Optimizing Incentives for Rooftop Solar: Accounting for Regional Differences in Marginal Emissions

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Abstract

Although federal incentives for residential rooftop solar do not discriminate between US states, there is substantial variation in the marginal emission reductions associated with solar across states. This variation indicates significant efficiency gains may be possible by having flexible state-by-state incentives for a given level of spending. In this paper, I estimate the supply and demand elasticities for new rooftop solar installations, using state-level incentives as an instrument. I find a demand elasticity of 11% and supply elasticity consistent with the perfectly elastic case. I then use these parameters to show that the state-by-state subsidy scheme that minimizes yearly emissions is 61% more efficient than the uniform incentive. As the Inflation Reduction Act includes unprecedented funding allocation for climate policy, including incentives for residential rooftop solar generators, these results may help design better policies.

1 Introduction

The Inflation Reduction Act of 2022 (IRA), a groundbreaking piece of legislation addressing climate change in the US, includes major incentives for the adoption of residential photovoltaic solar generators (PV). The IRA accomplishes this mainly through extending the Investment Tax Credit (ITC), a 30% tax credit for PV installation. While the ITC does not discriminate across locations, the literature has pointed out that the reduction in greenhouse gasses (GHG) associated with adoption varies substantially across space.Differences in the carbon intensity of the regional energy mix explain much of this variation. For instance, Sexton et al. (2018) estimate that rearranging the sites of solar generators would generate an additional $1 billion per year in environmental benefits. Such differences suggest large efficiency gains may be had by changing subsidy rates state-by-state based on marginal emission reductions.

The impact of clean energy technologies depends crucially on local characteristics, especially the resource mix of local energy generation. Based on estimates from the Environmental Protection Agency (EPA), the same nominal solar capacity can have as much as twice the impact if installed in Nebraska versus New York. This marginal impact on emissions is uncorrelated with residential PV installations or existing installation incentives, suggesting no existing mechanisms to target installations along this margin. While I show this lack of correlation at the state level, Sexton et al. (2018) document the same the zip-code level.

In this paper, I estimate the gains from the optimal state-by-state subsidy schedule relative to a uniform subsidy for a given level of spending. To do so, I first produce new estimates of the supply and demand elasticities of PV adoption. I combine detailed data on installations and prices from two sources to identify elasticities based on variation in state-level incentives. Using zip-code level data on installations, I can focus on bordering counties to compare similar locations across states with different policies, minimizing unobserved heterogeneity. I then take my estimates to a simple supply and demand model and find that implementing the optimal incentive schedule decreases emissions by an additional 61%.

To assess the potential efficiency gains of fiscal incentives directing adoption to higher-impact states, we need to estimate a model of the PV adoption market. Besides the marginal impact per state, the crucial parameters are the elasticities and levels of demand and supply. The higher the price sensitivity of demand, the easier it is for incentives to redirect adoption leading to larger gains. Because subsidies are paid to submarginal adopters, it is more expensive to subsidize states with larger demand at a given price.

In the first part of this paper, I estimate the short-run elasticities of supply and demand in the residential PV market. I estimate key empirical parameters with minimal structural assumptions, using variation across US states for identification, following the approach detailed in Zoutman et al. (2018) and Dearing (2022). Identification is based on differences in incentive policies between bordering states, restricting the sample to counties along the border to minimize unobserved heterogeneity. This approach extends previous work on estimating reduced-form parameters in the PV market (Hughes and Podolefsky, 2015; Pless and van Benthem, 2019; Dong et al., 2018). While these papers often focus on the largest markets, especially California, I can incorporate data from several states and estimate supply and demand parameters. This reduced-form approach complements previous work focused on structural dynamic models of adoption (Williams et al., 2020; van Blommestein et al., 2018; Islam, 2014). While my results do not speak to the "deep parameters" of the PV adoption problem, they provide empirical facts that may help calibrate structural models.

I find evidence for a highly elastic supply curve while the elasticity of demand is well below one. My regression analysis shows that higher incentives are associated with (1) significantly higher PV installations, (2) significantly lower price net of incentives, and (3) no difference in gross prices. Together, (1) and (3) imply a large elasticity of supply and full pass-through of incentives, consistent with a highly competitive environment. Dong et al. (2018) and Pless and van Benthem (2019) find similar results in analyses of PV incentives in California. My estimated elasticity of demand is 12%. While an extensive literature studies the relationship between incentives and adoption or prices, this is, to the best of my knowledge, the first paper to produce estimates of supply and demand elasticity for a large share of the American PV market.

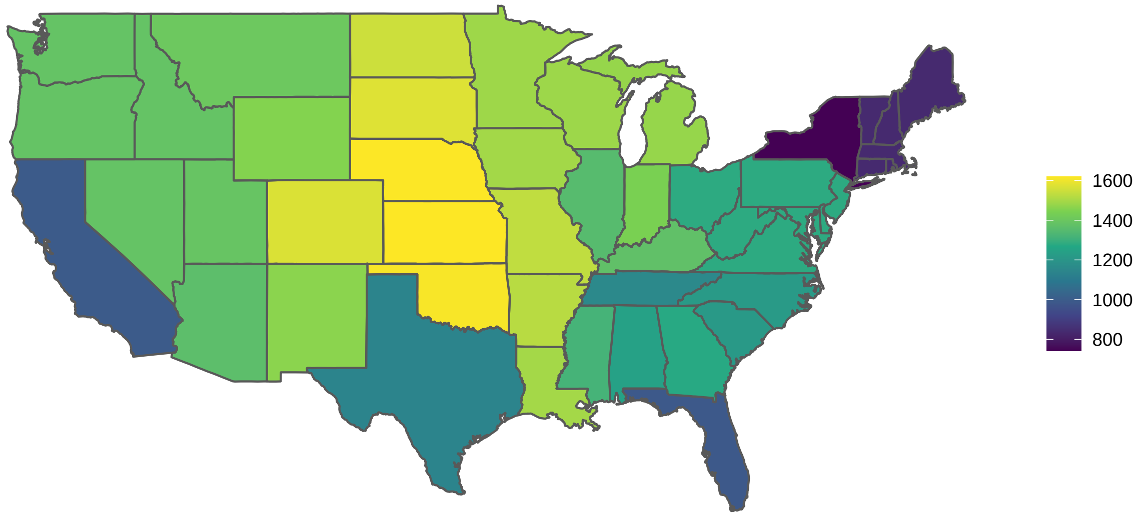
In the second part of the paper, I take these elasticity estimates to a simple supply and demand model over states and find that targeting incentives improves outcomes by 61%. Assuming states have identical constant elasticities but different supply and demand levels, the model simulates the spending of $1 billion in addition to existing incentives. I compare the scenario implementing a fixed incentive capacity unit against state-specific incentives. Supply and demand parameters, as well as existing incentives, are calibrated from 2021 data. Optimal state-specific incentives are highly concentrated in a few states, with Arizona responsible for a large share of the efficiency generated.

This paper contributes to the growing literature on encouraging environmental technologies with geographically varying benefits. Tibebu et al. (2021) derive optimal subsidies in the context of an explicit dynamic adoption model with technological progress. Holland et al. (2016) study this problem in the context of electric vehicle purchases.

2 Background

Residential PV generators are one technology that stands to grow even faster due to the incentives in the IRA, helping the US transition to clean energy. The Inflation Reduction Act is the most significant piece of legislation ever passed dealing with climate change, amounting to $390 billion of spending in this area. Among many other stipulations, it includes $128 billion for renewable energy, including $9 billion for home energy improvement programs. It also extends for ten years the consumer tax credits under the ITC for direct ownership of residential PV generators.

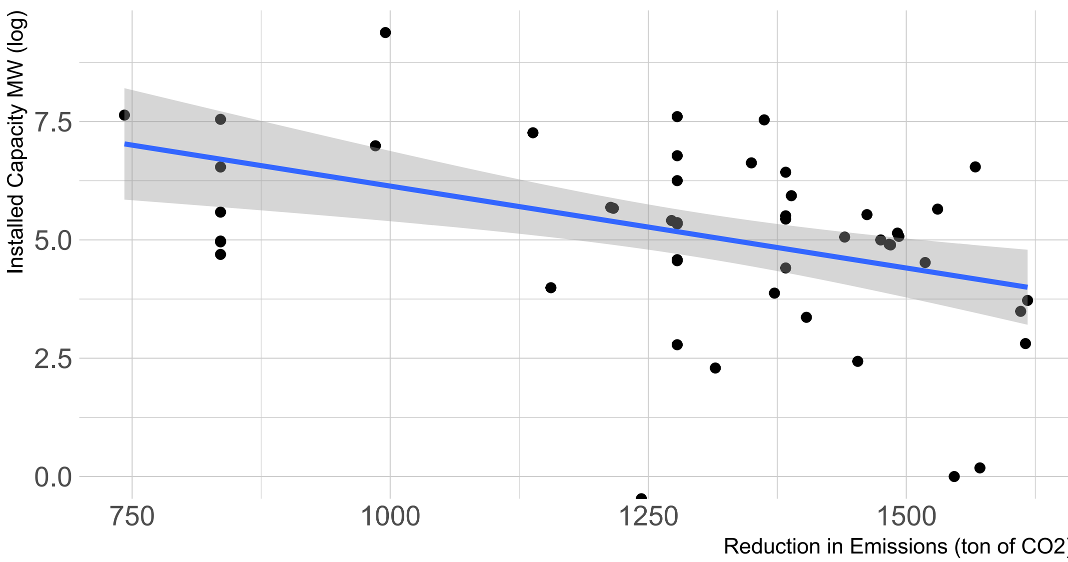
Figure 1: Reduction in yearly CO2 emissions caused by 1MW of PV



However, there is substantial heterogeneity in the effect of solar installed in different states on emissions. Figure 1 shows the impact of adding 1MW of distributed nominal capacity in each state, estimated with the EPA's AVERT model (EPA, 2023), in tons of CO2 per year. The effects range from as low as 800 tons parts of New England to as high as 1600 tons in the central plains region. These differences are not mainly due to the physical potential for solar generation but to the emission intensity of the marginal alternative energy source.

This pattern suggests potentially significant gains from directing PV installations toward high-impact areas, but actual residential installations have, if anything, gone in the opposite direction. Figure 2 shows the relationship between the marginal emission reduction in the horizontal axis and the log of cumulative installed capacity in 2021 in the vertical axis. In the largest solar market, California, 1 MW of solar capacity reduces emissions by less than 1000 tons, putting it in the bottom fifth in marginal impact. On the other hand, the adoption of residential solar has been very modest in the Midwest and Central Plains areas.

Figure 2: Effect of PV on Emissions vs Installed Capacity



Notes: This figure shows, on the horizontal axis, the marginal reduction in CO2 emissions caused by an additional 1 MW of installed solar capacity. On the vertical axis, the log total installed capacity as of 2021. Each point represents one US state among the lower 48. Alabama is excluded because, according to SEIA data, it has zero installations.

To assess the potential efficiency gains of fiscal incentives directing adoption to higher-impact states, we need to estimate a model of the PV adoption market. Besides the marginal impact per state, the crucial parameters are the elasticities and levels of demand and supply. The higher the price sensitivity of demand, the easier it is for incentives to redirect adoption, leading to larger gains. Because subsidies also benefit submarginal adopters, it is more expensive to subsidize states with higher demand at a given price.

3 Data

I rely on three primary data sources to identify supply and demand parameters and compute counterfactual emissions, complemented by several others. Data on emissions is from the EPA's AVERT model. Berkeley Lab's Tracking the Sun report is the main source for PV installations and prices, complemented by EnergySage's price data. The NC Clean Energy Technology Center's DSIRE database compiles information on federal and state-level incentives.

3.1 Emissions

To estimate the marginal reduction in emissions caused by PV installations, I use the EPA's AVERT model (EPA, 2023). EPA created the model explicitly to evaluate the emission impacts of energy policies such as PV installations. It takes EPA's data on energy load and emissions in every fossil fuel plant over a year as inputs and estimates solar energy output at a given site. From this, the model outputs the predicted reduction in CO2 emissions resulting.

The first step in the estimation is modeling the relationship between fossil fuel energy load and emissions. The total hourly grid load on fossil fuels over the year is sorted in ordered bins. Then, for each fossil fuel power plant, AVERT computes a) the probability it is operational and b) a probability distribution of its power output as a function of grid load. It also estimates the distribution of emissions in each plant given its power output.

The next step is to predict the hourly generation from a given solar installation and subtract it from the grid load using the National Renewable Energy Laboratory's PVWatts model (Dobos, 2014). This tool takes as input the nominal capacity of a rooftop solar generator and specific geographical coordinates for its location and estimates expected hourly generation across a year. It considers factors such as solar irradiance, weather variability, and efficiency losses. The generators are assumed to be placed in several cities, representing the largest load centers for each state.

Finally, using each plant's generation and emissions distributions, AVERT simulates the expected emissions given the lower grid load. Figure 1 shows the estimated effects of installing 1 MW nominal capacity at each state. Differences between states are largely driven by the intensity of the use of coal versus gas within the fossil fuel category. The share of fossil fuels out of total power generation is comparatively unimportant.

Two limitations of this method are particularly relevant for this study. First, the analysis takes the generation profile of a given year as given. Changes to fossil fuel prices, plant openings or closings, or transmission changes could meaningfully affect results in ways the model does not consider. Any possible endogenous price responses, as well as the evolution of these characteristics over time, will impact these results in ways that are difficult to predict.

Second, AVERT models each state separately and assumes power imports and exports to other regions remain constant. These energy flows are substantial in practice; for instance, California imports around 25% of its electricity, making it the largest gross importer. Meanwhile, the Midwest and Central areas are net energy exporters and relatively more carbon-intensive than average. These patterns may be of particular concern, given we are studying the allocation of PV between states. If adjustments to the flows between balancing authority areas are a relevant margin of adjustment to additional solar energy, our estimates could be biased.

3.2 PV Installations

I use Berkeley Lab as the primary source for residential PV installations (Barbose et al., 2022). This dataset, compiled in collaboration with state governments and utilities, provides data on individual installations. It includes zip-code-level location, installation date, price, capacity installed, installer identity, and several system characteristics. The dataset covers 30 US states, with all large solar markets represented.

Berkeley Lab data is crucial because it includes geographic information at a level finer than the state. This information allows us to compare prices and quantities in bordering counties, minimizing unobserved heterogeneity. We complement this information with demographic data from the American Community Survey, including the number of housing units, mean house value, and median household income by zip code.

This dataset has two important limitations. The first is that coverage is not perfect, and different states may have different misreporting rates. We deal with this problem by comparing total installations to state-level data from the Solar Energy Industry Association (SEIA) and checking the sensitivity of results to different adjustments.

The second is that price data are unavailable for every included state. Since price information is crucial, I supplement Berkeley Lab's data with proprietary data from Energy Sage. Energy Sage is a web-based platform that catalogs residential PV installers and recommends them to consumers based on their location, preferences, and other characteristics. I observe a random sample of searches and use prices of winning offers where price data is missing from Berkeley Lab.

For the simulation of results covering all the US states, I use data from 2021 by Wood—Mackenzie and SEIA (Mackenzie and SEIA, 2021). This dataset comprises information on residential PV installations at the state level across the entire country. It is based on proprietary industry information. Since it does not have the same coverage issues as the Berkeley Lab data, I consider it the "ground truth" in this paper.

3.3 Incentives

For my main instrument, I use the Database of State Incentives for Renewables and Efficiency (DSIRE) as a source for federal- and state-level incentives for PV adoption Cummings (2009). I observe tax credits, rebate programs, and other types of incentives from 2018 to 2021. Local and utility-level incentives are not included in the analysis. For incentives that only went into effect after September of a given year, I only include them in the analysis as affecting the next year.

Because some types of incentives are difficult to quantify, I focus on a) tax credits, b) direct rebates, and c) tax exemptions (mainly sales tax). These categories include the most important programs, particularly the federal ITC. I also include an estimate of the value of programs that give a rebate or tax credit depending on the assessed or actual production over a specific time horizon. Among the excluded incentives are property tax exemptions and carbon credit appropriations.

4 Model

I present a stylized model of the market for PV installations. The first part of this paper is concerned with estimating the price elasticities in the model from US data. The second part uses the estimates and the model to study the effects of counterfactual policy experiments changing the subsidy rate.

Let's consider a standard supply and demand system at each state, with constant elasticities. Denoting quantities demanded and supplied at location j, year t, respectively Q_{jt}^d and Q_{jt}^s; prices p_{jt}, subsidies τ_{jt}, and the number of housing units N_{jt} that do not already have a PV system.

$$Q^s_{jt} = N_{jt} \exp(\gamma X_{jt})(p_{jt})^{\delta} u_{jt} \tag{Supply}$$

$$Q^d_{jt} = N_{jt} \exp(\alpha X_{jt})(p_{jt} - \tau_{jt})^{\beta} \epsilon_{jt} \tag{Demand}$$

With u_{jt} and ϵ_{jt} as error terms. Taking logs and with $q_{jt} := Q_{jt}/N_{jt}$:

$$\ln q^s_{jt} = \delta \ln p_{jt} + \gamma X_{jt} + u_{jt} \tag{Supply (log)}$$

$$\ln q^d_{jt} = \beta \ln(p_{jt} - \tau_{jt}) + \alpha X_{jt} + \epsilon_{jt} \tag{Demand (log)}$$

The equilibrium condition:

$$Q^d_{jt} = Q^s_{jt} \tag{E.C.}$$

I denote $Q^*(\tau)$ the quantity that solves the system as an implicit function of subsidies.

In the next sessions, I first deal with the question of identifying and estimating elasticities β and γ. Then, I use the model and the elasticity estimates to study the effects of variable subsidies τ.

5 Estimating elasticities

I estimate supply and demand parameters relying on changes in state incentives for PV adoption, following the approach outlined in Zoutman et al. (2018) and Dearing (2022). In order to compare areas as closely comparable as possible, I focus on bordering counties between states with different incentive rates. By estimating the effect of incentives on prices to producers and to consumers, I am able to identify both supply and demand elasticities.

Results suggest supply is very highly elastic, while demand elasticity is only around 12%. Results are imprecisely estimated, but are corroborated by alternative methods.

5.1 Estimation

Zoutman et al. (2018) provides the theoretical framework for identifying both supply and demand elasticities using as instrument only the variation in a single tax rate. In our case, we can identify β and δ using the variation in state-level incentives as instruments. The key intuition for this result is that the supply and demand model provides theoretical restrictions that we can leverage to identify the relevant parameters.

The first assumption we need corresponds to the usual exclusion restriction. The require changes in subsidy rates to be uncorrelated with unobserved determinants of adoption. This assumption would fail, for example, if states where the population is becoming more worried about the environment are more likely to increase subsidies and also see increased demand for PV adoption.

The second assumption is what Zoutman et al. (2018) terms the Ramsey Exclusion Restriction, which stipulates that changes in subsidy rates can only affect demand and supply through their effects on prices. This assumption would fail if, for instance, higher subsidies increase the salience of solar energy and have an outsized effect in demand beyond the one through price. Alternatively, because incentive programs are often implemented as tax rebates, they may be themselves be less salient, as Chetty et al. (2009) find with sales taxes.

Under these assumptions, we can easily recover the supply and demand elasticities by instrumenting, respectively, the net price $(p_{jt} - \tau_{jt})$ or the full price p_{jt} by the subsidy rate. The identifying assumption is that τ_{jt} is uncorrelated to unobserved variation, condition on covariates: $E[\tau_{jt} u_{jt} | X_{jt}] = 0$, $E[\tau_{jt} \epsilon_{jt} | X_{jt}] = 0$.

To minimize the role of unobserved heterogeneity, I restrict the sample to bordering counties between two states. While market conditions may differ between contiguous states, including physical conditions, i.e., solar irradiance, we can minimize these differences by focusing on the counties to either side of the border. This restriction focuses on areas with the identifying variation, assuming that the relevant unobserved heterogeneity changes continuously over space.

Therefore, my unit of observation is a county-by-border-by-year. I use only counties adjacent to a state border between two states if I have data for both during at least one year between 2018 and 2021. My measure of log quantity is the total capacity installed, divided by the number of housing units in the zip code, to make locations with different populations comparable. Similarly, prices are measured in dollars per kW capacity.

Two related issues exist when using fiscal incentives as instruments. First, most federal and state incentives have complicated, non-linear rules depending on prices and system sizes and usually include maximum values per household. Properly including these kinds of incentives in a regression framework is not straightforward. Second, demand for PV systems of different characteristics adjusts in response to the incentive design. For instance, smaller systems are relatively cheaper for consumers in states that include a lump-sum rebate for PV systems above a specific capacity.

I deal with these two issues using "simulated instruments" that apply the incentive rules of each state to a shared pool of installations. I start by taking each pair of states, say A and B, and pooling together all installations in a given year. Then, I compute the net price given system characteristics under the incentive scheme in state A for every installation in both A and B. The simulated incentive for state A is the average ratio between total price and net price (and correspondingly for B). Because the instruments for A and B are calculated using the same sample of installations, the differences are driven entirely by the incentive rules themselves, not any differences in composition. This type of approach has often been used to study the effects of different policy regimes in, e.g., taxation (Gruber and Saez, 2002), health (Cohodes et al., 2016), and labor (Cullen and Gruber, 2000).

To make the construction more explicit, let's call $I_{A,t,B}$ the collection of indices in the sample corresponding to installations in state A, year t. Each installation i has information on total price paid P_i and total capacity installed C_i. Let $f_{A,t}(P_i, C_i)$ be a function describing the total incentives due to an installation with total price P_i and capacity C_i according to the state laws in A during year t. Denote B the bordering state, remember the sample is restricted to counties along the border, and $n_{s,t}$ the total number of installations in the sample in state s, year t. Then, the instrument for incentives in A, bordering B, at year t is:

$$z_{A,t,B} = \frac{1}{n_{A,t} + n_{B,t}} \sum_{i \in I_{A,t} \cup I_{B,t}} f_{A,t}(P_i, C_i)$$

Therefore, our main estimating equations are the following.

$$\ln q_{j,t} = \eta_1 z_{s(j),t,s'(j)} + \eta_2 X_{j,t} + e^r_{j,t} \qquad \text{(Reduced form)}$$

$$\ln p_{j,t} = \theta_1 z_{s(j),t,s'(j)} + \theta_2 X_{j,t} + e^S_{j,t} \qquad \text{(First stage: Supply)}$$

$$\ln(p_{j,t} - \tau_{j,t}) = \phi_1 z_{s(j),t,s'(j)} + \phi_2 X_{j,t} + e^D_{j,t} \qquad \text{(First stage: Demand)}$$

$$\ln q_{j,t} = \delta p_{j,t} + \gamma X_{j,t} + u_{j,t} \qquad \text{(IV: Supply)}$$

$$\ln q_{j,t} = \beta(p_{jt} - \tau_{jt}) + \alpha X_{j,t} + \epsilon_{j,t} \qquad \text{(IV: Demand)}$$

With $X_{j,t}$ a vector of controls that includes an intercept, median household income, average home values, and energy prices.

5.2 Results

Table 1 below summarizes the results. Column 1 shows that an extra thousand dollars in incentives is associated with an increase of 3.7% in capacity installed per capita. The same incentive increases prices by only 0.1%, with a wide confidence interval (Column 2). Net price, however, decreases strongly by 26% (Column 3). Although this effect has even larger errors, we reject the hypothesis that it equals zero.

Column 4 shows the IV estimates of the structural supply elasticity, that is, the effect of log price on log capacity installed per capita. Since the incentive instrument does not have an appreciable effect on price, that implies a highly elastic supply. A consequence of price insensitivity to the instrument is that the elasticity estimate is extremely noisy. The practical implication is that supply is close to the perfectly elastic case. Column 5 shows the estimates of the demand curve's elasticity. I find an elasticity of 12%, with the correct sign. Precision is low, with a 90% confidence interval covering from 23% to close to 0.

Table 1: Regression Results

	(1) ln Capacity pc	(2) ln Price	(3) ln Net Price	(4) ln Capacity pc	(5) ln Capacity pc
Incentive	0.0373	0.00141	-0.259		
	(0.0126)	(0.0640)	(0.108)		
ln Price				21.83	
				(986.4)	
ln Net Price					-0.119
					(0.0690)
N	6622	5871	5871	5871	5871
Clusters	83	81	81	81	81
Year FE	Yes	Yes	Yes	Yes	Yes
Border FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	OLS	OLS	IV	IV

6 Optimal Incentives

To quantify the potential gains from target incentives, I apply the estimated elasticities to a simple supply and demand model calibrated to the 2022 PV market. I study the problem of maximizing the policy's emissions impact, given a budget constraint. My results indicate that, for a target spending of 1 billion dollars, the impact of state-specific incentives is about 60% larger than that of the uniform incentive.

6.1 Model

I study the problem of minimizing emissions, given an incentive budget constraint. The planner has a budget B and uses it to implement adoption incentives. In the first case we study, this budget only finances extra incentives on top of existing ones, which I take as given. This framework represents the problem of enacting a new subsidy given existing policies. Write the total incentive in state j, τ_j as the sum of the already existing incentives $\bar{\tau}_j$, that are taken as given, and new incentives τ_j^*.

$$\tau_j = \bar{\tau}_j + \tau_j^*$$

Denote e_j the marginal emissions associated with one PV installation in state j. Then the problem is:

$$\min_{\tau_j^*} \sum_J e_j Q_j^*(\tau_j)$$

$$s.t. \sum_J \tau_j^* Q_j^*(\tau_j) \leq B,$$

$$\forall \tau_j^* : \tau_j^* \geq 0$$

Our key interest lies in comparing the objective function the planner can reach with flexible incentives compared to uniform incentives. The uniform incentives case is represented simply as the additional restriction $\tau_j^* = \tau^*$.

I take the model to US data from 2022, using installation data from SEIA and Wood and Mackenzie and price data from Energy Sage. I dropped two states from the analysis, Alabama and Tennessee because they have zero residential PV installations in the year. Thus, our model implies that no amount of incentives will induce demand. For another seven states, we do not have price data (KS, MS, MT, NB, ND, SD, WY). In these cases, we impute the average price across all other states. Because these are all small markets for PV, the sensitivity of results to this imputation is small.

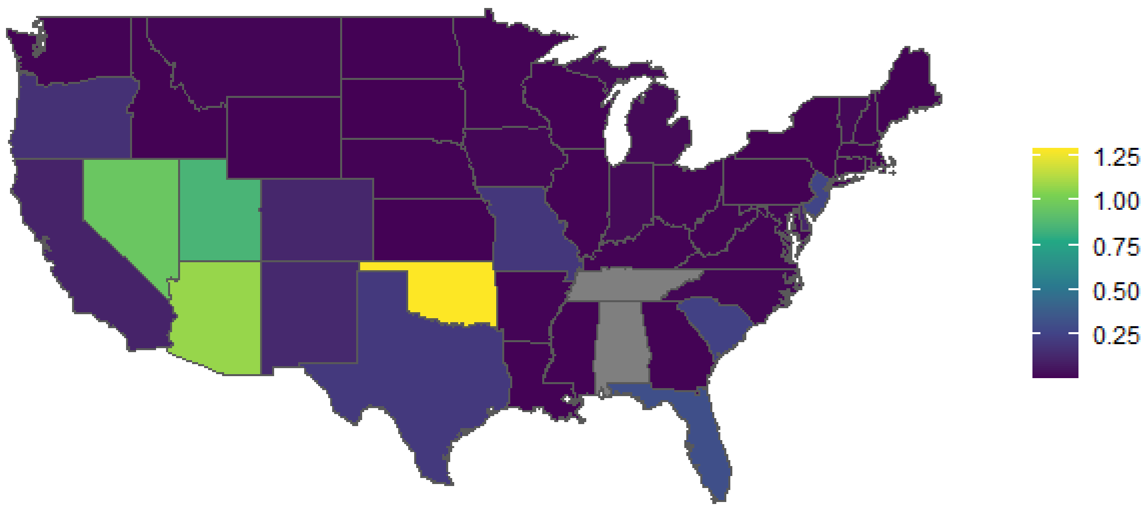
6.2 Results

My main result is that, in the marginal expenditure exercise, targeting by state induces a 61.5% larger reduction in CO2 emissions compared with a uniform incentive spending the same amount. The distribution of this incentive is very concentrated, with large discounts for installations in Oklahoma and three Southwestern states, with close to zero allocated to northern states. Each taken alone, marginal emissions, population size, or the scale of existing demand cannot fully explain the resulting distributions.

In the baseline exercise, I model the expenditure of $1 billion in a flat incentive per installed unit of capacity. At this level of extra spending, the flat subsidy offered is $0.244 per W, or about 8.8% of the average price before incentives. This level of incentives implies a reduction of 50.38 million tons of CO2 emitted per year, on top of the business-as-usual estimated effect of 4.6 billion tons of CO2.

Figure 3 shows the estimated optimal additional incentives. Four states stand out very clearly: Oklahoma (1.29), Arizona (1.08), Nevada (0.96), and Utah (0.86) have the largest incentives. Florida, New Jersey and South Carolina also have slight increases relative to the uniform incentive. Seven other states have lower levels that are still $0.11 per W,

Figure 3: Optimal Additional Incentives: τ_s^*



while the others have rates close to zero. Figure 4 shows the optimal additional incentives added to existing federal and state incentives. While existing incentives are negatively correlated with marginal impact, the total incentives after adding this spending are not.

The emissions impact of the optimal subsidy schedule is 81.35 million tons of CO2 per year, a 61% increase relative to the uniform subsidy case. Arizona is responsible for a large part of the efficiency gains, as the model predicts the increased subsidies will lead to an extra 31 million tons of CO2.

Figure 5 shows how the estimated optimal incentive depends on four key variables: marginal emissions, existing incentives, the number of housing units in the state, and the scale parameter of demand B_j. The four states with high optimal incentives have relatively high marginal emissions and demand and relatively low current incentives and number of units.

Figure 4: Optimal Total Incentives: τ_s

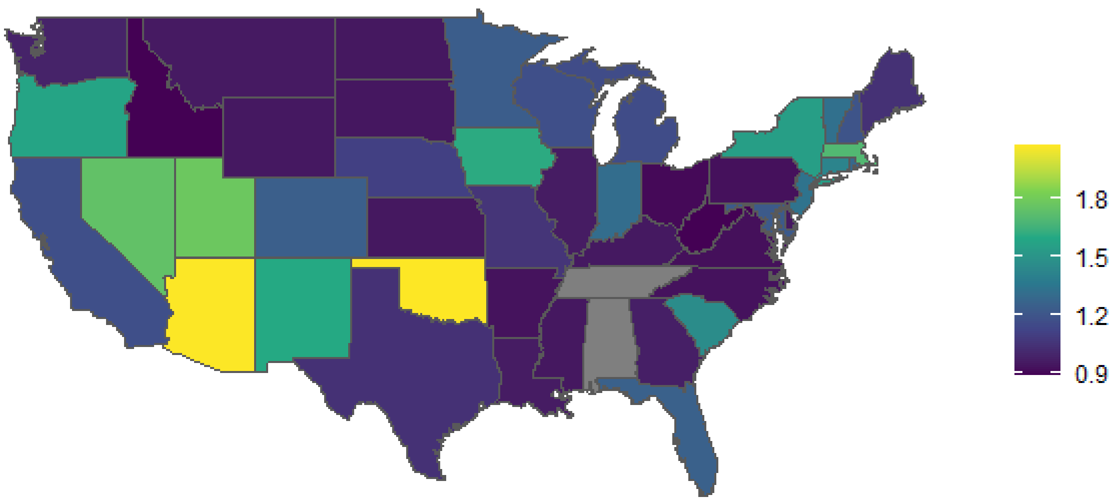
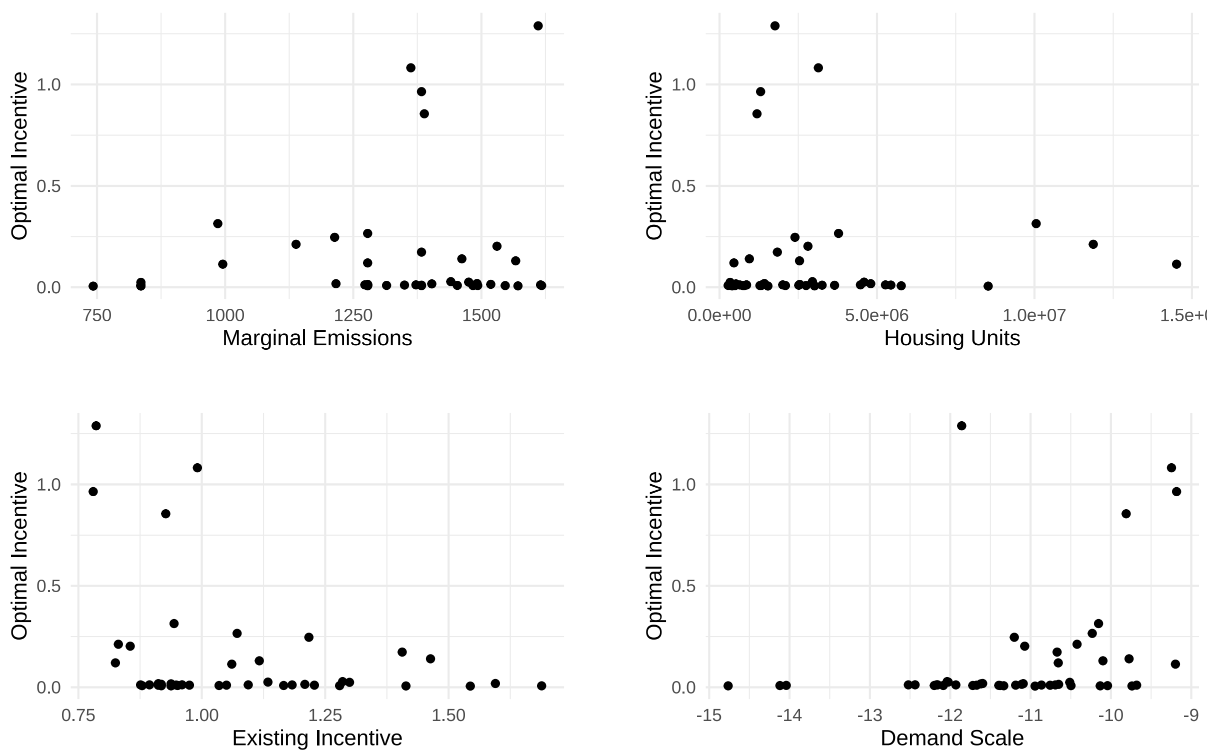


Figure 5: Optimal Incentive vs State Characteristics



7 Conclusion

This paper highlights the potential for optimizing the state-by-state subsidy schedule for residential PV under the Inflation Reduction Act of 2022 (IRA). By leveraging new estimates of supply and demand elasticities of PV adoption, I demonstrate that implementing an optimal incentive schedule can lead to a 61% larger reduction in emissions than a uniform subsidy approach. This finding underscores the importance of tailoring incentives to the specific characteristics of each state's energy landscape, as indicated by the substantial variation in greenhouse gas reduction benefits across different locations.

This paper also reinforces the potential value of improving data reporting standards to help address practical challenges in environmental policy. The need for standardized, representative data on the PV market severely limits what we can learn about how to improve government policy in this area. Considering the amount of public investment, creating and distributing better data may be a public good with significant social returns.

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