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

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MEEW - 2023-11-30

Introduction

- Among the measures of the 2022 Inflation Reduction Act, there is the extension of the Investment Tax Credit
  - 30% tax credit on installations of household solar
- The effect of additional solar capacity on emissions varies substantially across space
  - The same nominal capacity in PV in Nebraska reduces GHG by twice as much as in NY

Introduction

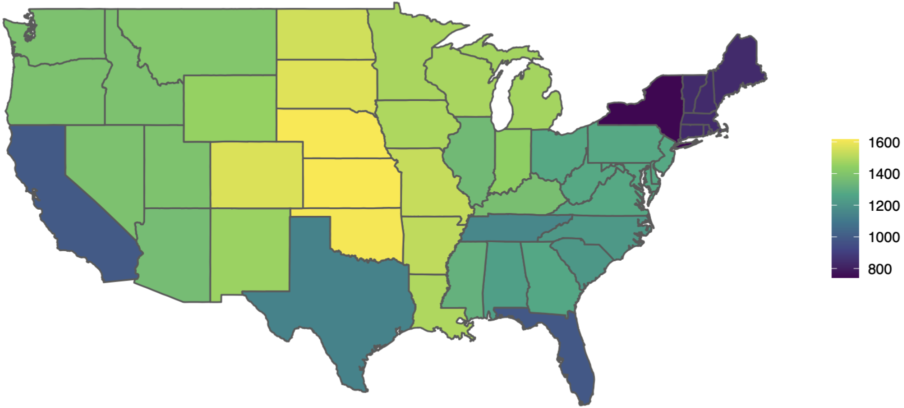

Figure 1: EPA: Reduction in yearly tons of CO2 emissions caused by 1MW of PV

Introduction

- Current installations do not reflect marginal effects on emissions

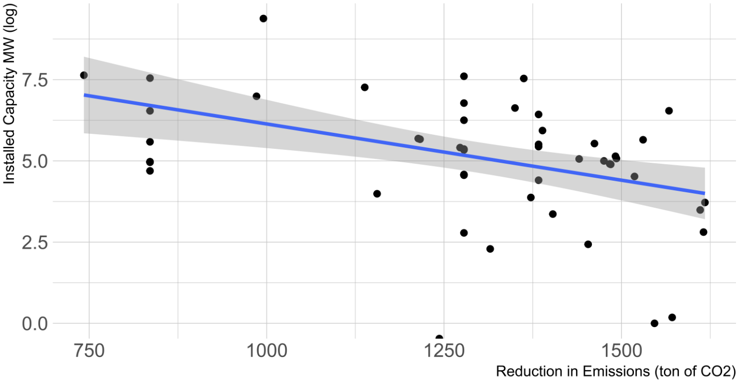

Figure 2: Effect of PV on Emissions vs Installed Capacity

Introduction

- **Question:** How large are the gains of optimally targeting federal subsidies to PV installation based on marginal emission reductions?
- **Method:**
  1. Estimate supply and demand elasticities leveraging variation in state-level incentives.
  2. Use a simple model to compare reductions of uniform vs targeted subsidies with a given budget.
- **Results:** I find that optimally target incentives reduce emissions by 61% more than the uniform incentives for a given budget.

Introduction

- Investment in clean energy adoption and variable benefits: Sexton et al. (2018), Holland et al. (2016), Tibebu et al. (2021).
- Reduced form parameters of PV installation market: Hughes and Podolefsky (2015), Dong et al. (2018), Pless and van Benthem (2019)
- Dynamic PV adoption models: Williams et al. (2020); van Blommestein et al. (2018); Islam (2014)

Data

Data

- Marginal emissions from EPA's AVERT model
- Berkeley Lab: Installations and prices at zipcode level
- Additional data on installations from SEIA/WoodMac
- Additional data on prices from EnergySage
- State incentives from NC Clean Energy Technology Center

Data

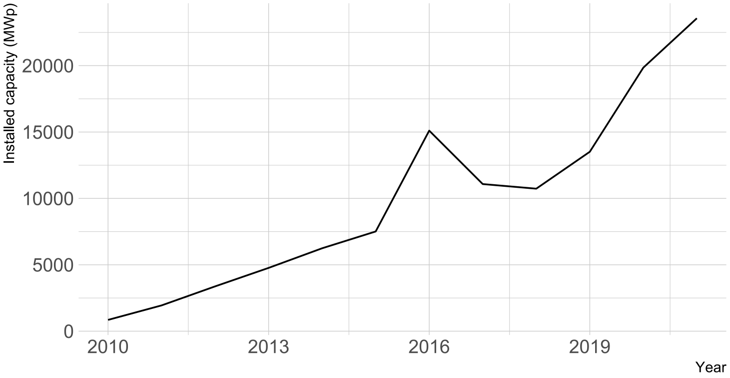

Figure 3: Residential photovoltaics increased very fast in the US

Data

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- To get the impact of rooftop solar, get a generation profile from NREL's PVWatts, subtract from fossil fuel demand.

Data

Some important limitations of this method:

1. Takes the grid characteristics as given. Changes to fuel prices or opening/closing of plants could affect results in ways that are difficult to predict.
2. Imports/Exports of energy between regions are taken as given.

Data

In practice, the coal intensity among carbon sources is an important driver

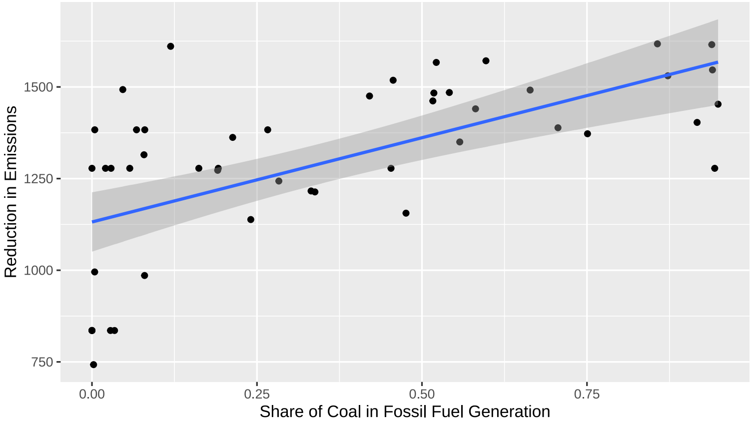

Figure 4: Marginal Emissions Reduction vs Share of Coal in Fossil Fuels

Model

Model

- Supply:

$$Q_{jt}^{S} = N_{jt} \exp(\gamma X_{jt})(p_{jt})^{\delta} u_{jt}$$

- Demand:

$$Q_{jt}^{D} = N_{jt} \exp(\alpha X_{jt})(p_{jt} - \tau_{jt})^{\beta} \epsilon_{jt}$$

Taking logs and denoting $q_{jt} = Q_{jt}/N_{jt}$:

$$\ln q_{jt}^{S} = \delta p_{jt} + \gamma X_{jt} + u_{jt}$$

$$\ln q_{jt}^{D} = \beta(p_{jt} - \tau_{jt}) + \alpha X_{jt} + \epsilon_{jt}$$

Estimating the key parameters

Estimating the key parameters

- To estimate price elasticities, we need instruments.
- I leverage variation in state subsidies
  - Rebates, tax credits and exemptions
- Allows identification of both supply and demand elasticities.

Estimating the key parameters

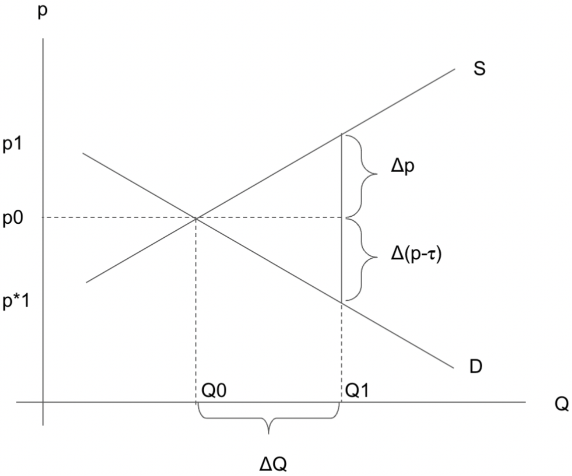

Figure 5: Illustration of identification argument

Estimating the key parameters

- Key identification assumption: changes in incentives are uncorrelated with unobserved supply or demand shocks
- To reduce the role of unobserved heterogeneity, I focus on comparing counties along state borders
- Controls include: state-border FE, year FE, median household income, average home prices, energy prices

Estimating the key parameters

- Two issues with incentives data:
  - Often nonlinear and complicated
  - Affect characteristics of installations
- I deal with these issues using "simulated instruments:"
  - Apply incentive rules of each state to the common pool of installations
  - Compute average incentive
- With I_S the set of installations in state S, with price P_i, capacity C_i, and with incentive rule $f_S(P, C)$:

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

Estimating the key parameters

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

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Elasticity results

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

Optimizing Incentives

Optimizing Incentives

- The social planner seeks to minimize emissions, using incentives for adoption *on top of existing incentives*.
- Write e_j as the marginal emission reduction per kW installed in state j, and decompose incentive τ_j into existing incentives $\bar{\tau}_j$ and new incentives τ_j^*.

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

$$\text{s.t.} \sum_J \tau_j^* Q^*(\tau_j) = B$$

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

In the uniform case:

$$\tau_j^* = \tau^*$$

Results

- I use estimated elasticities, and quantities and prices from 2022 to back out the scale parameters.
- I simulate the effects of an expenditure of 1 billion dollars.
- I find that the uniform subsidy causes a reduction of 50 million tons of CO2 per year.
  - Extra subsidy of 0.24 USD per W (8.8% of current prices)
- Under optimally targetted incentives, CO2 reduction is 61% larger.

Results

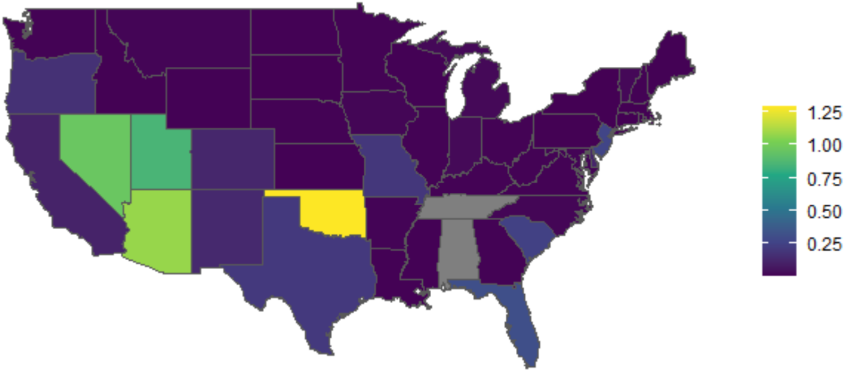

Figure 6: Increased Incentives: τ_s^*

Results

- Optimal incentives are very concentrated:
  - OK, AZ, NV and UT receive much larger incentives
  - FL, NJ and SC have slight increases, and seven other states have incentives above 0.11 USD
  - Most other states receive almost zero
- Arizona alone is responsible for almost all of the additional emission reductions.

Conclusion

- I show that accounting for regional differences in marginal emission intensity can have a substantial impact on the effectiveness of environmental policy.
- To do so, I develop novel estimates of the price elasticities in the PV market.
- However, in the US context, resulting incentives would be very concentrated, potentially running into political constraints.