The Price to Site: Cost-Effective Incentives for Solar Deployment

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Abstract

Historically, tax incentives have been the most important tool used by the United States federal government to influence the future of solar installations. In 2026, the current 30% tax credit for residential and rooftop solar will be rescinded, marking the largest change to this policy in over 20 years and naturally prompting questions about the effects it will have on adoption. Changes in solar adoption patterns have been recently shown to correlate with changes in progress on overarching societal goals such as carbon emissions reduction, clean energy capacity, and distributional equity. In this paper, we present a fine-grained agent-based model to simulate nationwide households and their reactions to a variety of different incentivization policies, including the scheduled rescission of the 30% tax credit. By simulating adoption patterns, we attempt to characterize possible trajectories for rooftop solar installations in the near future. Over the next five years, we find that continuing a 30% tax credit would increase carbon emissions reduction by 51.8%, new energy generation capacity by 38.7%, income equity by 13.8%, and racial equity by 11.0% compared to the baseline scenario where new rooftop solar installations are not eligible for any tax incentives. Furthermore, we explore the trade-off of these, and other, incentive possibilities under our studied metrics of carbon, energy, and equity, finding that incentives offsetting more than 22.9% of the upfront installation costs exhibit diminishing returns in all metrics. We estimate that this undiminished 22.9% incentive would achieve a 25% reduction in costs relative to the former 30% tax credit over a five-year period, while preserving more than 90% of the realized benefits across all metrics, making it a good candidate for a cost-efficient alternative policy.

ACM Reference Format:

Cooper Sigrist, Anupama Sitaraman, Alice Zhang, Adam Lechowicz, Mohammad Hajiesmaili, and Yuvraj Agarwal. 2026. The Price to Site: Cost-Effective Incentives for Solar Deployment. In *The 13th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation (BuildSys '26), June 22–25, 2026, Banff, AB, Canada.* ACM, New York, NY, USA, 12 pages. https://doi.org/10.1145/3744256.3812576

BuildSys '26, Banff, AB, Canada

ACM ISBN 979-8-4007-2012-3/26/06
https://doi.org/10.1145/3744256.3812576

1 Introduction

Incentives have been used by governments world-wide to encourage the adoption of solar PV systems. In the United States, for example, incentives have been implemented in several forms, including as tax credits, grants, rebates, and net-metering. At the federal level, there has historically been a 30% tax credit (of the cost of a solar system)—referred as the Investment Tax Credit (ITC) [60] for commercial use or the Residential Clean Energy Credit (RCEC) [31] for residential use. At the state level, there are a wide variety of incentives, such as the Massachusetts Residential Energy Credit, which offers a personal tax credit of 15% up to $1000 for the installation of renewable energy systems, including rooftop solar photovoltaic systems [16]. There are also incentive programs that target specific communities and demographics, such as the Federal Solar For All program, which provides funding for incentives targeting low-income and disadvantaged communities [1], and California's Self Generation Incentive Program, which offers up to $3,100 per kW of solar and battery storage capacity [15].

These "upfront" tax incentives at the federal level have been in place since 2005, and have been found to be effective in promoting adoption of rooftop solar [34]. As of the time of writing, however, the RCEC is scheduled to be phased out in 2026 [65], with changes to other incentive programs also expected [44]. These changes reflect a time of uncertainty, but also prompt broader questions about incentives. In this paper, we consider the following: *Assuming that incentives for rooftop solar will continue in some form, how should they be designed for the best effectiveness? What will the projected impact of a reduction in these incentives mean in terms of solar adoption, new generation capacity, and national decarbonization goals? Further, who (i.e., demographic groups and states) will be most affected by this change's economic effects, and is there a more cost-effective policy that may mitigate this inequity?*

A number of studies have simulated and studied the effects of different kinds of solar incentives over the past few decades—we refer the reader to Matisoff and Johnson [41] for a review, and Section 2 for a comprehensive summary of related work. Recent works have highlighted that the decentralized nature of residential and rooftop solar introduces an inherently *multi-objective* problem [11, 48, 51, 54, 64]—in particular, the societal value of a solar installation is not uniform; its placement has vastly different impacts on key goals like carbon reduction [54], new generation capacity [48], and distributional equity along socioeconomic lines [64]. For instance, an installation in a region with more coal power plants offers a greater marginal decarbonization benefit than one in a region with an already clean energy mix [54]. Intuitively, a similar dynamic exists for energy generation—an installation in a region with plentiful sunlight will generate more energy over its lifetime [52]. Similarly, several studies have shown that disparities in race and income affect solar PV adoption and the distribution of financial returns [18, 45].

A few recent works have modeled this multi-objective nature of solar siting [54, 55] in simulations of future installations, demonstrating that there is significant potential "on paper" to greatly improve outcomes on all of these metrics and more *if* a decision-maker has full control over where new installations are placed. Of course, in reality, decision-makers cannot dictate the placement of new rooftop solar installations—instead, solar adoption is an "opt-in" choice made independently by many individual stakeholders (e.g., homeowners). This motivates our work: specifically, we study *how the potential of rooftop PV can be better realized by using the familiar lever of incentives to influence adoption.*

To do this, we study the effect of varying flat-rate incentives on solar adoption and its downstream consequences on multiple objectives using nationwide data for the United States. Our contributions are as follows:

We explore an extensive search-space of flat-rate incentives and measure the efficacy of these incentives under three different "baseline" scenarios: the "Status Quo" scenario, which refers to the 30% Residential Clean Energy Credit policy (as of 2022), the "No Incentive" scenario, in which no incentive is offered, and a "Tariff" scenario, where no incentive is offered and there is an *increase* in cost. We *measure* the efficacy of incentives under these three baselines using metrics describing carbon-offset, energy potential, racial equity, and income equity.

To gauge the efficacy of incentives under each of the three scenarios, we simulate homeowner reactions to incentives at a national scale. To achieve this, we present an agent-based model inspired by the state-of-the-art incentive model for solar adoption, NREL's dGen model [62]. The dGen model simulates households that are representative of the demographics of a state as "agents" and the likelihood of solar adoption of these agents is based on several factors, such as the payback period of an installation, the upfront cost, and incentives, among others. Although the dGen model contains agents that are representative of a given state population, these agents are represented at a state-level granularity and are therefore not well-suited for our problem. This is because population demographics and adoption-related factors can vary widely *within* each state—our metrics rely more on ZIP code level measurements rather than state-wide measurements. Thus, our model is distinguished from prior work by instantiating a unique agent-based model for each ZIP code (postal code) in our data set covering roughly 25% of all ZIP codes, and 76% of the total U.S. population.

Using our agent-based model, we first quantify the estimated effects of the "no incentive" scenario—our model suggests that a continuation of the 30% tax credit for the next five years would increase the additional carbon offset by 51.8%, residential solar energy generation by 38.7%, income equity by 13.8%, and racial equity by 11.0% compared to a simulation of the no-incentive policy.

In exploring the search space of flat-rate incentives, our primary finding is that flat-rate incentives exhibit *diminishing marginal returns*. In other words, a modest incentive, namely a 22.9% tax credit (i.e. a 25% decrease from the status quo), provides substantial gains in all metrics, but successively larger incentives produce smaller and smaller improvements while increasing cost exponentially. Compared to the current 30% federal tax credit, these results mean that similar outcomes (on the studied metrics) could be achieved at a lower cost using alternative incentive levels (e.g. the 22.9% tax credit). Furthermore, we find that flat-rate incentives are not effective for equalizing the distribution of installations along socioeconomic lines—in particular, increasing the incentive across the board, even by large amounts, continues to predominantly benefit demographics that already have disproportionately high levels of rooftop solar adoption. Additionally, we discuss the implications of our findings for the design of more effective and cost-efficient solar incentive policies.

2 Background and Related Work

In this section, we situate our work within prior research on rooftop solar adoption, incentives, and multi-objective deployment, while providing the background needed for our case study.

2.1 Modeling Solar Adoption, Incentives, and Policy Context

Residential rooftop solar has grown substantially over the last decade and can reduce both household energy costs and grid carbon emissions [23, 35]. These systems also provide direct financial benefits to households, including through avoided electricity purchases and policies such as net metering, and they are long-lived assets with typical lifetimes of roughly 25 years [35]. Adoption, however, remains highly sensitive to installation cost, payback period, and policy conditions such as incentives and tariffs.

There is substantial prior work on modeling solar adoption behavior [9, 21, 29, 33, 39, 53, 69, 70, 73, 74]. Cost-benefit models often explain adoption through the tradeoff between upfront installation cost and long-term savings [4, 37], but they generally abstract away factors such as preference heterogeneity, capital constraints, and other human factors. Agent-based approaches address some of these limitations by modeling households individually and simulating decisions based on financial gains, peer effects, and other behavioral factors [3, 24, 26, 36, 42, 62, 71, 72]. For example, prior work has used the California Solar Initiative to fit data-driven agent models of rooftop adoption and has later extended these models to incorporate peer influence and carbon considerations [71, 72]. Since 2020, the dGen (agent-based) model has become influential for policy analysis [43, 62]. However, dGen operates at a coarser granularity, does not explicitly model demographic data, and relies on some proprietary data sets. Our model builds on this line of work while instantiating agents at the ZIP-code level, which is necessary because the energy, carbon, and equity outcomes we study vary substantially within states—to our knowledge, no previous agent-based model exists at this granularity for solar adoption modeling.

Empirical studies of deployed incentives consistently find that upfront incentives are more effective for adoption than long-horizon benefits such as production incentives or interest-free loans, because households discount future benefits [9, 70, 74]. In the United States, these incentives typically include federal flat-rate tax incentives as well as smaller state-level programs such as rebates, net metering, and feed-in tariffs [20]. In our analysis, we focus on flat federal incentives rather than state-level policies because they are larger in magnitude and more directly affect upfront installation cost in the scenarios we model. Prior work has shown that rebates and grants can substantially increase PV capacity, though their cost-effectiveness remains contested [17, 34, 51]. More recent work highlights that incentive effectiveness is shaped by broader policy design, including net metering and timing effects [5, 7, 63]. Our work primarily focuses on modeling the effects of future incentive scenarios rather than evaluating the effects of existing incentives, although we use empirical observations to inform our data-driven agent model (see Section 3.1).

In recent years, tariffs have become another important part of the policy context around PV solar—these can increase the cost of imported components across the solar supply chain and therefore raise installation prices faced by households [59, 68]. In 2025, tariff changes were associated with a 7% year-over-year contraction in new U.S. solar installations relative to 2024 [59]. In this paper, we model tariff effects through future cost-increase scenarios; the specific assumptions underlying those scenarios are detailed later in Section 4.2.

2.2 Multi-Objective Siting, Energy, and Carbon Context

The benefits of rooftop solar depend strongly on location. The energy generated by a system varies with irradiance, roof conditions, shading, and local weather; in our case study, these factors are captured using Project Sunroof estimates [38]. Carbon benefits also vary geographically because the emissions displaced by solar depend on the local grid mix and carbon intensity [40]. These geographic differences make simple installation counts insufficient for evaluating policy outcomes.

Several studies therefore examine objectives beyond adoption alone, especially carbon reduction and distributional equity. Prior work has quantified the decarbonization potential of residential solar at national and global scales [2, 10, 25], while more recent studies emphasize that carbon offset depends on where solar generation is added relative to the broader electric grid [11, 46]. Other work shows large geographic differences in rooftop solar energy generation potential [48]. Alongside these technical differences, adoption disparities persist across income and race; studies using Project Sunroof and related data show lower rooftop solar adoption in low-income and high-Black communities, while targeted incentives can help reduce these gaps [19, 47, 54, 64]. Financial returns also vary across ownership models and demographic groups [6, 18, 45]. Together, these findings suggest that a policy can increase total adoption while still performing poorly on where installations occur and who benefits from them.

Only a smaller body of work considers these objectives jointly. Earlier evaluations of incentive programs reported impacts on adoption, conventional energy demand, and environmental outcomes together [50]. More recently, hypothetical solar-siting studies have shown that if new installations could be placed optimally, substantial gains in carbon offset and equity would be possible [54, 55]. Our work studies the same multi-objective outcomes, but under a more realistic policy lever: federal incentives that influence where households actually choose to adopt.

3 Methodology

In this section, we describe in detail the methodology that we use to conduct both our incentive reaction and deployment modeling.

3.1 Modeling Incentive Impact on a Population

Here, we describe in detail the methodology for modeling incentive impact on the likelihood of solar adoption at a ZIP code granularity.

Modeling a Home's Likelihood of Adoption. Prior work in solar adoption modeling suggests that *payback period*, expressed as the number of years needed for a homeowner to recoup the cost of their investment in solar panels, is a strong indicator of the likelihood of adoption [4]. Intuitively, *lower* payback periods increase the likelihood of solar adoption.

We utilize *simple payback period* to determine the payback period for a given home h as a function of incentive I, given as a dollar amount. This is calculated as follows:

$$P_h(I) = (D_h - I)/S_h \tag{1}$$

where D_h is the cost of installation for home h in USD and S_h is the yearly monetary savings due to the solar PV system being installed for home h in USD.

In our formulation, we assume the solar installation size is the same for all homes. However, the household savings S_h vary because households of different income brackets vary in energy burden (the proportion of income spent on electric bills) as well as the portion of their electricity bill that would be covered by a solar installation. We calculate the **yearly monetary savings** to vary based on the average energy burden and average proportion of energy savings due to solar installation across all households in a given income bracket. Then, we consider S_h to be influenced by the yearly energy consumption of home h. That is,

$$S_h = h_{\text{income}} * b(h_{\text{income}}) * p(h_{\text{income}}) \tag{2}$$

where h_{income} is the income of household h, $b(\cdot)$ is a function mapping the income to the appropriate average energy burden given the income bracket of h, and $p(\cdot)$ is a function mapping the income to the appropriate average proportion of energy savings due to the solar installation given the income bracket of h.

In calculating S_h in this manner, we assume that the average energy burden and the average proportion of energy savings due to installing solar will be the same for all homes in a given income bracket. In reality, this may not be the case, although we do not have the fine-grained energy consumption data to adequately model all of the factors of individual homes that may affect solar savings. We make this assumption to be able to model variance in (total) bill savings across homes in the same income bracket.

Using our simple payback period function $P_h(I)$, we are able to model whether the home will adopt solar or not given some incentive I. We determine that there is some threshold payback period in years T, such that all homes who are able to recoup their investment within the given threshold will adopt solar. Conversely, all homes that are unable to "break even" within T years will not adopt solar. Thus, our adoption function $A_h(I, T)$, is the function of solar adoption given an incentive I in home h, and is defined as:

$$A_h(I,T) = \begin{cases} 1, & \text{if } P_h(I) \leq T, \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

The threshold payback period T is a parameter of the adoption modeling that varies under different modeling scenarios. We demonstrate how we calculate T in various scenarios in Section 4.

In our modeling, we do not consider a *discount rate* [61]—in classic net present value (NPV) analysis, a discount rate serves to give a higher value to savings that come sooner compared to the same savings arriving later in time. Prior work finds that discount rates does impact decision-making about adoption substantially [4]. However, there is significant variability in personal discount rates [12], and relatively little data to model them appropriately in this work [14].

Modeling a Population of Homes. We primarily utilize *agent-based modeling* techniques to model solar adoption as it has been used for this purpose in the past [3, 24, 26, 36, 42, 62, 71, 72]. In our scenario, we create a model conceptually similar to the NREL dGen model, where agents are homeowners that are "representative" of true homeowners in a given population, and each considers adopting solar PV based on factors such as payback period [62].

In our case, we generate representative homeowner agents based on the income distribution of homes in a given ZIP code. For each agent, we assign a yearly income value. Next, we utilize a distribution of yearly energy consumptions by income and region to assign a yearly energy consumption value to each home. We additionally calculate the cost of electricity of the ZIP code, and the cost of a solar installation in their state (as ZIP codes do not have individual solar installation costs associated with them).

By using this technique, our modeling becomes probabilistic rather than deterministic, as there can be stochasticity in how home owners are modeled, where agent income and energy consumption are randomly sampled from distributions representative of the population. Due to this probabilistic modeling, we are able to incorporate uncertainty about individual home-owner income and energy information in our modeling.

Estimating the Proportion of Adopters per ZIP Code. Given a set of household agents $\mathcal{H}_z$ that are representative of the population of a ZIP code z, a flat incentive I, and a threshold T, we formulate the proportion of adopters in a given ZIP code z, $y_z(I,T)$, as

$$y_z(I,T) = \frac{\sum_{h \in \mathcal{H}_z} A_h(I,T)}{|\mathcal{H}_z|} \tag{4}$$

where T is the threshold payback period of the state where z is located. Intuitively, this value (between 0 and 1) should be thought of as the fraction of the total homes in ZIP code z that adopt solar given the current incentive I.

Limitations of the Agent-Based Model. In the model we have outlined above, we have made a few simplifying assumptions.

Assumptions about technologies modeled. We assume in this work that homes will adopt a standard size of solar installation, and will not adopt any other supplemental renewable energy technology, such battery storage. We assume a standard solar size, because determining an appropriate solar sizing for a given home is prone to high error in the absence of more fine-grained data. For example, data such as rooftop tilt and rooftop size, are not available to us at a zipcode level. Further, we do not include net-metering and battery storage in this work, as it is out of scope for our current problem. We discuss future works that may incorporate net-metering and battery storage in Section 6.

Assumptions about likelihood of adoption. We have assumed that homes will adopt (or not adopt) based on the payback period of the home. Prior work has indicated that payback period is a strong indicator of adoption behavior in a rooftop solar context, but is not the sole influence of adoption behavior [4]. Specifically, there are influences such as peer effects, personal values and interests, and other psychological elements that factors into a household's decision to adopt solar—however, due to a lack of suitable widespread data to adequately model these, we are unable to directly incorporate these effects into our modeling. Thus, our model assumes that, irrespective of peer effects and preferences, households are unlikely to adopt solar without a positive return on investment (note that the payback period is measuring this). To incorporate potential effects outside of payback period, we additionally assume that there is a zip code-wide adoption growth rate that captures these auxiliary factors. This adoption growth rate is grounded in real-world data, and is described in Section 3.3. As a result, our model is likely to overestimate adoption rates, essentially quantifying an *upper bound* on adoption that we then compare between incentive strategies.

3.2 Metrics

We define four key metrics to quantify the quality of outcomes of different incentivization policies. These are Carbon Offset, Energy Generation Potential, Racial Equity, and Income Equity. We draw heavily from the metrics used in Sigrist et al. [55], where these metrics were used to design optimal strategies for unilaterally orchestrating the placement of solar installations.

Energy Generation Potential: This metric measures the amount of new energy that will be generated due to the estimated new installations (and their locations) under an incentive policy. To calculate this value, we utilize the yearly average energy generation estimates per ZIP code given by the Project Sunroof data set [38].

Carbon Offset: This metric estimates the amount of carbon (in metric tons) that would be avoided for the estimated new installations of rooftop solar achieved by a given incentive policy. We calculate this value via the non-baseload carbon emissions rate (and equivalent greenhouse gas emissions rate) from EPA eGRID data [67], and multiplying this with the yearly average energy generation (as estimated using the Project Sunroof dataset [38], in kWh).

Racial Equity: This metric measures the distribution across self-reported racial lines of estimated total installations after a given incentive policy is simulated. Demographics data is obtained at a ZIP code granularity from the U.S. Census Bureau's 5-year American Community Survey (ACS5) [8]. We define Racial Equity as 2 minus the difference in the number of installations in below-median Black neighborhoods, and above-median Black neighborhoods. We calculate this as:

$$2 - \frac{|\text{installations}_{\text{low Black}} - \text{installations}_{\text{high Black}}|}{\text{installations}_{\text{total}}}.$$

Income Equity: Using ACS5 data, we measure the distribution across income lines of estimated total installations after a given incentive policy is simulated. We define Income Equity as 2 minus the difference in the number of installations in high-income (i.e. above median, median income) areas versus low-income areas. We calculate this as

$$2 - \frac{|\text{installations}_{\text{high income}} - \text{installations}_{\text{low income}}|}{\text{installations}_{\text{total}}}.$$

3.3 Simulating Incentive Policies

In this subsection, we detail our procedure for modeling the outcomes of different incentive policies and projecting outcomes over the five year period considered in our case study.

Immediate Effects on Key Metrics. For a given incentive, I, and payback threshold, T, we calculate $y_z(I,T)$ via simulation of household agents for each ZIP code. We then multiply the estimated adoption proportion ($y_z(I,T)$) by the estimate of "viable installation rooftops" (provided by the Project Sunroof data set for each ZIP code [38]) to obtain an estimated installation count, $C_z(I,T)$. Using these installation counts for each ZIP code, we can simulate outcomes for each of our key metrics using using the SunSight library [54] and thus estimate the outcomes for each of our key metrics. While this provides the estimated *instantaneous* effect of an incentive, we have to estimate future projections separately.

Projection Over Multiple Years. To simulate the effects of a given incentive I after it has been "deployed" for n years, we additionally need to capture the *year-over-year growth rate* of installations in each ZIP code z, henceforth denoted as $g_z \geq 0$.

Note that in our problem formulation, we estimate g_z to be the same for all ZIP codes in a given state. This is because we do not have adequate data to measure year-over-year growth rates at a ZIP code granularity.

Based on the growth rate g_z, we assume that the percentage of added growth will be increased by g_z on a yearly basis. Thus, given a projection n years into the future, we calculate the proportion adopted to be $g_z \cdot n$. We then calibrate the future payback threshold T_n based on this proportion adopted. This process is described further in Section 4. Finally, using this estimate, we can recalculate $C_z(I, T_n)$ for any requisite n and simulate outcomes using the SunSight library as discussed above.

Limitations of the Incentive Policy Model. We highlight some limitations of this method for simulating incentive policies. First, g_z is assumed to be known and constant. In reality, assuming a constantly increasing payback threshold limits the analysis to a short "lookahead window" of a few years, because the estimated adoption rate (based on an initial assumed growth rate) would become less accurate over time and tend to overestimate adoption. Second, a few important data points, notably the estimated "viable installation rooftops" and payback thresholds, are not available for all ZIP codes in the US and must be extrapolated from partial data, in that we estimate energy prices at the state level if ZIP code level prices are unavailable, and we estimate the number of viable installations based on proportions of viable installations in ZIP codes where complete data exists. Further, because we cannot make assumptions about what the "right size" of solar installation will be for each agent based on their roof size and tilt, we make an assumption that a standard sized solar panel will be used for each home. We note that this may affect our simulated results in some cases, as we may be under-estimating or overestimating the likelihood for solar adoption for some homes. Finally, we acknowledge that a "discount rate" may be used in many scenarios for decreasing the value of benefits that are earned further out from the present (i.e, savings gained in year N are "worth more" than savings earned in year N+1). Discount rates depend on the income status of the home, as well as current economic conditions, and the amount of savings gained by each home with the use of solar panels. Although prior work has derived these discount rates for some locations, or at a coarser-grained level, to our knowledge, there is no prior work that describes an appropriate discount rate based on social and economic factors, such as home income level, location, and potential savings [4, 12]. To mitigate the risk of systemically over or under-estimating adoption rates for different demographics, we opted to leave out discount rate all together and assume that homes make decisions purely based on a standard payback rate.

Despite these limitations, we believe that our modeling, especially the *ratio* between different incentive policy outcomes, is sufficiently accurate to represent possible future scenarios. Our model attempts to use the most comprehensive publicly available data (that we are aware of) at each modeling step, at the finest granularity available. Furthermore, our techniques can be augmented with private data and/or more comprehensive data sets as they become available to further refine these estimates.

4 Experimental Setup

In this section, we detail how we instantiate the agent-based model described in Section 3.1 for our case study using U.S. data, and define the different baselines that we compare against.

4.1 Modeling Setup

We describe the parameters and setup of our agent-based model below, based on the methods described in Section 3. We detail the data sources and assumptions made throughout.

Generating Agents. As described in Section 3.1, for each ZIP code we generate 1,000 agents to represent the population within that ZIP. For our modeling, we assume that each home will be able to install a *fixed-size solar installation* of 7 kW.

(1) *Household Income.* We utilize ACS5 census data [8] to obtain estimates of the household income concentration in a given ZIP code (e.g., half of the ZIP code's households have incomes between $65,000 USD and $95,000 USD, a quarter of the ZIP code's households have incomes over $135,000 USD, etc.). Based on this estimated distribution of incomes, each agent is randomly assigned an income by first choosing an income bracket proportional to its incidence in the ZIP code, and then uniformly randomly sampling within the income bracket.
(2) *Household Energy Consumption.* We utilize the U.S. Energy Information Administration (EIA)'s Residential Energy Consumption Survey (RECS) to obtain estimates of regional energy consumption (specifically, the RECS publishes average energy consumption disaggregated by state and income level) [66]. Based on the household income assigned to agents

in the previous step and the state containing the given ZIP code, we assign the agent a yearly electricity consumption value. We utilize EIA data which contains the average household energy consumption per year, as well as the RSEs for these values, for 8 income brackets and 4 regions of the United States (Northeast, Midwest, West and South). [66]. For a given ZIP code, we determine the region corresponding and determine the mean and RSE value for each income bracket. From the mean and RSE, we generate a normal distribution for each income bracket. For each agent, we select the distribution that corresponds to the agents income level and sample randomly from this distribution to get the agent's yearly electricity consumption.

(3) *Existing Yearly Cost of Energy Consumption.* Using the yearly household energy consumption of each agent, we calculate and assign the agent's yearly energy bill by multiplying the price of electricity (in the form \$ per kWh) by the annual electricity consumption. The price of electricity is based on 2022 ZIP code-level prices obtained from the Open Energy Data Initiative [30]. If a ZIP code-level price is not available for this ZIP code, we assume the electricity cost is equal to the average electricity cost for the state containing this ZIP code.

(4) *Cost of Solar Installation.* Since the installation size is fixed, we model the total upfront installation cost as a fixed rate for each agent in each state. We assume that the cost of the solar PV system is \$2.5/W, resulting in a total cost of \$17,500 for the entire system per home [38].

(5) *Potential Savings Impact From Solar.* We estimate the impact of yearly energy savings from the solar installation based on estimated generation, income, and consumption. Across all agents in the ZIP code, and for each income bracket, we calculate the average proportion of energy consumption that a rooftop solar installation would fulfill. To do so, we use sunlight and energy generation estimates from Project Sunroof [38], which accounts for solar irradiance within the ZIP code. We then calculate the average *energy burden* and average *portion of energy savings* for agents in each income bracket. Using these values, we calculate the estimated yearly savings from solar as described in Equation 2.

Determining the Threshold Payback Period T under Different Modeling Scenarios. To specify T, we use empirical data on residential capacity added per state per year [66]. We consider the *average increase* in residential capacity during years where no changes in solar incentives occurred to be the *natural adoption growth rate* for a given state. This natural adoption growth rate represents the state population that would adopt solar *regardless* of incentivization. We determine the increase in residential capacity (per state) based on data provided by the EIA on a monthly basis [66], and determine the years where state-wide incentives were changed based on the DSIRE database of state incentives [20]. Since we only have data for yearly added residential capacity at the state level, we calibrate T by using the agent-based modeling technique described above Section 3.1 at a state-level granularity, (that is, we simulate 1,000 agents for each state, where each agent is representative of the true state population). Using this simulation, we calculate the payback period for each agent. We then determine T for a 5-year horizon. We do this by first sorting the agents by payback period, from shortest payback period to longest. We assume that the agents with the smallest payback period will adopt first. We then assume that the proportion of agents who will adopt during year 1 without an incentive is equivalent to the natural adoption growth rate. We then consider T^1 to be the payback period of the agent at the percentile equal to the natural adoption growth rate. That is, all agents that have payback periods that fall within the percentile of the natural adoption growth rate will adopt solar, otherwise, they will not. We apply this same process to get T^2, T^3, T^4 and T^5, by simply exponentiating the natural adoption growth rate by 2, 3, 4, and 5 respectively. We utilize these T values when simulating the agents at the ZIP code level. We simulate 10,544 ZIP codes (~25% of all ZIP codes, and ~76% of the total U.S. population) for our experiments. Note that payback periods and the proportions of agents adopting solar are calculated based on Equations 1 and 3 from Section 3.1.

4.2 Baselines

Our experiment results are contextualized against three key baseline scenarios, described below.

Status Quo: This refers to the 30% Residential Clean Energy Credit (RCEC)) that was extended by the Inflation Reduction Act in 2022 and will be rescinded at the beginning of 2026. To model this we treat the 30% tax credit as a direct cost-reduction for new installations. As we assume each installation is a 7kW installation with a cost of \$17,500, this equates to a \$5,250 flat cost-reduction. We simulate this as described in Section 3.3.

No Incentive: This is the policy prescribed by the 2025 U.S. budget reconciliation law ("One Big Beautiful Bill"). We treat this as a flat \$0 incentive (i.e. no policy) and simulate it using the procedure in Section 3.3, with $I = 0$.

Tariffs: To explore possible futures with no incentivization and additional tariffs placed on imports of panels and materials for panel production we consider cases of negative incentivization (i.e. cost *increases*). While the apriori effect of tariffs on residential installations is not known, historical statistics allow us to sketch a range of possibilities:

- Hardware (photovoltaic modules, inverters) accounted for approximately 35% of the cost of a new residential installation in 2019 [58].
- 56% of all installations are imported [27, 49].
- Based on the most recent policies, U.S. tariffs on both panels and materials for production of panels would be set to a minimum of a global 10% [13].
- It has been estimated that a \$1 tariff on a solar panel import equates to approximately \$1.35 in additional cost to the consumer [22, 28].

With these statistics we estimate a lower bound for additional costs due to tariffs calculated as:

$$0.35 \cdot 0.56 \cdot 0.1 \cdot 1.35 \cdot 17500 = 463.05$$

For our upper bound we choose a 25% effective tariff, which would correspond to a tariff much lower than the proposed rate on major solar exporting countries (i.e., proposed rate increases of 46% for

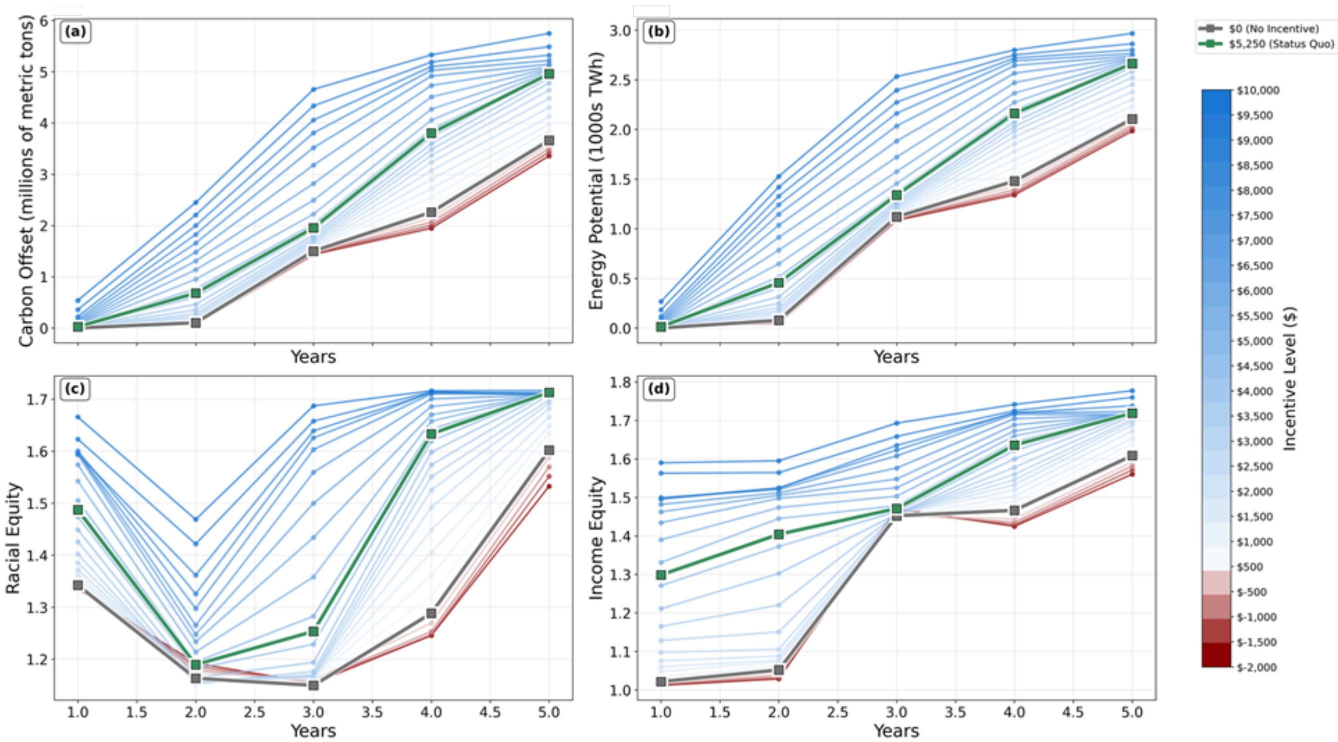


Figure 1: Projection of different incentivization amounts ($0 - $10,000 USD per install) as well as tariff amounts ($500 - $2,000, represented as negative incentives in this figure) over the next 5 years based on our four key metrics. For each metric, a higher value is better (calculations of each are fully detailed in Section 3.2). The previous 30% tax credit is highlighted in green and a no-incentivization policy is in gray. At the 5 year mark, we show that the no-incentive policy scores 34.1% lower in Carbon Offset and a 27.9% lower in Energy Generation Potential, 9.9% lower in Racial Equity, and 12.1% lower in Income Equity compared to the hypothetical continuation of the 30% tax credit. There is also a substantial sensitivity of the Income Equity of new installations to incentive changes in the next 2 years, with a 38% decrease from the 30% tax credit scenario.

Vietnam, 24% for Malaysia, 36% for Thailand and 49% for Cambodia [49]). We additionally assume that domestically produced panels will incur a 10% increase in price due to tariffs. This scenario gives an effective cost increase calculated as:

$$0.35 \cdot (0.56 \cdot 0.25 + 0.44 \cdot 0.1) \cdot 1.35 \cdot 17500 = 1521.45$$

Based on these rough estimates, we simulate "incentive" amounts that vary between -$2000 and -$500, representing possible tariff outcomes that would *increase* the cost of solar for consumers.

5 Experimental Results

In this section, we present results using the experimental setup we described in the preceding section for a five-year time horizon. We focus on comparing against two baselines with particular policy relevance: *(i)* "no incentive" ($0) and *(ii)* the 30% Residential Clean Energy Credit (RCEC)), modeled as a flat $5250 incentive per installation, corresponding to the current U.S. federal baseline. Additionally, we compare possible incentivization and tariff policies against these two key baselines. Specifically, we report outcomes under alternative flat incentive levels ranging from $500 to $10,000 at $500 increments. We also simulate "negative incentives" in the range -$2,000 to -$500 to estimate different tariff policies as outlined in Section 4.2.

5.1 Incentive Policies' Projected Outcomes

In Figure 1, we show the effect of the different incentivization policies for a 5 year period across four key metrics (Carbon Offset, Energy Generation, Racial Equity and Income Equity). Unsurprisingly, we find that the largest incentives produce the largest Carbon Offset and Energy Potential—per our simulation, a higher incentive strictly increases the total number of installations. The magnitude of differences is notable however, particularly between the $0 incentive and 30% RCEC (Status Quo)—with a 34.1% increase in Carbon Offset and a 27.9% increase in Energy Generation Potential in five years. A Carbon Offset increase of this magnitude would have substantial impacts on the U.S. decarbonization timeline [54].

Perhaps less obviously, we also see a general increase in both Racial and Income Equity across all years as the incentive amount increases. Most dramatically, we observe that the first 2 years of a "no incentive" policy the income equity would actually drop as lower-income households could no longer afford solar installations. Though our modeling shows this gap closing over the years it is important to note that we assume an optimistic consistent natural growth rate as described in Section 3.3—a more pessimistic prediction could result in an even larger gap.

The tariff cases continue this trend, with a minimal tariff estimation (10% global—~$500) decreasing Carbon Offset by an additional 2.9%, Energy Generation Potential by 2.1%, Racial Equity by 0.5%, and Income Equity by 0.4% compared to the "no incentive" case. A higher effective tariff (25%—~$1500) would decrease Carbon Offset by 7.5%, Energy Generation Potential by 5.3%, Racial Equity by 1.4%, and Income equity by 1.0% from the "no incentive" case.

Interestingly, for each of our metrics, the marginal improvement between the 30% RCEC incentive case and $7,500 (i.e. 42.85% tax credit) is relatively negligible—this implies that "status quo" is at, or beyond, the point of diminishing returns. We explore this further in Section 5.2.

Key Takeaway. *There is a substantial decrease in the predicted outcomes on all four of our key metrics when choosing to remove the current 30% RCEC incentive. We predict this will result in a 24.9% decrease in Energy Generation, 31.9% decrease in Carbon Offset, 8.9% regression in Racial Equity, and 9.7% regression in Income Equity after 5 years. Over the next two years, this may also cause more dramatic inequity for new installations (a predicted 27.5% decrease in Income Equity). However, in the next section, we show that the 30% RCEC may be larger than necessary to obtain comparable outcomes.*

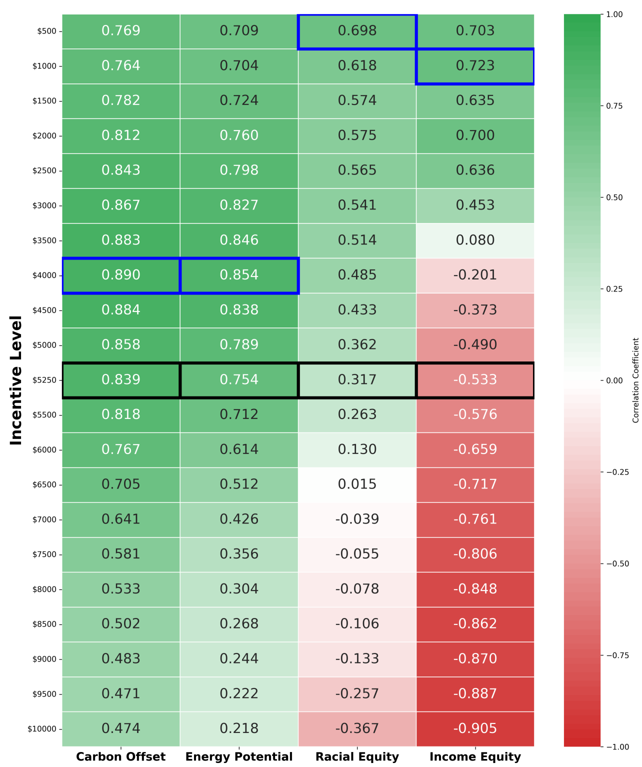


Figure 2: Pearson correlation statistics comparing the increase over the "no incentive" scenario against the cumulative cost of each incentive policy across all metrics. The 30% RCEC policy is highlighted with a black outline and the highest value for each metric is highlighted in blue.

5.2 Cost Efficiency

We now analyze the cost efficiency of each of these existing (i.e. 30% RCEC and "no incentive") and other possible incentive policies. In Figure 3, we show the projected effect that cumulative spending has on each key metric under each of incentive policy. The "no incentive" (red) policy acts as a baseline for natural solar adoption without incentivization, whereas the 30% RCEC (green) shows the cost efficacy of the status quo policy before the impending cuts. We observe that the improvements seen by the 30% RCEC in Figure 1 would come at an estimated cost of approximately $400 billion in lost tax revenue in the next 5 years. Interestingly, we also observe that the $9000 (equivalent to a 51.4% tax credit) policy exhibits little to no improvement over the 30% RCEC on key metrics while increasing the 5-year cumulative lost revenue by $600 billion. This suggests that the 30% RCEC policy is at, or possibly beyond, the point of diminishing returns.

In Figure 2, we report the Pearson correlation of the expected improvement over the "no incentive" case against cumulative cost by year for each positive incentivization policy. These correlation statistics act as an estimate of the cost-efficacy of each incentive amount across the four key metrics. We find that an incentive of $4,000 (22.9% tax credit) is most cost-efficient for both Energy Generation and Carbon Offset, with incentivization amounts as low as $2,000 (11.4% tax credit) achieving comparable cost efficiency to the 30% RCEC policy. Likewise, Income Equity correlations are maximized at $1,000 (5.5% tax credit) and drop dramatically for policies greater than $3,000. The correlation of Racial Equity improvement to cost monotonically decreases, showing that while an increase in incentivization improves Racial Equity (see Figure 1), there are diminishing returns for large incentives. Importantly, these correlations represent a linear cost efficiency. That is, while there are diminishing returns for high incentives by absolute value of these metrics, it is likely the case that there are non-linear knock-on effects of improvement. For example, a 5% increase in Energy Generation Potential past some threshold may lead to significantly lower energy prices or greater grid stability. However, we do not explore this possibility in this work.

Key Takeaway. *The 30% RCEC incentive policy is found to have suboptimal cost efficiency in all key metrics and is estimated to cost the U.S. approximately $400 billion over the course of the next five years (if continued). Incentives up to $1000 (5.5% tax credit) are shown to have a significant impact on Income Equity, but diminishing returns beyond. Cost-efficiency for Carbon Offset and Energy Generation are both maximized with a $4,000 (22.9% tax credit) policy which would cost the U.S. approximately $300 billion, a $100 billion dollar savings with comparable outcomes. This analysis supports the idea that there exists a compromise between a "no incentive" and 30% RCEC incentive policy that could achieve significant improvements in each of our key metrics for significantly less cost to the U.S. government.*

5.3 State-level Energy Outcomes

In this section we explore the energy distribution of different incentivization and tariff policies at a state level. The future effect on energy generation is particularly important as additional energy generation in a region implies knock-on effects for energy prices,

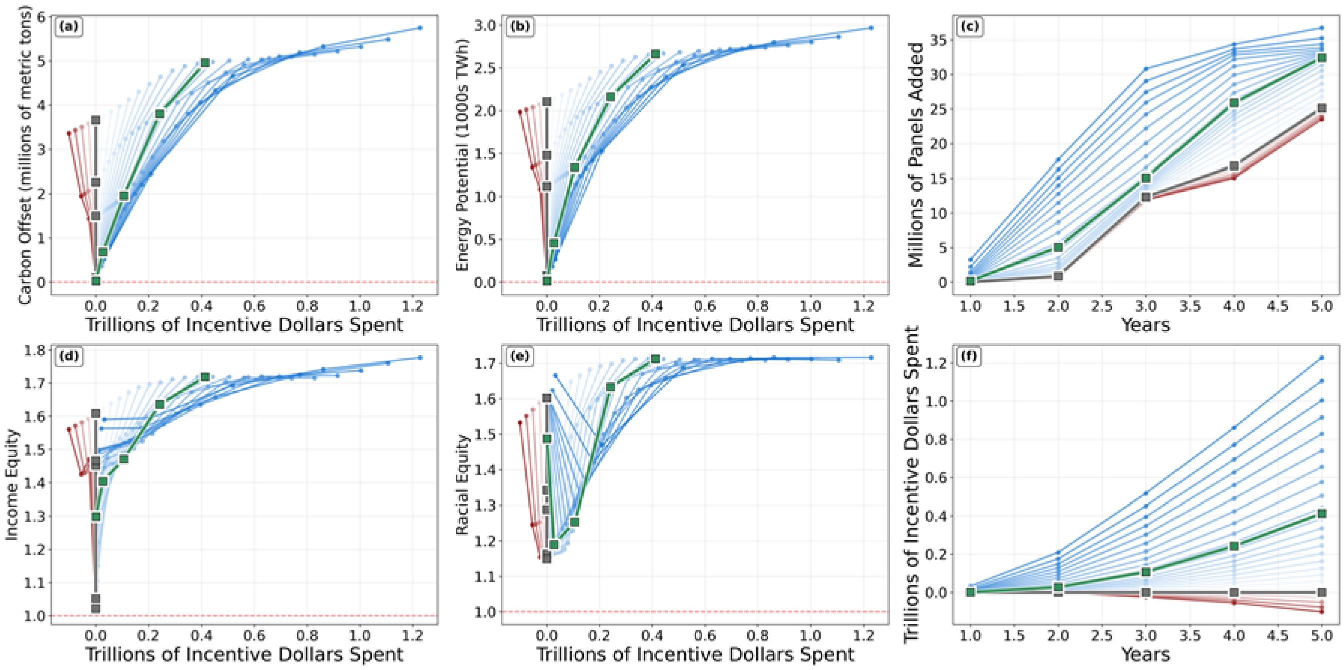
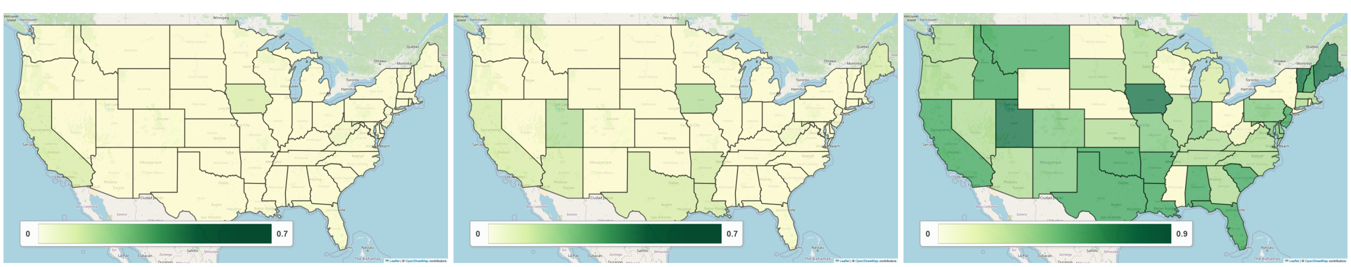


Figure 3: The projected effect of dollars spent on incentives (calculated as number of installations * incentive dollar amount) on each of our four key metrics: a) Carbon Offset and b) Energy Potential very similarly show that additional spending is effective, though the flattening curve of larger incentives show a clear diminishing return. We also see that for d) Income Equity a steeper slope at lower spending, indicating that high incentives are not cost-effective for income equality. e) Racial Equity is projected to decrease over time regardless of incentivization for the first two years, but then recover and exhibit similar diminishing returns. Particularly, we note that the \$7,000 (40% RCEC) policy does not substantially improve in any of the key metrics but accrues ~50% additional cost (f) compared to the 30% RCEC. We also see, for each of our metrics and additional panel counts (c) the baseline growth in the "no incentive" case. Likewise, we see that each of the tariff scenarios accrue less than \$200 billion in revenue (f).



(a) 25% tariff (b) "no incentive" (c) 22.9% RCEC

Figure 4: By state values of the estimated energy generation added for predicted installations in 2 years divided by the expected generation added given the Status-Quo 30% RCEC for the (a) 25% tariff , (b) "no incentive", and (c) 22.9% (\$4,000) cases.

grid stability, and viability for new data center construction, all of which impact standard of living and economic growth.

In Figure 4, we report the ratio of energy generation of predicted future installations against the predicted outcome given the existing 30% RCEC. These values are taken from the 2 year estimations for the 25% tariff, "no incentive", and 22.9 % tax credit policies. This demonstrates the energy inequity of incentives and tariffs. Particularly, we notice that a transition to a tariff from the 30% RCEC is estimated universally reduce the new energy generation capacity of all states. Likewise, the "no incentive" policy will cause widespread reductions, but will be somewhat inequitable in its effects. A more moderate reduction (i.e. to a 22.9% tax credit policy as found in Section 5.2) is able to maintain higher energy generation, though it disproportionately benefits some regions (e.g., Utah, Maine, Iowa).

To estimate the equitability of these outcomes, we calculate the normalized standard deviation of the proportion decline in solar from the 30% RCEC policy for each of these policies. We find that the 25% tariff scenario's state outcomes has a normalized standard deviation of 1.42, compared to the "no incentive" case's 1.17, and the 22.9% tax credit's 0.58.

Key Takeaway. *We estimate that the proposed "no incentive" policy and the moderate tariff policy would significantly decrease state-level new energy generation in every U.S. state compared to current trends. These scenarios are also distributed unevenly, that is, certain states are impacted disproportionately, potentially increasing variance in energy prices and stability between states. Similar analysis on a decreased 22.9% tax credit incentive policy demonstrates a small state-level decline in energy generation compared to the status quo 30% RCEC, but it is not as significant and is more evenly distributed across states.*

6 Discussion

In this section, we discuss the implications of our results and possible future directions. and improvements.

The five-year outlook. Our results predict that the removal of the 30% RCEC tax credit will reduce the four key metrics we measure over a five-year period. We also find that tariffs will likely exacerbate this effect. However, we still see a substantial growth in solar adoption regardless of the policy that may be implemented in the future. We also note that our modeling is optimistic in terms of solar adoption rates, and hence may provide an upper bound to the carbon offset and the energy potential. Our modeling shows that overall the solar industry will keep growing, especially given an increase in on-shore manufacturing of solar cells in 2024 from 23% to 44%, which could lead to price decreases even despite tariffs.

One caveat to this is that we also predict short-term (< 2-year) increases in income- and racial-inequity as far as solar adoption and ownership are concerned due to the rescission of the federal tax credit and tariffs. Our model suggests that these equity impacts would recover over time due to the natural year-over-year growth in the rooftop solar industry, but the unforeseen knock-on effects of new uncertainty in rooftop solar could invalidate the modeling assumptions that are based on historic (stable) data about growth.

Metrics of cost efficiency. In this work, we consider the cost efficiency of different policies as the linear effect on our metrics per federal dollar spent through Pearson correlation. This quantification, though reasonable to determine a point of diminishing returns, misses some aspects of these metrics' importance. For example, given the projected increase in energy demand due to new data centers for AI workloads, and the long lead times for construction of traditional generation sources such as natural gas turbines and nuclear plants, increasing the cumulative capacity of solar PV may become a necessity. It may also be prudent to consider the cost per kWh in comparison to other possible energy generation subsidies or projects, rather than a flat cost, to determine if a policy is cost inefficient. Similar considerations can be made for each of the key metrics. These policy decisions are somewhat outside of the scope of this work, though we do believe our modeling suggests that incentivization in general is cost-efficient. **Co-locating solar installations with battery storage.** Prior works have highlighted the potential benefits of co-locating solar installations with other renewable energy technologies, such as battery storage [56, 57]. Although adoption rates of storage with solar installation is rising, the majority of solar installations do not include battery storage [32]. While we do not explore incentive schemes that include both solar installation and battery storage solutions, we believe that jointly allocating incentives for both technologies at scale is a valuable future research direction.

Net-metering. Net-metering programs enable homeowners to be credited with excess solar energy that they sell back to the grid. Although this facet of modeling is interesting and important for capturing the full incentives of a given solar installation, we were unable to model net-metering benefits in this work. Reasonable modeling of net-metering would require high-resolution energy consumption and production data for each home, which was not possible to generate, given the limited data on energy use and generation at the zipcode level. We believe that, if more utilities were able to share anonymized fine-grained home energy consumption data at a zipcode level, this facet of incentivization would be important to explore.

Alternative options. Historically, the U.S. government has only directly subsidized residential solar installations through a flat-rate, percentage tax credit. As a result, we only explore this category of incentivization policy in this work. There are, however, other possibilities that may prove to be more cost efficient. In particular, there are programs such as SGIP in California that incentivize differently based on, e.g., demographics, generation potential, and installation size [15]. We hypothesize that an incentivization strategy that divides the country's ZIP codes into incentive brackets based on a multi-objective scoring (e.g., such as the one used by Sigrist et al. [55]) could achieve a much higher cost efficiency. We plan to pursue work in this direction in the future.

7 Conclusion

Our data-driven analysis of the efficacy of tax credit-based incentivization of rooftop solar installations shows two major results:

- There exists a diminishing returns behavior on investment in solar incentivization. In particular, the previous policy (30% tax credit prior to 2026) falls beyond this point of diminishing returns for all four of our metrics. By our analysis in Section 5.2, the point of diminishing returns for a federal tax incentive with respect to our four metrics is approximately at a 22.9% tax credit. We show the cost efficacy of a range of possible incentivization amounts on each of our four objectives.
- Chief among our analyzed policies, we quantify the adverse effects, and cost savings, of removing the status-quo 30% tax credit in favor of state-only incentivization (current as of Spring 2026), and further the predicted effects of tariffs in the short term, though this is somewhat more unpredictable. In particular, we show an expected reduction of 27.9% in Energy Generation, 34.1% in Carbon Offsetting, 9.9% less Racial Equity, and 12.1% less Income Equity.

We note that this analysis modeling consumer behavior at a national-level, using ZIP code granularity, and predicting future behavior is quite ambitious, and so, requires quite a few assumptions. The major assumptions we make are listed in Section 3.1, and are largely the byproduct of data limitations and uncertainty about future market changes. Despite these limitations, we believe our results are within acceptable bounds of uncertainty, can meaningfully inform policy decisions, and be used as a basis in further analysis.

With more publicly-available, fine-grained, and reliable datasets future works may be able to more accurately model consumer behavior (e.g. peer influence, individual home installation/energy needs), as well as consider other possible incentivization strategies (e.g. co-incentivizing battery storage, dynamic/scheduled incentivization). We also note that other meaningful analysis is yet to be done on the simulations presented in this paper. Notably, further analysis can be done per state to understand the mechanics of incentivization effects and more formal sensitivity and ablation analysis on our assumptions may be enlightening. These analyses are out of scope of the current work and we plan to explore them in future work.

Acknowledgments

This research is supported by National Science Foundation grants 2045641, 2325956 and 2533814, and the U.S. Department of Energy, Office of Science, Office of Advanced Scientific Computing Research, Department of Energy Computational Science Graduate Fellowship under Award Number DE-SC0024386 and the National Science Foundation Graduate Research Fellowship Program under Grant Number DGE2140739.

Disclaimers

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