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Household Discount Rates and Net Energy Metering Incentives for Rooftop Solar Adoption

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Abstract

Net Energy Metering policies common to 41 U.S. states and parts of Europe subsidize distributed solar electricity generation by affording the generator displacement of grid electricity and export sales at retail electricity rates that value the electricity at greater than wholesale prices. This subsidy has engendered criticism on equity grounds because it affects cost shifting from relatively wealthy households who adopt solar photovoltaic capacity to poor households who bear greater shares of electric grid supply costs. This paper explores the efficiency implications of NEM policies that subsidize a future stream of electricity generation that may be highly discounted by households relative to market rates. We estimate an implied discount rate of NEM subsidies equal to 10.9-13.7% in preferred specifications, far greater than prevailing market rates, suggesting that planners could arbitrage discount rates to achieve greater solar generation per public dollar expenditure.

1 Introduction

Amid concerns about the depletion of fossil fuels and the unpriced damages their combustion imposes upon human and environmental health, authorities throughout the world promote renewable electricity generation technologies that can substitute for polluting power plants. In the United States and other Western countries, policy favors the small-scale, renewable generation of electric utility customers over large-scale generation undertaken by utilities and independent power generators. By 2016, solar PV was installed at 1.1 million U.S. homes and businesses, and distributed solar capacity totaled 11 gigawatts (GW), about 40 percent of total solar capacity nationwide. Though solar accounted for 26

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percent of U.S. electricity generating capacity additions in 2015, it constituted less than 2 percent of total generating capacity and provided only 0.6 percent of electricity generation (EIA 2016a, EIA 2016b).

Policy support for renewables is justified as second-best policy in the absence of pollution pricing. In the U.S., solar PV capacity additions are promoted by a federal investment tax credit equal to 30 percent of system cost. In addition, more than 30 states provide subsidies for distributed solar capacity, as do various municipalities and regulated utilities. Forty-one states subsidize distributed solar generation through net metering policies that compel utilities to buy excess distributed generation at rates exceeding wholesale prices. These rates exceed the feed-in tariffs utility-scale generators receive for their electricity.

Since 2006, when the federal tax credit for solar capacity was introduced, the cost of solar panels has declined dramatically and installed capacity has grown exponentially. Installed residential capacity increased from fewer than 100 Megawatts (MW) in 2006 to more than 2500 MW in 2016. Prices fell by a factor of four to less than \$2 per watt net of installation costs¹. Yet, accumulating evidence highlights efficiency and equity concerns associated with existing incentives. None of these incentives has proven more controversial than the net energy metering (NEM) incentives that subsidize rooftop solar generation.

Net energy metering policies allow rooftop solar adopters to offset kilowatt-hours (kWh) of electricity consumed from the grid at retail rates by kWh exported to the grid from rooftop solar panels. Exports to the grid are said to “rewind the meter”. Because retail electricity rates typically reflect cost adders beyond the wholesale cost of electricity, namely fixed cost recovery charges, rooftop solar adopters are compensated for the electricity they supply to the grid at rates exceeding those of utility-scale solar generators. Moreover, they are effectively paid for grid services that the utilities provide and that they consume as a virtual battery to align their rooftop generation with their household consumption.

Though most policies preclude solar households from exporting more solar to the grid than they consume from the grid over a month or year (restricting utility bills to be non-negative), NEM subsidies are estimated to greatly exceed the value of distributed renewable generation, i.e. “the value of solar” (Borenstein 2008, 2012). Distributed generation capacity is often assumed to avoid transmission and distribution capacity investments and maintenance costs, warranting subsidization beyond the value of electricity generated. But as Borenstein (2012) and others have noted, there is little evidence that such benefits have so far materialized. The value of solar is the subject of ongoing debate and academic inquiry.

NEM policies not only offer generous subsidies to adopters, but they affect cost-shifting from solar adopters to non-adopters. In particular, adopters do not pay fixed recovery charges incorporated into retail rates for any consumption from their rooftops. But they also do not pay any variable fixed cost recovery charges for consumption from the grid that is offset by exports to the grid. Thus, a household that generated electricity equal in quantity to its consumption but that exported all of its generation and imported all of its consumption would owe the utility nothing under typical NEM policies, and consequently would pay for none of the fixed costs of the grid. This would be despite

¹See <http://www.seia.org/research-resources/solar-industry-data>

the fact that the household was consuming grid services more intensively than the non-adopting household by exporting and importing in equal quantities. As adopters avoid paying for fixed system costs, these costs must be borne more intensively by non-adopters. Borenstein and Davis (2016) have shown that solar adoption occurs preferentially among the rich, implying cost shifting from rich solar adopters to poor non-adopters.

Such cost shifting is of concern to regulators for equity reasons alone. Also of concern, however, is the viability of traditional utility models if NEM policies are unreformed. As fixed cost recovery charges are spread across only non-adopters, the higher charges induce more solar adoptions. Additional solar adoptions leave fewer non-adopters to pay for grid costs, compelling still higher charges among non-adopters, which, in turn, induces additional adoptions, in a market unraveling termed the utility death spiral (Kind 2013) It could yield, over time, to autarchic electricity markets, without investments to allow smoothing of consumption and generation across space.

Because of these concerns, NEM policies were under review in 28 states in 2016. Some states have eliminated or substantially restricted previously generous NEM policies. In Nevada, a 2015 reduction in compensation for rooftop solar exports by \$0.02/kWh and \$5 increase in monthly service charges to solar adopters sparked outrage that has led to a partial policy reversal. Last year, Arizona regulators changed its NEM policy to pay rooftop solar adopters a rate commensurate with the long-term contract rates received by utility-scale generators. Hawaii, with an ambitious goal of 100% renewable generation by 2050, reduced NEM rates for new customers to wholesale prices in 2015. State utility regulators also restricted the quantity of new capacity that will be eligible to receive wholesale price compensation. Ineligible systems will receive no payments for exports to the grid. Substantial reforms to NEM have also been considered, though postponed, in California, home to nearly 700,000 rooftop solar PV systems.

Despite the prevalence of NEM policies and the vigorousness with which they are defended, we are aware of no previous research that has evaluated their effectiveness in spurring additional solar PV capacity or generation. Upfront rebates, on the other hand, have been studied in the context of the California Solar Initiative, which offered rebates per unit capacity that declined from \$2.50 to \$0.20 per watt during the seven-year program. Hughes and Podolefsky (2015) estimated a rebate elasticity of 0.9, implying a program cost per additional kWh equal to approximately the wholesale price of solar electricity at \$0.06. Rogers and Sexton (2015) estimated the cost per ton of CO₂ avoided by the California rebates at \$144-328, about 3-8 times greater than the estimated social cost of CO₂ emissions. The relatively low additionality of the program is despite evidence that a relatively large fraction of the rebates are passed onto consumers (Pless and van Benthem 2016).

Though NEM subsidies may more closely target the objective of the social planner, namely to increase solar generation as opposed to solar capacity, they may less effectively spur rooftop solar adoption (and electricity generation) than upfront rebates. NEM subsidies are paid out over the 20-25-year lifetime of solar PV systems as they generate electricity. If households exhibit higher discount rates than market rates, then public resources could be more effectively deployed in the form of upfront rebates, effectively arbitraging household impatience. Moreover, NEM subsidies are uncertain. Even if electricity rates are expected to only increase overtime, the policy commitment to solar generation subsidies may not persist, as evidenced by recent NEM reforms. Households may

have highly non-linear risk preferences, such that the injection of even a modicum of uncertainty into the benefits of NEM subsidies diminishes their value to potential adopters. Uncertainty about the benefits of future energy investments introduces option value associated with the option not to invest (Hassett and Metcalf 1993). Present bias may also cause households to be more responsive to upfront rebates than to a stream of future subsidies (O’Donoghue and Rabin 1999, O’Donoghue and Rabin 2015).

This paper, therefore, evaluates the effectiveness of NEM subsidies in increasing adoption of rooftop solar. First, household adoption is modeled as a two-step recursive process to demonstrate how NEM policies influence the adoption decision on both an intensive margin, i.e., the optimal size of the system to install if adopting, and on an extensive margin, i.e., whether to adopt. Then discrete changes in the benefits of California’s NEM policy across utility service territories and climate zones are exploited to identify an elasticity of adoptions with respect to NEM benefits. We estimate greater responsiveness to upfront rebates than to the expected stream of NEM benefits. These differences can be rationalized by constant discount rates of 10.9-20.5%, far above market discount rates that prevailed during the period of study.

These results are important in the context of solar policy. They suggest that regulators could more cheaply induce additional solar electricity generation by awarding adopters an upfront rebate equal to the present discounted value of the NEM subsidy stream using a discount rate as high as 10 or 11%, well above prevailing market rates. To demonstrate the magnitude of this arbitrage opportunity, consider the difference in the NPV of NEM subsidies for the average adopting household in our data and the NPV of NEM subsidies perceived by the market. A typical 4kW system in California would generate 6,000 kWh per year and receive a subsidy equal to the retail rate less wholesale cost of \$0.10. Assuming a 20-year life of the system, the NPV of the NEM subsidy stream is \$5,300 at an 11% discount rate, but \$8,500 at a 4% discount rate.

Our estimates of an implied discount rate for durable goods investments also inform a substantial literature on the Energy Paradox, or Energy Efficiency Gap, and on household adoption of energy efficient durables. Our estimate of an implied discount rate is consistent those estimated by Hausman (1979) and Dubin and McFadden (1984). Both papers estimate implied discount rates in the range of 15-25%, substantially higher than market rates, but not substantially different from credit card interest rates. Newell and Siikamäki (2015) estimated modal and median discount rates from a survey elicitation of 1200 households equal to 11% and 10%.

This paper proceeds in section 2 with a discussion of the efficiency of solar policy and a model of household solar adoption that characterizes the affect of NEM subsidies on intensive and extensive margins. Section 3 presents our data and empirical strategy, while Section 4 reports results. Section 5 discusses these results, while Section 6 characterizes ongoing research related to this analysis. A final section concludes.

2 Solar policy and household adoption of solar PV

The primary rationale for government intervention in the market for solar capacity and generation is the unpriced cost of pollution from coal and natural-gas-fired electricity generation for which solar generation can substitute.²

Economists agree that the efficient solution to such pollution externalities is a tax on emissions equal to their marginal damages, or a tradable permit system that attains an equivalent permit price (e.g., Borenstein 2012; Pigou 1920). Were such a tax imposed, the pollution externality would be internalized by the plant operator and the cost of dirty electricity would rise. Solar generation, which emits no pollution, would become relatively cheaper. However, such pollution taxes are uncommon. Instead, command and control regulations are the norm in jurisdictions that regulate pollution at all. In the absence of policy that fully corrects the pollution externality, solar generation is undervalued and, therefore, justifiably subsidized in a second-best setting.

A common policymaker objective in subsidizing solar is to maximize—subject to a budget constraint—the value of the induced displacement of fossil fuels, i.e., to maximize solar generation in areas where it is most valuable. Because the feedstock for solar generation is free, the marginal cost of solar generation is essentially zero. Therefore, incentives for solar capacity installation can operate as efficient incentives for generation. The magnitudes of capacity subsidies, however, should reflect spatial heterogeneity in the value of displacing fossil generation, as should subsidies that directly target generation.³ The nature of solar energy technology renders the upfront rebate and the future stream of NEM subsidies first-order-equivalent policies from a neoclassical perspective. Behavioral phenomena, and imperfect credit markets, however, may cause outcomes to differ across the two instruments, as we hypothesize they do.

To demonstrate the equivalence of the policies and to motivate empirical approaches exploiting aggregated variation in electricity rates and planned work exploiting micro-variation in rooftop irradiance, we model household adoption decision.

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

²Potential learning spillovers provide an alternative justification, e.g. Gillingham and Sweeney 2012; Nordhaus 2011). Such spillovers would constitute positive externalities in the technology market that weaken incentives for innovation. Combined with the negative externalities from pollution, they likely cause clean technologies to be "doubly under-provided" in the absence of policy (Fischer 2008; Fischer and Newell 2008; Jaffe et al. 2005).

³Most capacity subsidies, including the federal investment tax credit, are not differentiated according to variation in the value of solar generation. The California Solar Initiative is an exception. The program offered upfront rebates to rooftop adopters, but rebates were scaled to the performance-rated capacity of installations, which partly accounted for heterogeneity in the value of capacity.

of some solar irradiance by surrounding structures and vegetation, as well as panel orientations and pitches that may fail to capture all irradiance due to rooftop characteristics. Effective irradiance, thus, admits micro-level variation in the electricity generation of a unit of solar capacity, namely from household to household within neighborhoods. Moreover, for a given home, effective irradiance varies across the rooftop, with some portions of the rooftop receiving more sunlight than others.

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

Let $TC(K)$ denote the total cost to a household of a solar installation of size K . It is comprised of a fixed cost, F and a cost per panel, V . The panel cost is reduced by available per-capacity subsidy, S . The total cost of the system net of rebates is reduced by a fraction I equal to the investment tax credit.⁴ Thus,

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

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

Let $q(K)$ be the annual electricity generated by a system of size K (and q^* is the annual electricity produced by a system of optimal size K^*). Then $q'(K)$ is marginal generation, i.e., the electricity produced by an incremental unit capacity. We assume $q'(K)$ is weakly decreasing in K because the first unit of solar capacity is installed on the highest solar irradiance surface of a rooftop, i.e., $q'(K) \geq 0, q''(K) \leq 0$. The cost per kWh of electricity generated by the marginal unit of capacity over its (20-year) lifetime, $c(K)$, is then equal to $(V - S)(1 - I)/20q' = C/20q'$. An interior solution to the sizing problem equates the present value of the levelized cost of electricity generated by the marginal unit capacity to the present value of the 20-year future stream of utility payments for the marginal unit of consumption from the grid.⁵ Assuming annual discounting at a rate δ , the present value cost of the marginal unit of grid electricity consumption over the lifetime of the solar capacity is $\sum_{t=1}^{20} \frac{1}{(1+\delta)^t} p$, where p is the annual cost of the monthly marginal unit of electricity consumption. Thus, the optimal system size is implicitly defined by:

$$c(K) = \sum_{t=1}^{20} \frac{1}{(1 + \delta)^t} p,$$

where $c(K)$ is increasing in K because q' is decreasing in K . Because q' is decreasing in K , for constant and increasing block rate prices, there will be a unique optimum. With increasing block

⁴This assumes federal income tax liability. The absence of tax liability is a likely reason why low-income populations are less likely to adopt rooftop solar. For the empirical methods that follow, this modeling assumption is not important.

⁵We assume households take electricity consumption as given and seek to minimize the cost of that consumption.

prices, the first units of displaced grid electricity bear the highest marginal costs, and marginal costs of displaced electricity decline discretely as solar capacity increases. For decreasing block prices, the opposite is true, and the interior optimum may not be unique. Optimal size is increasing in q' , p , S , and I and decreasing in δ and V .

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

The optimal sizing function is piece-wise defined according to the number of tiers in the tariff structure. We illustrate this in the context of a tariff with two distinct tiers of volumetric charges. We abstract from consideration of fixed charges because we assume no households prefer to disconnect from the grid. Let τ be the monthly grid consumption threshold at which rates change from p_0 to p_1 for $p_0 < p_1$, and let q_0 denote monthly household consumption. The marginal price of grid electricity p depends upon the residual grid demand, i.e., consumption net of solar generation, such that:

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

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

$$K^* = \begin{cases} 0 & c(0) > p_1 \\ (q')^{-1} \left(\frac{C/20}{\sum_{t=1}^{20} \frac{1}{(1+\delta)^t} p_1} \right) & c(0) \leq p_1, c(q_0 - \tau) \geq p_1 \\ (q')^{-1}(q_0 - \tau) & p_0 \leq c(q_0 - \tau) < p_1 \\ (q')^{-1} \left(\frac{C/20}{\sum_{t=1}^{20} \frac{1}{(1+\delta)^t} p_0} \right) & c(q - \tau) < p_0, c(q_0) \geq p_0 \\ (q')^{-1}(q_0) & c(q_0) \leq p_0 \end{cases}$$

The household will optimally install a system large enough to exactly offset all consumption if the levelized cost of electricity generation from the marginal unit capacity is less than or equal to the lowest electricity rate, p_0 . It does not install any capacity if the levelized cost of electricity generated from the first unit capacity is greater than the highest grid electricity rate. And if levelized costs of the marginal solar capacity are less than the highest grid electricity rate but higher than the lowest grid electricity rate, then the household optimally sizes the solar array to offset just the fraction of

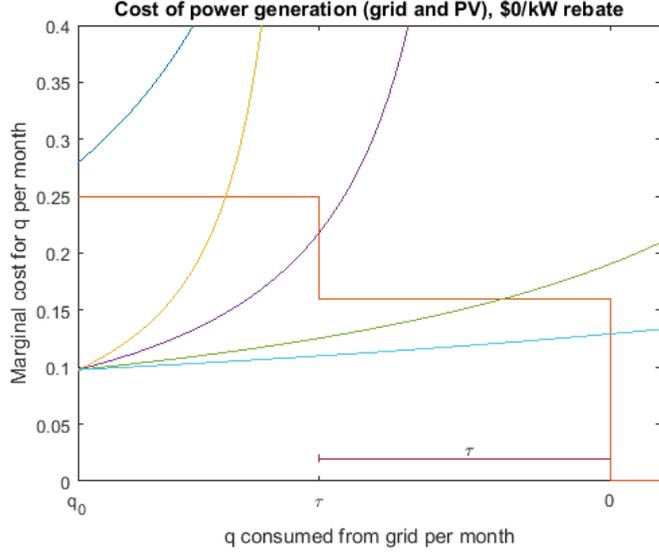


Figure 1: Optimal sizing of solar PV arrays is depicted as a function of alternative modeled q' functions, i.e., the electricity generation of marginal units of solar capacity. Depicted are the costs per kWh for alternative q' s and a tariff with two tiers of volumetric charges. Grid consumption increases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

grid electricity consumed at the highest rate, $q_0 - \tau$. Figure 1 depicts these cases for given alternative q' s that define c . Solar capacity K is increasing left to right, and grid consumption is increasing right to left.

Given fixed costs of solar adoption, the household adopts if the present value cost of electricity from solar PV is less than the present value cost of grid electricity that would be displaced by the solar array, i.e.,

$$TC(K^*) = (F + K^* \cdot (V - S))(1 - I) \leq \int_{q_0 - q^*}^{q^*} \sum_{t=1}^{20} \frac{1}{(1 + \delta)^t} p(x) dx.$$

Adoption, therefore, is increasing in electricity rates and in effective irradiance, which increases the quantity of displaced electricity for given solar capacity costs. Moreover, the higher are electricity prices, the greater is the return from high effective irradiance. Importantly, the likelihood of adoption is decreasing in δ , the discount rate. The higher is δ , the less the potential adopter values the future stream of subsidy benefits implicit in the ability to avoid future retail grid prices for the quantity of electricity generated by the rooftop solar array. The lower are electricity rates, the lower is the implicit NEM subsidy, and the less likely is the household to adopt.

This conceptual model has assumed away uncertainty for ease of exposition. However, households face uncertain generation from solar arrays, uncertain future electricity rates, uncertain future solar costs, and uncertain future policy. Though this uncertainty is unimportant for our estimation, it is important for interpretation of the implied discount rates that we recover as high discount rates may also reflect risk aversion among households.

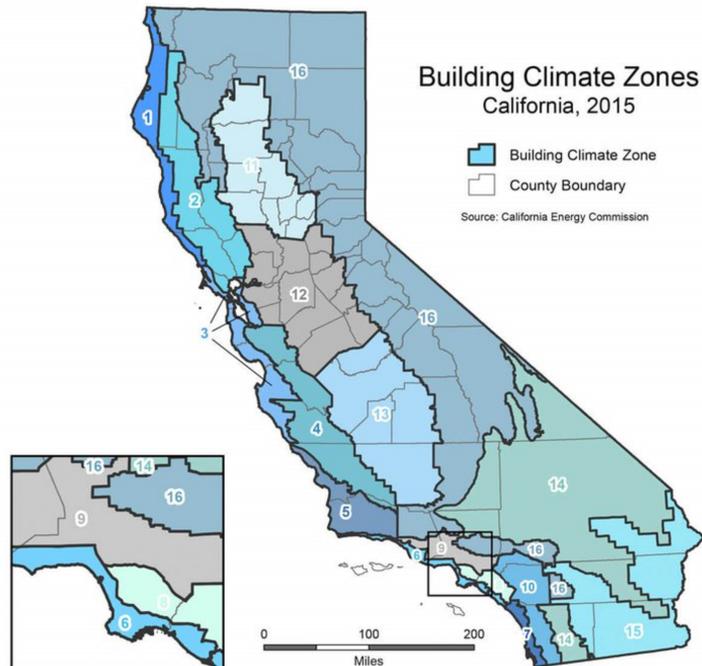


Figure 2: Climate zones established by the California Energy Commission to represent heterogeneity in the cost of heating and cooling buildings across the state.

3 Empirical strategy and data

3.1 Effect of NEM subsidy on adoption probability

In order to estimate household responsiveness to NEM subsidies, we exploit discrete changes in electricity rates across the service territories of California’s three investor-owned utilities (IOUs), Pacific Gas & Electric (PGE), Southern California Edison (SCE), and San Diego Gas and Electric (SDGE). Rates vary across the utility service territories due to distinct rate cases with the state’s Public Utilities Commission. Rates vary principally according to the costs of capital investments. Though multi-part tariffs are homogeneous throughout service territories, the tiers at which rates change vary across 16 distinct climate zones established by the California Energy Commission. These are depicted in Figure 2. The climate zones reflect heterogeneity in the costs of heating and cooling buildings across the state. Consequently, homes consuming the same quantity of electricity in different climate zones may face distinct marginal rates for grid electricity. From 2001-2010, the three IOUs offered tariffs with five tiers. From 2010-2016 tariffs included four tiers, and in 2016, tariffs were reduced to three tiers.

Restricting our attention to neighborhoods on the borders of these utility and climate zones, our empirical strategy relates solar adoption rates to spatially and temporally varying electricity rates and tiers that induce variation in average costs of grid electricity consumption. Conditional on regional (utility-border-area) fixed effects and month-of-sample fixed effects, identification of a causal effect of

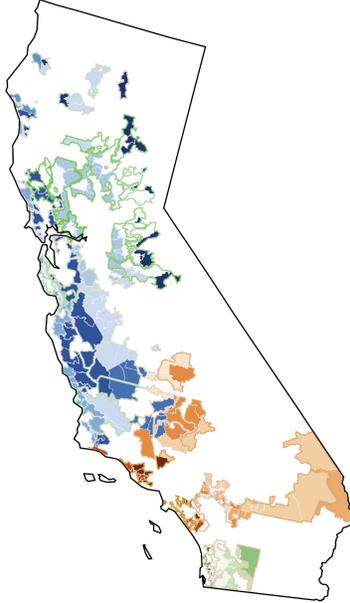


Figure 3: California Zip codes that border utility boundaries or climate zones.

NEM subsidies on adoptions assumes proximal households on opposite sides of these boundaries are similar, e.g., similar distributions of household utility from electricity services, but for the electricity rates and tiers they face. With respect to utility territory boundaries, such assumptions are common in the energy economics literature. Ito (2014) and Hughes and Podolefsky (2015) employ the same identification strategies using the same boundaries as we do to identify other parameters. The climate zones are designed to reflect climatic differences across the state of California, and so it may be likely that average household characteristics are not common across these regions. However, by limiting our attention to only those zip codes on the borders of the climate zones, the assumption of common household characteristics is more reasonable. These same boundaries and this strategy are employed by Deryugina et al. (2016), to identify the effects of building codes on electricity consumption. While climate is presumed to vary across zones, it presumably does so in a continuous fashion, whereas electricity tiers vary discretely at the climate zone boundaries. Figure 3 depicts the 65 IOU and climate zone boundaries, as well as the 466 zip codes that border one or more of these boundaries and comprise the spatial extent of our sample.

Aggregate variation in electricity rates is exploited to estimate the effect of NEM subsidies on the likelihood of PV adoptions because there is limited temporal variation in NEM policy until recently. Although NEM policies vary across states, they do so in a way that would raise concern about omitted variables if the cross-sectional variation were used to identify the effects of policy. That is, the pattern of variation does not permit clean border identification.

In ongoing work, we exploit micro-level variation in the effective irradiance of systems to identify NEM policy effects. We employ data from Google’s Project Sunroof, which has modeled effective irradiance at approximately one-half-meter resolution for 50 million rooftops across the U.S. Though

not all rooftops across the U.S are modeled, coverage is virtually complete in those regions that have been modeled, including California. Google’s model employs high-resolution aerial imagery and a variety of satellite-based data to precisely model the rooftop, including pitch and orientation, as well as surrounding structures and vegetation. Its model of effective irradiance estimates the electricity generation for a given rooftop pixel-by-pixel accounting for irradiance, shading, local weather, and rooftop characteristics. On the assumption that households are not choosing homes as a function of their intentions to install solar or not, then effective irradiance is plausibly exogenous.⁶ It then introduces exogenous variation in the benefit of NEM subsidies as a function of expected system generation, allowing identification of the NEM effect on adoptions using very micro-level variation and high-resolution controls.

3.2 Effect of upfront rebate on adoption probability

Because policymakers can subsidize solar generation via NEM subsidies or via upfront rebates and in order to estimate implied discount rates associated with the NEM subsidy stream, we are also interested in estimating the effect of upfront rebates on adoption probability. Just as in Hughes and Podolefsky (2015), we do so by exploiting discrete changes in upfront capacity rebates offered by California pursuant to the California Solar Initiative (CSI). The CSI offered per-unit-capacity subsidies to rooftop solar adopters from 2007-2014, during which time approximately \$2 billion in ratepayer and taxpayer funds were expended. The level of rebates declined ten times at pre-determined thresholds of cumulative installed capacity. They started at \$2.50 per watt for residential customers, approximately a third of the total cost per watt. The final rebate level was \$0.20 per watt, equal to less than 10% of system cost per watt at the time the subsidy was offered. Not only did the rebate levels change discretely, in a manner exogenous to potential adopters, but they also changed independently across the three IOUs as individual utility capacity thresholds were reached. Thus, at a given time, rebate levels could vary across the three utilities. Controlling for secular trends, like the declining cost of solar PV, and time-constant heterogeneity in the cross-section, as well as utility-specific time trends in some specifications, we identify the responsiveness of solar adoption to upfront rebates exploiting changes in rebate levels.

Because progress toward cumulative capacity thresholds was public and monitored, and because consumers are typically in the market for durable goods like cars, homes, and home appliances for several months, they may “pull forward” their purchases of durable goods ahead of anticipated effective price increases. This results in a spike in sales just before the price increase and lower-than-average sales following the price increase as future sales were “stolen” by earlier periods. For instance, Mian and Sufi (2012) document a substantial pull forward effect in response to the U.S. government’s 2009 “Cash for Clunkers” program, which offered incentives for vehicle scrappage during a limited period of time: a “peak” in new car sales during the policy resulted in a sustained “trough” following the policy.

⁶In so far as one is concerned about home purchase decisions motivated by interest in solar adoption, then attention can be restricted to homes that have not been transacted since approximately 2007 when generous subsidies were introduced.

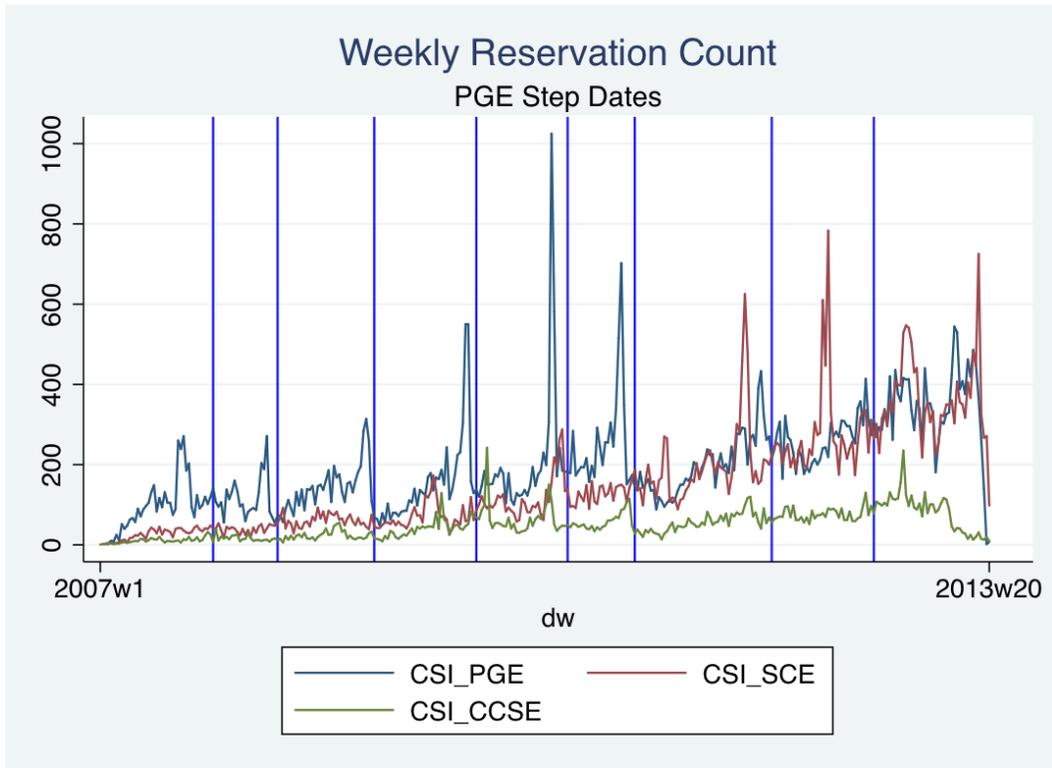


Figure 4: Anticipation of rebate declines induces a pull-forward effect as evidence in this time series depicting the capacity reservations for rooftop solar in PG&E.

There is similar evidence of a pull-forward effect on solar adoptions in California. Figure 4 depicts weekly solar adoptions in PGE along with the dates of rebate changes in the Pacific, Gas and Electric service territory over the duration of the program. It shows that adoptions spike during the few weeks before rebate program administrators begin awarding lower rebates to applicants, as depicted by vertical lines in the figure. Shallow troughs follow the rebate changes. It is not surprising that the peaks precede the administrative rebate changes by several weeks because the rebates changed not at dates certain, but rather when benchmark installation capacities were achieved. Thus, consumers were able to only imperfectly anticipate the rebate changes. As the installed capacity in each region neared thresholds, consumers in the market with sufficient willingness to pay would rationally purchase sufficiently ahead of rebate changes to minimize the risk of applying after capacity thresholds were achieved. Moreover, some administrative delay causes the processing of applications (and assignment of rebate levels) to lag rebate applications.

The pull-forward effect biases upward estimates of adoption responsiveness to rebates. A portion of adoptions before the rebate change are attributed to the generosity of the particular rebate even though they would have occurred after the rebate change had consumers not had the opportunity to anticipate rebate changes. In order to avoid this bias, we exclude from our consideration weeks surrounding rebate changes that may be contaminated by the pull-forward effect.

3.3 Estimation

For the empirical analysis, we adopt a random utility expression of the adoption model introduced in section 2. Thus, we respectively define utility from solar adoption, u_1 , and utility from non-adoption, u_0 as:

$$u_1(q_0, q^*) = 20 \int_0^{q_0} \mu(x) dx - TC(K^*) - \int_0^{q_0 - q^*} \sum_{t=1}^{20} \frac{1}{(1+\delta)^t} p(x) dx + X\beta + \eta + \sigma\epsilon_1$$

$$u_0(q_0, 0) = 20 \int_0^{q_0} \mu(x) dx - \int_0^{q_0} \sum_{t=1}^{20} \frac{1}{(1+\delta)^t} p(x) dx + \eta + \sigma\epsilon_0,$$

where $\mu(x)$ is utility per unit electricity consumption and $X\beta$ is heterogeneous ancillary utility derived from solar adoption.

The probability of adoption is:

$$Pr(adopt) = \Phi \left(\frac{1}{\sigma} \left(TC(K^*) - \int_{q_0 - q^*}^{q^*} \sum_{t=1}^{20} \frac{1}{(1+\delta)^t} p(x) dx + X\beta + \eta \right) \right)$$

Assuming an extreme value type 1 distribution on the ϵ 's, we obtain an aggregate solar market share equation. Let s_{it}^1 denote the share of households in zip code i that adopt solar at time t and $s_{it}^0 = 1 - s_{it}^1$ be the share of households not adopting solar. We estimate:

$$\log(s_1) - \log(s_0) = \theta_1 \bar{p} - \theta_2 \frac{TC_{it}(K)}{20q_i(K)} + \beta X + \varepsilon,$$

where \bar{p} is the average variable cost of grid electricity per kWh, and $\frac{TC(K)}{20q(K)}$ is the cost per kWh of electricity generated from a solar installation of size K .⁷ The average cost of grid electricity varies over time and across zip codes due to differences in average consumption within zip codes and differences in rates and tiers across utilities and climate zones. Rates also vary over time with limited frequency. The cost of solar, TC varies exogenously across time and utility territory because of discrete changes in state rebates. Because of variation in solar irradiance, q_i varies across zip codes. The vector X represents a suite of fixed effects that we vary across specifications. Interest centers on the θ s. If households do not discount the future, then $\theta_1 = \theta_2$. An implied discount rate is calculated as: $\frac{1}{20} \int_0^{20} e^{-rt} dt = \frac{\theta_1}{\theta_2}$.

⁷As demonstrated in the adoption model of the prior section, optimal sizing and, therefore, adoption depend upon the prices charged in each tier of multi-part tariffs. Our use of \bar{p} in lieu of a vector of rates for each tariff is for convenience due to data limitations. In future work, with the benefit of better data on electricity consumption within zip codes, we will implement this model with the vector of tier prices. As Ito (2014) documented, however, typical households behave as though they only perceive an average cost of electricity as opposed to distinct marginal rates depending upon quantities of consumption. If this is a better characterization of household behavior, then the econometric model is correct and the conceptual model could be simplified to reflect optimization according to average prices.

3.4 Data

Data on rooftop solar adoptions by zip code and month are obtained from the administrative records of the CSI for the period 2007-2014. These records indicate the timing and zip code of each rooftop solar installation for which a CSI rebate was requested, as well as system characteristics, including cost. This yields a count of quarterly adoptions in the zip codes of interest. Shares of adopters by zip code were calculated using U.S. Census Bureau’s Decennial Census (2000, 2010) and American Community Survey (2011-2014) counts of owner-occupied households.

The cost per kWh of solar generation is calculated as the average after-rebate cost of systems installed in each zip-code and each quarter of the year divided by the zip-code-specific lifetime system generation per watt as estimated by the National Renewable Energy Laboratory’s (NREL) PVWatts2 model.⁸ Average electricity rates paid by zip code are derived from the NREL Utility Rate Database (URDB), supplemented by rate data published by each utility, and calculated using the zip code average household consumption, published annually by each utility. Table 1 reports the mean and standard deviations of adoption shares, average electricity prices, and cost per kWh of solar generation.

Table 1

Statistic	N	Mean	St. Dev.	Min	Median	Max
Solar adoption share	12,620	0.003	0.01	0.0001	0.002	0.17
Mean electricity rate	12,620	0.27	0.11	0.11	0.26	0.75
Solar cost per kWh	12,620	0.18	0.04	-0.02	0.18	0.55

Summary statistics by zip code.

4 Results

Table 2 reports results for two specifications of the estimating equation for each of two samples of solar adoptions. The two estimating equations differ by the fixed effects used to control for unobservables. Results reported in odd-numbered columns are from specifications that control for time-constant heterogeneity within utility territories and across each climate zone or service area boundary. Secular trends are controlled by a quarter-year fixed effect. In even-numbered-columns, region specific secular trends are controlled by unique quarter-of-year fixed effects for zip codes all sharing common boundaries. Columns 1 and 2 report results for all solar adoptions; columns 5 and 6 report results for all resident-owned (non-third-party-owned, Non-TPO) adoptions. For the subsamples of adoptions by owner status, the log-odds of adoption is computed as the log of the ratio of adopters of the requisite owner type to all non-adopters.

In each specification, coefficients on solar-generated electricity cost per kWh and average grid electricity price per kWh are of the expected sign. The higher is the cost of solar generation, the lower is the probability of solar adoption. The higher is the average electricity price, the greater is

⁸<http://pvwatts.nrel.gov/>

Table 2

	<i>Dependent variable:</i>			
	Log Odds (1)	(2)	(3)	Log Odds Non-TPO (4)
Solar cost per kWh	-1.464*** (0.447)	-1.800*** (0.369)	-2.204*** (0.4658)	-2.065*** (0.384)
Avg. grid rate per kWh	0.809*** (0.215)	1.121*** (0.246)	0.757*** (0.216)	1.010*** (0.230)
Constant	-7.662*** (0.209)	-7.249*** (0.121)	-7.602*** (0.427)	-6.581*** (0.084)
Implied Discount Rate	11.7%	10.9%	20.5%	13.7%
Utility FE	Yes	Yes	Yes	Yes
Zip FE	No	No	No	No
Quarter FE	Yes	Yes	Yes	Yes
Boundary FE	Yes	Yes	Yes	Yes
Boundary-Quarter FE	No	Yes	No	Yes
Observations	10,797	10,797	10,018	10,018
R ²	0.544	0.655	0.489	0.633
Adjusted R ²	0.539	0.574	0.484	0.542
Residual Std. Error	0.810	0.779	0.851	0.802
F Statistic	124.845***	8.115***	93.151***	6.958***

*p<0.1; **p<0.05; ***p<0.01

Cluster-robust SE in parentheses, clustered by border.

All single-utility boundary-adjacent zip codes.

Missing system cost replaced with zip-year mean per kw

the probability of solar adoption. In the even-numbered columns which represent estimates most robust to omitted variables, the odds of solar adoption are estimated to be 60-190% more responsive to upfront costs of solar PV systems than they are to grid electricity costs. Recall that if households did not discount future electricity costs, and absent uncertainty, we would expect the coefficients to be equal in magnitude. We can compute the implied discount rate that rationalizes the estimated coefficients, i.e., the magnitude by which the future stream of grid electricity costs must be discounted (geometrically) in order to equate the estimated sensitivities of adoption probabilities to solar costs per kWh and grid costs per kWh. These are also reported in Table 1. The implied discount rate in our preferred specifications is estimated to be between 10.9% and 13.7%, considerably greater than interest rates that prevailed in the market from 2007-2014.

Model estimates and implied discount rates are calculated for all adoptions and for non-third-party-owned adoptions. Future work will model third-party-owned (TPO) adoption decisions. But because many TPO systems are leased, the contracts imply particular discount rates, chosen by the solar installers. Thus, we check for robustness of our results to the exclusion of these adoptions, in which case TPO adopters are excluded from the market. TPO contracts may not respond quickly (or at all) to changes in electricity prices and upfront solar costs. Thus, potential TPO adopters would not be exposed to the variation in prices we exploit to identify implied discount rates. Unsurprisingly, when we exclude these adoptions from our sample, implied discount rates increase, from 10.9% to 13.7% in our preferred specification, and to as much as 20.5% in the alternative specification.

5 Discussion

Exploiting temporal and aggregated spatial variation in the cost of rooftop solar installations and grid electricity, we estimate that households are more responsive to upfront rebates relative to a future stream of NEM subsidy payments than is dictated by market discount rates. This is consistent with accumulating evidence that households exhibit relatively high discount rates when making durable goods investments, as discussed above. Such findings help to explain the so-called “energy paradox” in which households appear not to adopt technologies that would generate positive returns, even when accounting for the cost of funds. Such conclusions are typically drawn from analyses that assume a discount rate for households.

Some caution is appropriate in interpreting our implied discount rate. It may reflect a variety of other features of the consumer decision-making process besides the actual discount rate that consumers use. For example, it may reflect a certainty premium associated with the upfront rebate. NEM policy is subject to change, as has been evident in a few states in recent years. Typically, however, NEM policy reforms propose to grandfather previous adopters into existing policy such that there is limited uncertainty for adopters. When regulators in Nevada proposed to change NEM subsidies for previous adopters, they were ultimately compelled by political pressures to grandfather prior adopters into the subsidies that existed previously. Reforms to NEM policies have only been proposed in recent years, largely after our period of analysis ended in 2014. Thus, while there may exist some uncertainty about future generation subsidies among adopters today, there was likely little concern about this uncertainty during the adoptions we observe. Apart from NEM policy uncertainty,

households may have also expected electricity rates to change, affecting the value of solar generation. The trend in the U.S. is for electricity prices to rise overtime. If households expected prices to rise, then our estimate of the discount rate is biased down, because we do not observe the household expectations of rising electricity prices (and therefore rising NEM subsidies), which increases the undiscounted value of avoided electricity costs (or NEM subsidies), commanding a greater discount rate to rationalize observed responsiveness to grid and solar electricity cost changes.

To the extent that households exhibit high discount rates in considering solar investments, as this research suggests, then solar adoption and solar generation can perhaps better be incentivised by public investment in upfront capacity rebates. Even if policy makers faced costs of intertemporally substituting upfront rebates for a stream of subsidies, they would presumably incur interest at the market rate. Thus, they could still accomplish greater solar generation of capacity additions per public dollar by arbitraging the difference in discount rates. The NEM subsidies that are prevalent and controversial may not be the most cost-effective mechanism to boost solar capacity or generation. Germany, for instance, has offered very generous feed-in tariffs for household adopters of rooftop solar, totaling as much as \$0.43 per kWh in 2009 and \$0.137 per kWh more recently. These generation subsidies rival and exceed the subsidies implicit in NEM policies in many U.S. states. Germany's feed-in-tariff across all producing sectors was estimated to cost \$20 billion in 2014 alone.

As previously described, households facing capacity incentives have little incentive to curtail generation from their solar installations because the marginal cost of solar generation is essentially nil. Essentially the only margin along which households may affect generation, then, is with respect to maintenance of the solar array. Generation is maximized when the arrays are free of dirt, debris, and shade. It is conceivable that household maintenance effort would decline absent a generation incentive like NEM. We are not aware of any analysis that relates maintenance effort to electricity rates or generation subsidies, but our instincts suggest that even if households were only to receive a wholesale price for the electricity generated by solar arrays, such an incentive would be sufficient to induce the modest maintenance efforts necessary to maximize generation. Were it not, then the benefit of arbitraging household and market discount rates by substituting a stream of subsidies for an upfront rebate would need to be weighed against the cost of less closely targeting the planner's objective, i.e., the cost of less conscientious solar array maintenance by adopters.

Our findings of potential efficiency losses from NEM subsidies relative to upfront rebates, suggest efficiency may favor the latter. So, too, may equity concerns. Because NEM subsidies affect cost shifting from high-income households who adopt solar preferentially to low-income households who do not, such subsidies are likely to be regressive. The regressivity of solar policy is a growing concern among policy makers at the federal and state levels. To the extent policies like NEM are both inefficient and regressive, then policy reform may provide opportunities to better meet two often-competing policy objectives.

While these results are relevant to solar policy implemented by 41 states and other jurisdictions around the world, they also contribute to the literature on household discount rates for durable goods, particularly the literature assessing demand for energy efficiency. Most of the previous literature estimates discount rates in the context of household appliance purchase decisions. In these settings, the researcher must make assumptions about the utilization of appliances to infer energy savings

and the rate at which households trade off higher upfront costs for lower future energy consumption. In the present context, with the exception about maintenance effort just described, utilization is constant and common across households. That is, households constantly use the solar installations to generate savings of grid electricity. Thus, we can overcome uncertainty about utilization; systems are consumed to maximize generation. Admittedly, we do not observe system generation over the lifetime, but importantly, neither does the adopter at the point of adoption. The adopter likely observes the same expected system generation that we observe by relying on the PVWatts2 model, which is commonly used by solar installers to estimate system generation for customers.

Our estimated implied discount rate is representative of the discount rates applied by solar adopters when considering a durable good investment. Solar adopters, however, are likely not representative of all households. In particular, and as evidenced by Borenstein and Davis (2016), solar adopters are wealthier than the average household. In their review of the income characteristics of those households receiving the federal investment tax credit, 60% were among the top income quintile. Because wealthier households may have lower cost of funds than poorer households, they likely exhibit a lower discount rate than the average household. This suggests our estimated discount rate of 11-26% may be a lower bound on the discount rate that characterizes decision making by low and moderate income populations that have been relatively slow to adopt solar but are the focus of marketing effort and policy research at the U.S. Department of Energy. Our estimated implied discount rate can be reconciled with others in the literature estimated by observation on less selectively consumed durable goods, like kitchen appliances that are commonly adopted across a wider range of the income distribution.

6 Future work

The foregoing analysis suggests that generation-based subsidies may less-effectively induce solar generation than upfront capacity rebates because the marginal cost of solar generation—conditional on adoption—is so low and because households are shown to exhibit discount rates greater than market rates. There are a variety of other efficiency concerns associated with existing rooftop solar policy. First, subsidies are taken up by inframarginal consumers, i.e., those who would adopt rooftop solar in the absence of the rebate. To these “free riders,” the rebate constitutes a windfall gain. The policy cost per additional adoption, unit capacity, or unit generation is consequently diminished. Hughes and Podolefsky (2015), for instance, estimated the cost the the CSI program per additional kWh was \$0.06, approximately the wholesale cost of renewable electricity and considerably greater than value of displaced pollution (Borenstein 2012). Rogers and Sexton (2015) similarly estimate that the public cost per ton of avoided CO₂ emissions exceeded the social cost of carbon by a factor of three or more.

Second, most policy values all units of solar capacity and generation equally even though the value of capacity and generation varies spatially and temporally. For instance, the electricity generated by a unit of capacity varies regionally according to solar irradiance and locally according to rooftop characteristics and shading from surrounding trees and structures. While individual rationality suggests solar should be preferentially adopted on sunnier rooftops, there is scant evidence that solar

penetration rates correlate with irradiance. Moreover, the social value of solar generation varies according to the pecuniary costs of electricity generation and the environmental benefits of displacing grid electricity. Grid electricity in California, for instance, is relatively clean, causing the 0.7 million rooftop installations there to generate among the smallest environmental benefits of any capacity in the U.S. Sexton et al. (2016) estimate that as much as \$1.3 billion in avoided pollution benefits are annually forsaken by the suboptimal siting of rooftop solar capacity in the U.S. Moreover, Tanger and Wolak (2017) found that the value of solar capacity to the electricity grid varies considerably. Yet to our knowledge no policy acknowledges this heterogeneity.

Efficient policy would target incentives to those households who are on the margin and who are located in areas where solar capacity generates high value, as a function of the potential generation, the fossil fuel mix of the grid, and the grid services the solar capacity would provide. Thus, efficient incentives should vary from household to household. In ongoing research spurred by this paper, we intend to extend this analysis in at least two ways. First, we intend to employ high-resolution variation in effective solar irradiance from Google’s Project Sunroof to estimate implied discount rates with highly granular spatial fixed effects, and to combine these with household-level consumption data to increase the precision of our estimates. Second, we intend to develop a household model of solar adoption that would allow planners to better target incentives to high-value households. Such a model could also inform installer behavior, allowing contracts to vary in ways that would increase solar penetration.

7 Conclusion

Exploiting plausibly exogenous variation in the cost of solar capacity and in the cost of grid electricity, an implied discount rate is calculated for rooftop solar adopters. The discount rate is estimated to be between 10.9 and 13.7%, greater than prevailing market rates. This suggests that even though net energy metering subsidies target solar generation, which planners seek to maximize subject to constraints, upfront capacity rebates that effectively arbitrage market and household discount rates can better increase solar generation per dollar of public expenditure. NEM policies are criticized as affecting cost shifting from relatively rich solar adopters to relatively poor non-adopters. This analysis suggests such policies may not only hinder equity objectives, but may also be inefficient. Moreover, high household discount rates also likely present solar installers with arbitrage opportunities to increase solar adoption.

References

- Barbose, Galen, Naim Darghouth, Samantha Weaver, and Ryan Wiser**, “Tracking the Sun VI: An Historical Summary of the Installed Price of Photovoltaics in the United States from 1998-2012,” Technical Report, Lawrence Berkeley National Laboratory, Berkeley, CA July 2013.
- Borenstein, Severin**, “The Market Value and Cost of Solar Photovoltaic Electricity Production,” *UC Berkeley Center for the Study of Energy Markets Working Paper Series*, 2008, (176).

- , “The Private and Public Economics of Renewable Electricity Generation,” *The Journal of Economic Perspectives*, 2012, *26* (1), 67–92.
- **and Lucas W Davis**, “The distributional effects of US clean energy tax credits,” *Tax Policy and the Economy*, 2016, *30* (1), 191–234.
- Deryugina, Tatyana, Erica Meyers, and Chris Bruegge**, “The Distributional Effects of Energy Building Codes,” *Working Paper*, 2016.
- Dubin, Jeffrey A and Daniel L McFadden**, “An econometric analysis of residential electric appliance holdings and consumption,” *Econometrica: Journal of the Econometric Society*, 1984, pp. 345–362.
Energy Information Administration (EIA)
- Energy Information Administration (EIA)**, “Today in Energy: California Has Nearly Half of the Nation’s Solar Electricity Generating Capacity,” Technical Report, Energy Information Administration, Washington, DC February 2016. Online at <http://www.eia.gov/todayinenergy/detail.php?id=24852>. Last visited 2016-11-06.
Energy Information Administration (EIA)
- , “Today in Energy: Wind Adds the Most Electric Generation Capacity in 2015, Followed by Natural Gas and Solar,” Technical Report, Energy Information Administration, Washington, DC February 2016. Online at <https://www.eia.gov/todayinenergy/detail.php?id=25492>. Last visited 2016-11-06.
- Fischer, Carolyn**, “Emissions pricing, spillovers, and public investment in environmentally friendly technologies,” *Energy Economics*, 2008, *30* (2), 487–502.
- **and Richard G Newell**, “Environmental and technology policies for climate mitigation,” *Journal of environmental economics and management*, 2008, *55* (2), 142–162.
- Gillingham, Kenneth and James Sweeney**, “Barriers To Implementing Low-Carbon Technologies,” *Climate Change Economics*, 2012, *3* (04).
- Hassett, Kevin A and Gilbert E Metcalf**, “Energy conservation investment: Do consumers discount the future correctly?,” *Energy Policy*, 1993, *21* (6), 710–716.
- Hausman, Jerry A**, “Individual discount rates and the purchase and utilization of energy-using durables,” *The Bell Journal of Economics*, 1979, pp. 33–54.
- Hughes, Jonathan E and Molly Podolefsky**, “Getting Green with Solar Subsidies: Evidence from the California Solar Initiative,” *Journal of the Association of Environmental and Resource Economists*, 2015, *2* (2), 235–275.
- Ito, Koichiro**, “Do consumers respond to marginal or average price? Evidence from nonlinear electricity pricing,” *The American Economic Review*, 2014, *104* (2), 537–563.

- Jaffe, Adam B, Richard G Newell, and Robert N Stavins**, “A tale of two market failures: Technology and environmental policy,” *Ecological Economics*, 2005, 54 (2), 164–174.
- Kind, Peter**, “Disruptive Challenges: Financial Implications and Strategic Responses to a Changing Retail Electric Business,” Technical Report, Edison Electric Institute 2013.
- Mian, Atif and Amir Sufi**, “The Effects of Fiscal Stimulus: Evidence from the 2009 Cash for Clunkers Program*,” *The Quarterly Journal of Economics*, 2012, 127 (3), 1107–1142.
- Newell, Richard G and Juha Siikamäki**, “Individual time preferences and energy efficiency,” *The American Economic Review*, 2015, 105 (5), 196–200.
- Nordhaus, William**, “Designing a friendly space for technological change to slow global warming,” *Energy Economics*, 2011, 33 (4), 665–673.
- O’Donoghue, Ted and Matthew Rabin**, “Doing It Now or Later,” *The American Economic Review*, 1999, 89 (1), 103–124.
- and –, “Present bias: Lessons learned and to be learned,” *The American Economic Review*, 2015, 105 (5), 273–279.
- Pigou, AC**, “The Economics Of Welfare,” 1920.
- Pless, Jacquelyn and Arthur A. van Benthem**, “The Surprising Pass-Through of Solar Subsidies,” NBER Working Paper 23260, National Bureau of Economic Research, Cambridge, MA March 2016.
- Rogers, Evan and Steven Sexton**, “Distributed Decisions: The Efficiency of Policy for Rooftop Solar Adoption,” Online at <https://www.aeaweb.org/conference/2015/retrieve.php?pdfid=844> January 2015.
- Sexton, Steven, Justing Kirkpatrick, and Robert Harris**, “Optimal Siting of Rooftop Solar Capacity to Maximize Environmental Benefits,” 2016.
- Tanger, Thomas P. and Frank A. Wolak**, “Optimal Network Tariffs for Renewable Electricity Generation,” *Working Paper*, 2017.