}_{\text{Utilitarian Welfare}} \quad \text{s.t.} \quad \underbrace{\int_{i\in I}\int Pr_i(a)P_{i|a}s_i\,da\,di}_{\text{Fiscal Cost}} - \underbrace{\int_{i\in I}\int Pr_i(a)P_{i|a}N_iA_iB_i\,da\,di}_{\text{Environmental Benefit}} \leq C,$$

where C is the exogenously set maximum net cost.

The system of optimal subsidies must satisfy the first-order conditions of the government's Lagrangian, which implies

$$\int_{i\in I}\int Pr_i\left(a\right)\frac{\partial V_{i|a}}{\partial s^{\text{Inc}}\left(\hat{y}\right)}dadi- \\ \lambda\left(\int_{i\in I}\int Pr_i\left(a\right)\left(\frac{\partial P_{i|a}}{\partial s^{\text{Inc}}\left(\hat{y}\right)}\left(s_i-N_iA_iB_i\right)+P_{i|a}\right)dadi\right)=0. \quad (30)$$

B.24 Stochastic Income Details

Households begin the model with an initial persistent component of income z_{i0}. At the beginning of the model, they receive their idiosyncratic preferences for panels, ϵ_i, and make a once and for all decision of whether to install solar panels ($m_i \in \{0,1\}$).

After making this decision, households receive the persistent and transitory earnings shocks, η_{it}, and ε_{it}. Households then make a consumption and savings decision, taking an expectation over future earnings shocks. Each year, households continue to receive that year's two shocks and make consumption and earnings decisions.

Let $V_{it}\left(\Omega_{it},\eta_{it},\varepsilon_{it}\right)$ denote household i's value function in period t, conditional on state space Ω_{it}, and earnings η_{it}, and ε_{it}. The state space consists of lagged value of the persistent component, z_{it-1}, assets a_{it}, the amount of carried over federal tax credits s_i^{Carry}, value of electricity produced $\left(m_iN_iA_i\left(p_j+s_j^{\text{kwh}}\right)\right)$, and amount of property tax rebate. Note that this value function can be used for both households who choose to install solar panels and for those who do not by setting the appropriate state space variables to 0.

After making the initial installation decision, the household's value function is given by

$$V_{it}\left(\Omega_{it},\eta_{it},\varepsilon_{it}\right)=\max_{c_{it}}\frac{\left(c_{it}\right)^{1-\gamma}}{1-\gamma}+\beta\mathbb{E}\left[V_{it+1}\left(\Omega_{it+1},\eta_{it+1},\varepsilon_{it+1}|c_{it}\right)\right]$$

subject to the budget constraint ((7) and (8)) and the borrowing constraint (9). The expectation is taken over η_{it+1} and ε_{it+1}.

Calibration We set $\sigma_\eta = 0.022$, $\sigma_\varepsilon = 0.057$, and $\rho = 0.984$, based on the estimates from Panel B of Table 1 from Storesletten, Telmer, and Yaron (2004). We assume the initial value of the persistent component of earnings, z_{i0}, follows a normal distribution with tract-specific means and variances such that income in year 1 also follows a log-normal distribution. We choose the tract-specific means and variances of z_{i0} such that the income distribution in year $t=1$ matches tract-level average income and Gini coefficients. We assume that the income-contingent subsidies are awarded based on a household's income in year $t=0$. We assume there is no transitory income shock in year 0 such that $\log y_{i0} = z_{i0}$.