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 potentially large efficiency gains from having flexible state-by-state incentives. 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. These results can be useful as the Inflation Reduction Act of 2021 includes unprecedented funding allocation for climate policy, including incentives for residential rooftop solar generators.

1 Introduction

The Inflation Reduction Act of 2022 (IRA), a groundbreaking piece of legislation addressing climate change in the US, includes major incentives for 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. For instance, Sexton et al. (2018) estimates 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 available by changing subsidy rates state-by-state, based on marginal emission reductions.

In this paper I estimate the gains from the optimal state-by-state subsidy schedule relative to 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 distinct sources to identify elasticities based on variation in state-level incentives. By 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 extra 61%.

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 capacity of solar can have as much as twice the impact if installed in Nebraska versus New York. This marginal impact on emissions is uncorrelated with both residential PV installations and existing incentives for installations, 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) documents the same (lack of) relationship at the zip-code level through.

In the first part of this paper I estimate the short-run elasticities of supply and demand in the residential PV market. I opt to focus on estimating key empirical parameters with minimal structural assumptions, using variation across US states for identification and using only data from the specific US context. Identification is based on differences in incentive policies between bordering states, restricting the sample to counties along the border to minimize unobserved heterogeneity. This reduced-form approach contrasts with and complements previous work, which has focused more on structural dynamic models of adoption (Williams et al., 2020; van Blommestein et al., 2018; Islam, 2014).

I find evidence that supply is highly elastic in this context, while elasticity of demand is well below 1. This result is due to higher incentives causing significantly higher PV installations, significantly lower price after incentives, while prices before incentives remain unchanged. The estimates for the elasticity of supply are extremely noisy, consistent with the perfectly elastic case, while the estimated elasticity of demand is 12%.

In the second part of the paper I take these elasticity estimates to a simple model of supply and demand over states and find that targeting incentives improves outcomes by 61%. Assuming states have the same constant elasticities but different levels of both supply and demand, the model simulates the spending of $1 billion in addition to existing incentives. I compare the scenario implementing a fixed incentive per unit of capacity 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 a large share of the efficiency gains being generated by Nevada.

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

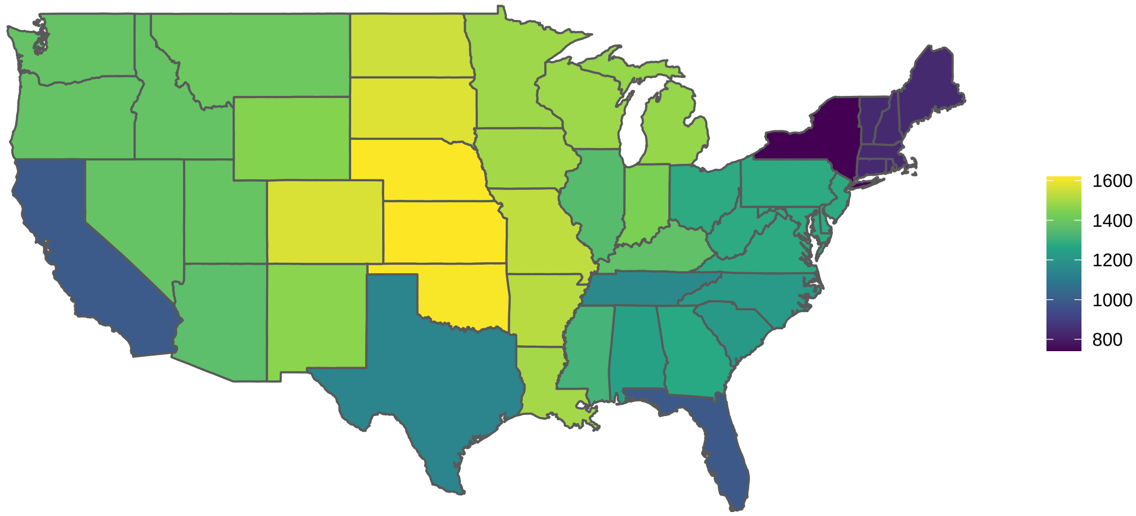
2 Background

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 largest piece of legislation ever passed dealing with climate change, amounting to 390 billion dollars of spending in this area. Among many other stipulations, it includes 128 billion for renewable energy, including 9 billion to home energy improvement programs. It also extends for 10 years the consumer tax credits under the ITC for direct ownership of residential PV generators.

However, there is substantial heterogeneity in the effect of solar installed in different states on emissions. Figure 1 shows the effects 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 in most of New England, to as high in 1600 tons in the central plains region. These differences are not mainly driven by the physical potential for solar generation, but by the emission intensity of the marginal alternative energy source.

This pattern suggests potentially large gains from directing PV installations towards high-impact areas, but actual residential installations have, if anything, gone 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 market for solar, California, 1 MW of solar reduces emissions by less than 1000 tons, putting it in the bottom fifth in marginal impact. On the other hand, adoption of residential solar has been very modest in the Midwest and Central Plains area.

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

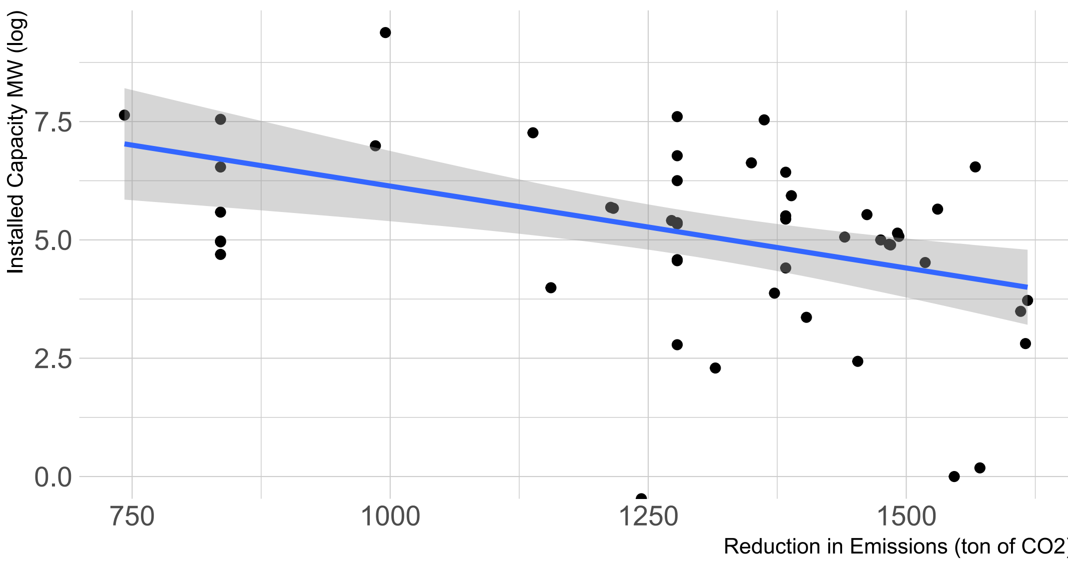


To assess the potential efficiency gains of fiscal incentives directing adoption to higher-impact states, we need to estimate a model of the PV adoption market. Besides the marginal impact per state, the crucial parameters are the elasticities and levels of demand and supply. The higher the price sensitivity 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.

3 Data

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

Figure 2: Effect of PV on Emissions vs Intalled 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. In the vertical axis is log total installed capacity as of 2021. Each point is one US state among the lower 48. Alabama is excluded for having zero installations according to SEIA data.

3.1 Emissions

To obtain an estimate of the marginal reduction in emissions caused by PV installations, I use the EPA's AVERT model (EPA, 2023). This model was explicitly created with the goal of evaluating county and state level emissions impacts of energy policies such as PV installations. It takes as inputs EPA's data on energy load and emissions in every fossil fuel plant over a given year, and estimates of 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 the generation in that plant.

The next step is to predict the hourly generation from a given solar installation and subtract it from the grid load. This is done using the National Renewable Energy Laboratory's PVWatts tool (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 takes into account factors such as solar irradiance, weather variability and efficiency losses. For every state, the generators are assumed to be placed in several cities, representing the largest load centers.

Finally, AVERT simulates the expected emissions given the lower grid load using the generation and emissions distributions at each plant. Figure X shows the estimated effects for the installation of 1 MW nominal capacity at each state. Differences between states are driven in large part 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 as given the generation profile in a given year. Changes to fossil fuel prices, opening or closing of plants, or changes to transmission could meaningfully affect results in ways the model does not take into account. Second, AVERT models each state separately, and assumes power imports and exports to other regions remain constant. This may be of particular concern, given we are studying the allocation of PV between states.

3.2 PV Installations

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

Berkeley Lab data is crucial in that it includes geographic information at a level finer than the state. This 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 number of housing units, mean house value and median household income by zip-code.

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

The second is that data on prices are not available for every included state. Since price information is crucial, I supplement this Berkeley Lab 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 simulation of results covering all the US states, I use data from 2021 by Wood-Mackenzie and the Solar Energy Industry Association (SEIA) (Mackenzie and SEIA, 2021). This dataset comprises information on residential PV installations at the level of the state, 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 it 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, c) tax exemptions (mostly 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 accessed or actual production over a certain 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 together with 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^d_{jt} and Q^s_{jt}; prices p_{jt}, subsidies τ_{jt}, and the number of housing units N_j that do already have a PV system.

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

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

Taking logs and with $q := Q/N$:

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

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

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. 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

We can identify the elasticities β and δ 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 be different 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. Under the assumption that most relevant unobserved heterogeneity changes continuously, this restriction focuses on areas with the identifying variation.

Therefore, my unit of observation is a county times border times 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 are present 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 including 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 adjust in response to the incentive design. For instance, in states that include a lump-sum rebate for PV systems above a certain capacity, smaller systems are relatively cheaper for consumers. This may generate bias if, e.g., smaller systems are also more costly due to fixed costs or economies of scale.

I deal with these two issues using simulated instruments. 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.

5.2 Results

Table 1 below summarizes the results. Column 1 shows that an extra thousand dollars in incentives are 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 larger errors still, we reject the hypothesis that it is equal to 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 the insensitivity of price to the instrument is that the elasticity estimate is extremely noisy. For practical purposes, the implication is that supply can be approximated by the perfectly elastic case.

Column 5 shows the estimates of the elasticity of the demand curve. 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)	(2)	(3)	(4)	(5)
	ln Capacity pc	ln Price	ln Net Price	ln Capacity pc	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

In order to quantify the potential gains from target incentives, I take the estimated elasticities to a simple supply and demand model, calibrated to the 2022 PV market. I study the problem of maximizing the emissions impact of the policy, given a budget constraint. My results indicate that, for a target spending of 1 billion dollars, the impact of state-specific incentives is about 70% 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, that can be used to implement incentives. In the first case we study, this budget only finances extra incentives on top of already existing ones, which are taken as given. This represents the problem of enacting a new policy given the existing policy framework and budget. 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^*.

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

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 that can be reached with flexible incentives compared to uniform incentives. The uniform incentives case being represented simply as the additional restriction $\tau_j^* = \tau^*$.

I take the model to US data from the year 2022, using installation data from SEIA and WoodMac and price data from Energy Sage. I drop two states from the analysis, Alabama and Tennessee, because they have zero residential PV installations in the year, and thus our model implies no amount of incentives will induce demand. For another five 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 total. 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. The resulting distributions cannot be solely explained by marginal emissions, population size or the scale of existing demand.

In the baseline exercise, I model the expenditure of 1 billion dollars, in a flat incentive per installed unit of capacity. At this level of extra spending, the flat subsidy offered is 0.244 USD 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. This figure is on top of the business-as-usual estimated effect of 4.6 billion tons of CO2.

The estimated optimal additional incentives are shown in Figure 3. 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 above $0.11 per W, while the others have rates close to zero. Figure 4 shows the optimal additional incentives added to the existing federal and state incentives. While existing incentives are negatively correlated with marginal impact, the total incentives after adding this spending is 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 very 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 de scale parameter of demand B_j. The four states with high optimal incentives have

Figure 3: Optimal Additional Incentives: τ_s^*

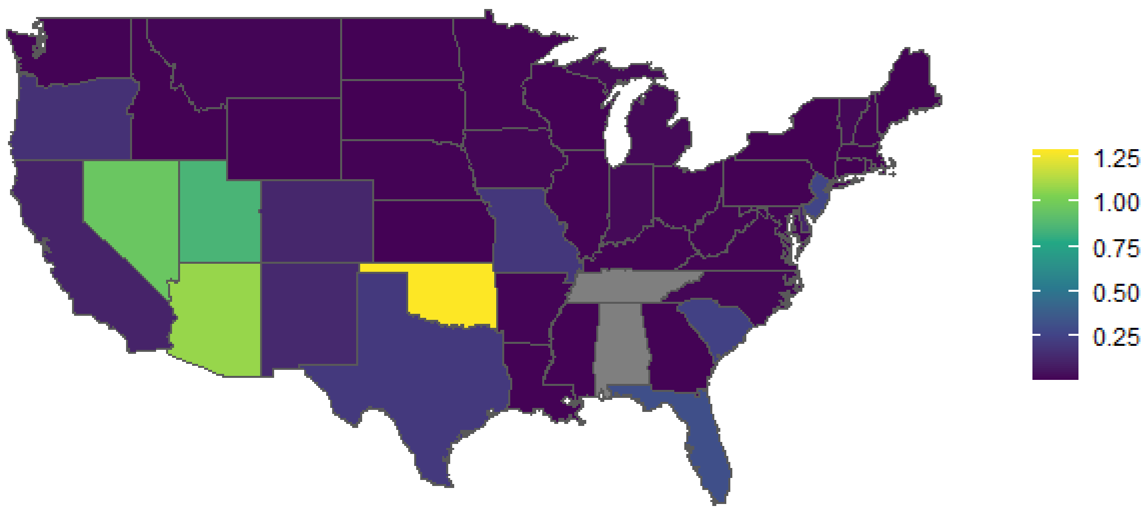


Figure 4: Optimal Total Incentives: τ_s

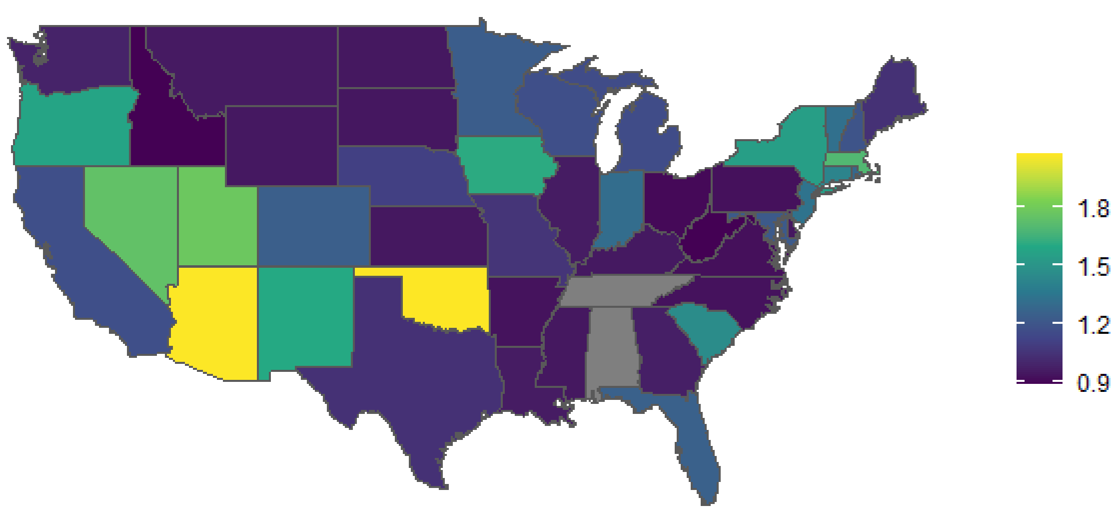
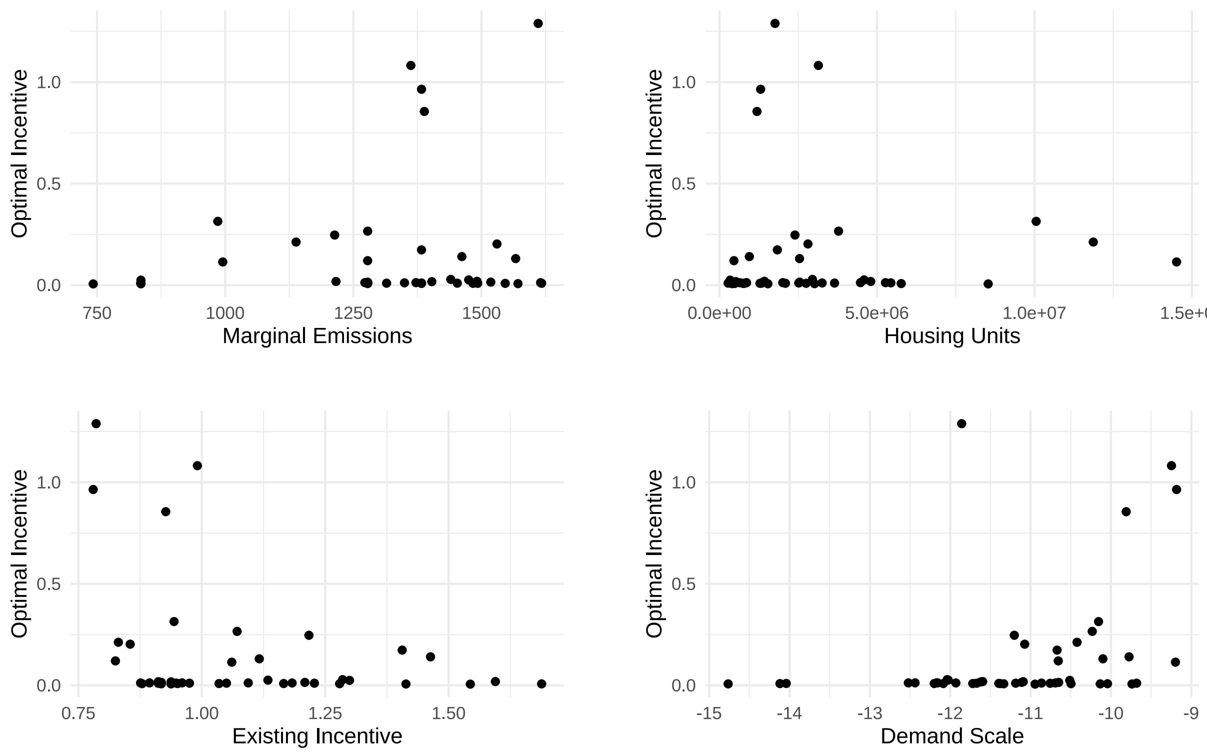


Figure 5: Optimal Incentive vs State Characteristics



relatively high marginal emissions and demand, and relatively low current incentives and number of units.

7 Conclusion

This paper highlights the significant 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 compared to 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 paucity of 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 large social returns.

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