

# Optimal Charging Infrastructure for Electric Vehicles

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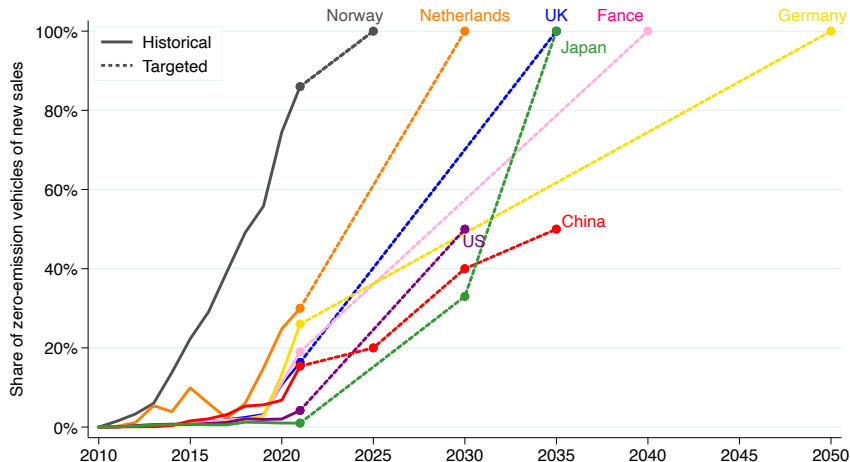
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Economics of Transportation in the 21st Century  
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Preliminary

# ZEV Targets and EV Shares in 2021



Note: ZEV target and EV market shares for major EV countries. Source: ICCT with authors' updates.

# Research Question

- The Bipartisan Infrastructure Law provides \$7.5 billion to build a national EV charging network by 2026
- Our research questions:
  - 1 What would the optimal charging network look like in terms of station density and the spatial pattern?
  - 2 How can the funding be allocated to effectively promote EVs and to improve social welfare?

# Research Framework

- 1 A model of the two-sided market on EV demand and charging stations
- 2 Estimation using granular data on EV sales and stations
- 3 Policy simulations
  - ▶ Solve for socially optimal charging network without budget constraint
  - ▶ Examine market outcomes under different cost-sharing ratios
  - ▶ Find subsidy policies to mimic the social optimal under a budget



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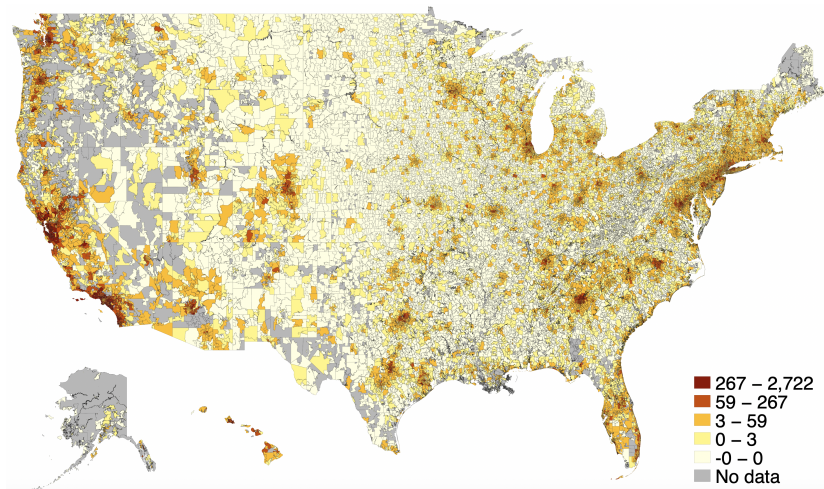
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- 1 Introduction
- 2 Data Description**
- 3 Empirical Model
- 4 Policy Simulations
- 5 Findings and Next Steps

# Data Description

- Annual EV sales by model by zip, and vehicle attributes 2013-19
- Charging stations with location, entry time, and characteristics
- 2017 National Household Travel Survey
- Demographics, foot traffic at POIs, road network and vehicle traffic

# EV Sales by Zip Code in 2019

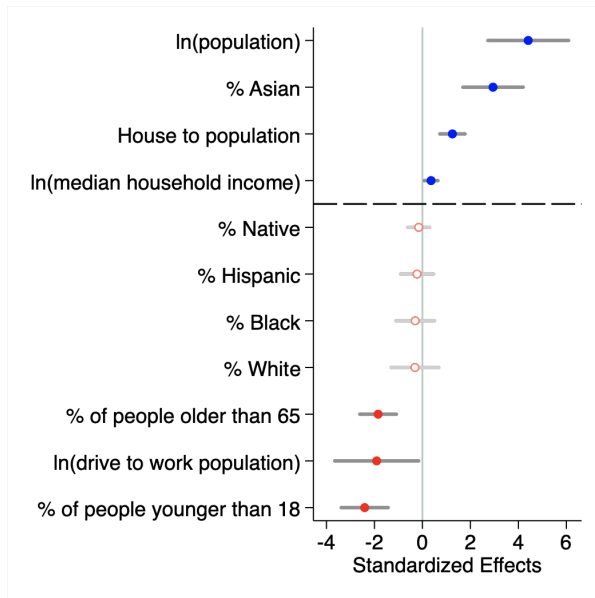


# Charging Station Density

[▸ 2022 Map](#)[▸ Facility Type](#)[▸ Networks](#)

- No. of stations within 20 miles by zipcode.

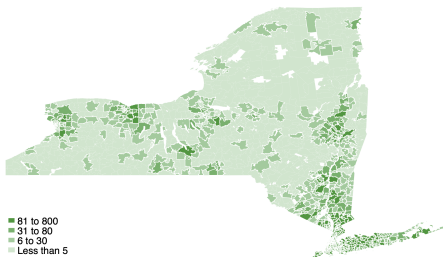
# Charging Stations and Demographics



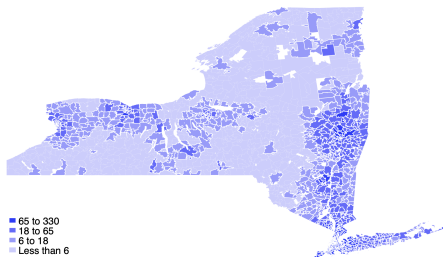
# EV Stock and Charging in New York in 2021

► Top 10 states

(a) EV Stock



(b) Chargers





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# Empirical Model Overview

▸ EV demand

▸ Station entry

## EV demand

$$\max_{j \in \{\mathcal{J}_{ev}, 0\}} u_{mij}(\mathbf{x}_j, \mathbf{z}_{mi}, \mathbf{k}_m)$$

**x**: product attributes

**z**: demographics

**k**: charging access

## Station entry

$$\pi_{mt}(\mathbf{w}_{mt}) \gtrless C_t - \delta C_{t+1}$$

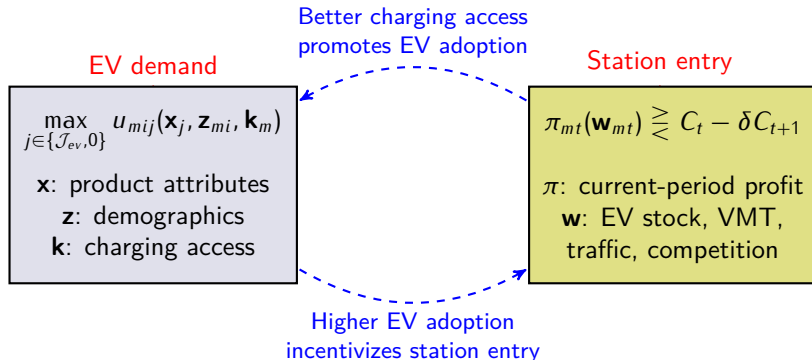
$\pi$ : current-period profit

**w**: EV stock, VMT,  
traffic, competition

# Empirical Model Overview

▸ EV demand

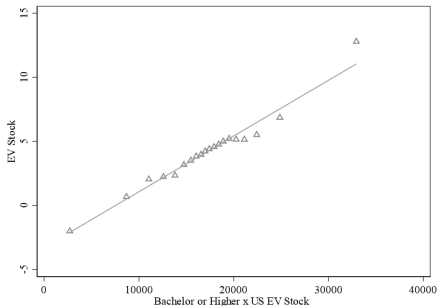
▸ Station entry



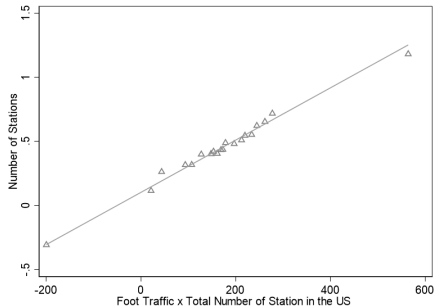
# Estimation Strategy

- GMM for EV demand and station entry
  - ▶ exclusion restrictions
  - ▶ Pop. share with college education in  $m \times$  national stock at  $t$
  - ▶ Foot traffic in  $m \times$  national stations at  $t$
  - ▶ Micro-moments: shares by income group among EV buyers, ...

(a) 1st-stage: residualized EV Stock<sub>mt</sub>



(b) 1st-stage: residualized station<sub>mt</sub>



# Estimation Results

- EV demand: ▶ parameter estimates
  - ▶ EV demand increases with charging station density
  - ▶ Average station elasticity: 0.88
  - ▶ Consumer preference heterogeneity based on observed (income, VMT) and unobserved demographics
  - ▶ Average price elasticity: -2.52
- Station entry: ▶ parameter estimates
  - ▶ Charging demand increases with foot traffic and decreases with distance
  - ▶ Demand for charging at level-3 stations is stronger than level-2
  - ▶ Average markup per kWh: 20 cents. Decreases with competition

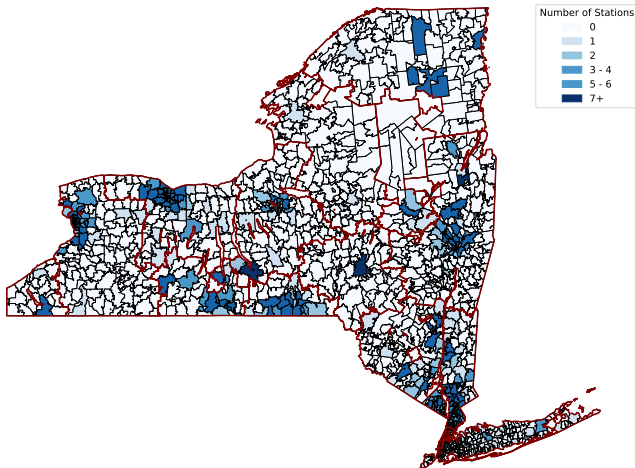
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# Simulation Setup

- Focus on level-3 stations and hold level-2 stations fixed
- Initialize the starting point at 2021 and simulate forward to 2026
- Assume certain cost-sharing ratio for the fixed cost
- Solve for investment decisions and EV sales for each commuting zone

▸ Key assumptions

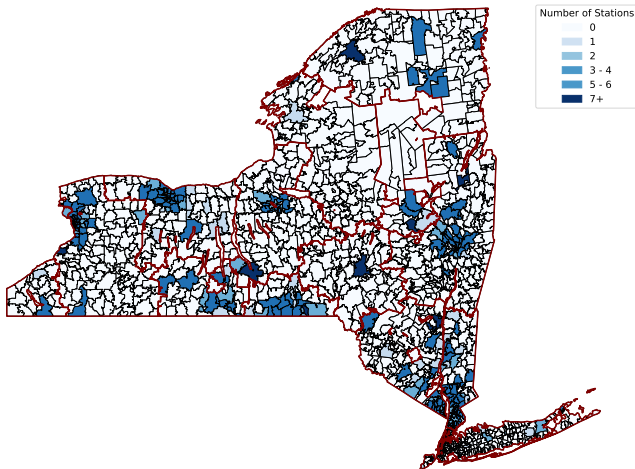
# No. of Level-3 Stations by 2026 at Baseline



- No subsidies for station entry. 1351 stations

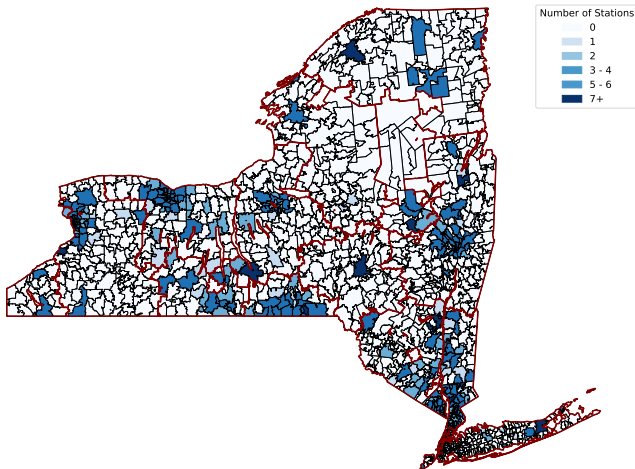


## No. of Level-3 Stations by 2026 with 30% Cost-sharing



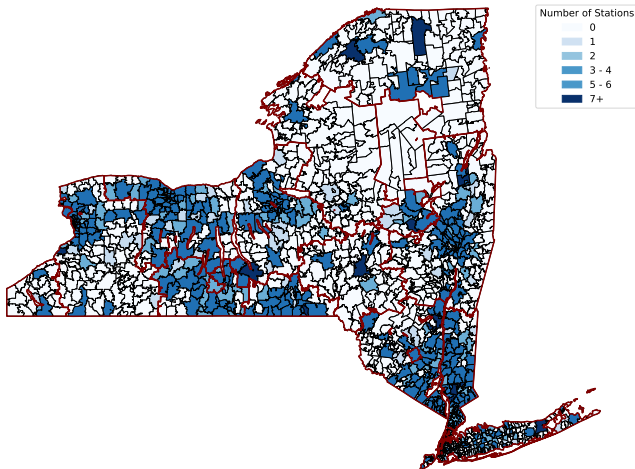
- Total subsidies (2012-2026): \$77 million. 1682 stations.

## No. of Level-3 Stations by 2026 with 50% Cost-sharing



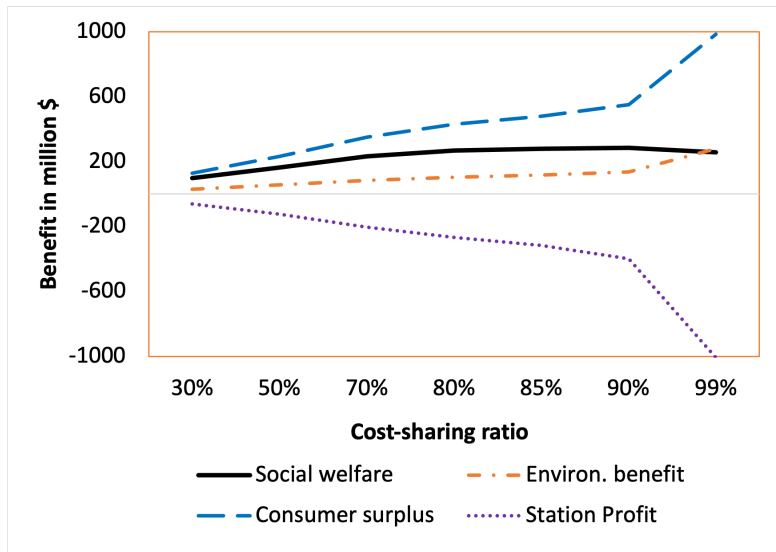
- Total subsidies (2012-2026): \$159 million. 2012 stations

## No. of Level-3 Stations by 2026 with 90% Cost-sharing

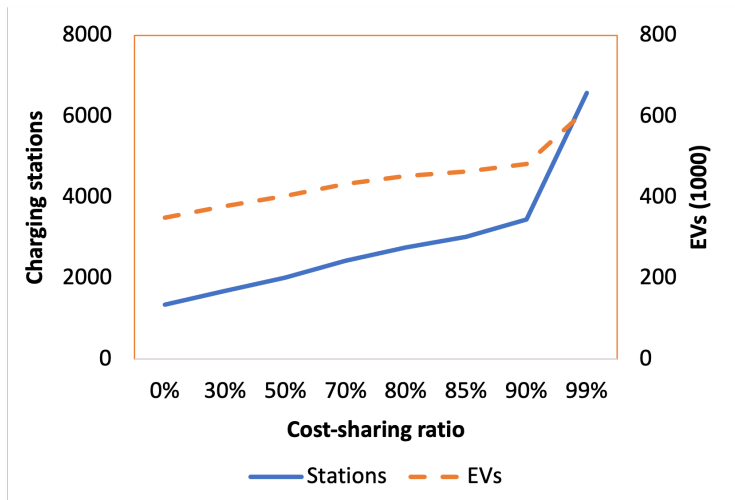


- Total subsidies (2012-2026): \$530 million. 3455 stations

# Welfare under Cost-sharing (relative to baseline)



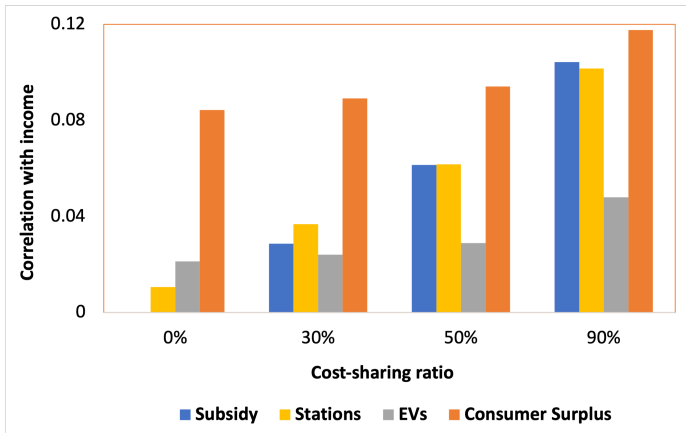
# EV Adoption and Charging Stations



# Impact Heterogeneity w.r.t. Income

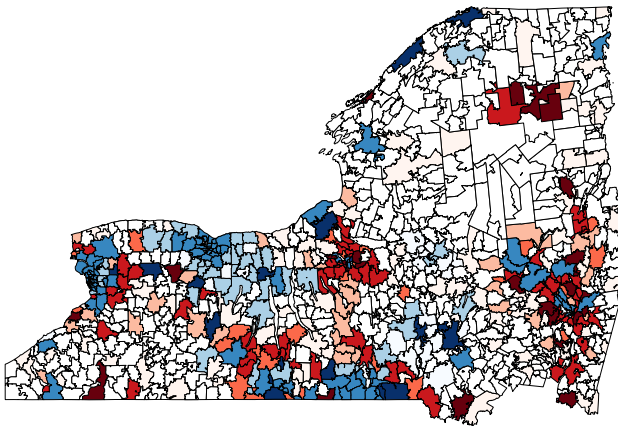
▸ Population size

- Correlation between zip-level income with outcomes



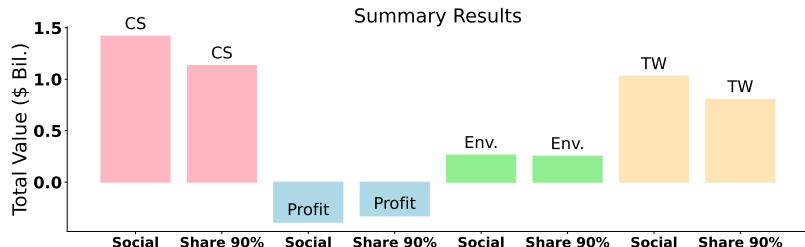
# Socially optimal vs. 90% cost-sharing

- No. of stations under socially optimal relative to 90% cost-sharing
- Warm color: under-subsidized areas; cool color: over-subsidized



# Socially optimal vs. 90% cost-sharing

- Better targeting leads to more stations, and higher consumer surplus
- Socially optimal network leads to a 30% increase in welfare





# Preliminary Findings

- \$175 million federal funding to NY during 2022-2026 can support about 50% cost-sharing. Increasing stations by 49% and EVs by 15%
- A higher cost-sharing appears justifiable. The cost-sharing ratio of 90%, or \$530 million during 2022-2026 for NY leads to the highest welfare
- Uniform subsidies benefit high-income areas more. More so for a higher cost-sharing
- Place-based vs. uniform cost-sharing. Lower subsidies for locations with stronger private incentives. Gains from targeted subsidies about 30%

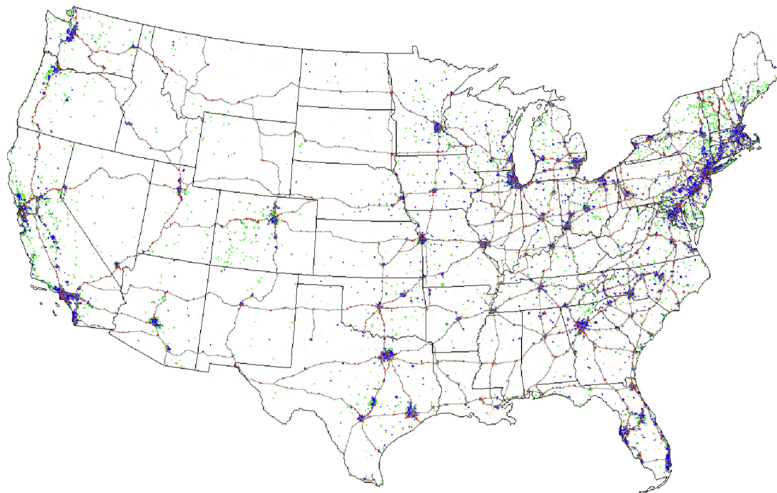
# Next Steps

- Allow long-distance trips
- Add road network and vehicle traffic in the analysis
- Distinguish facility types
- Expand the analysis to the whole U.S.
- Additional suggestions?

**THANKS FOR THE SUPPORT!**

# Charging Stations in 2022

[▶ Back to Map](#)

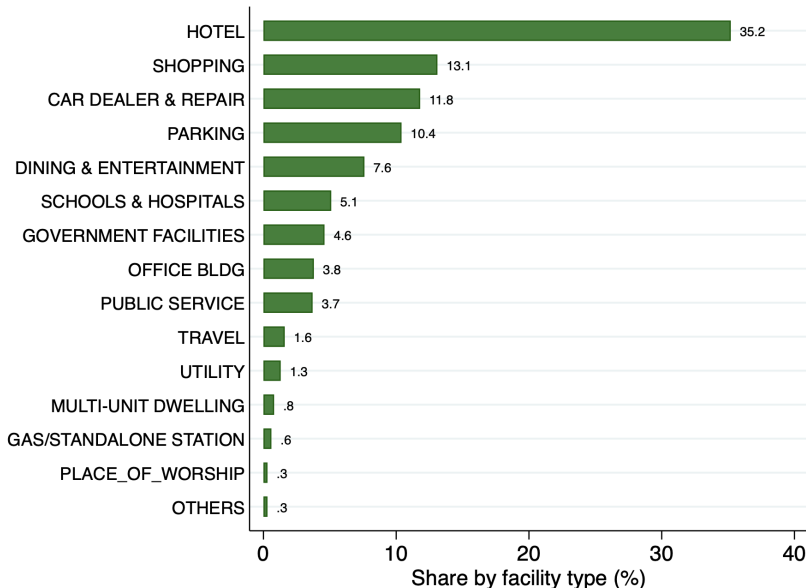


● Urban/suburban

● Rural/highway

● Interstate

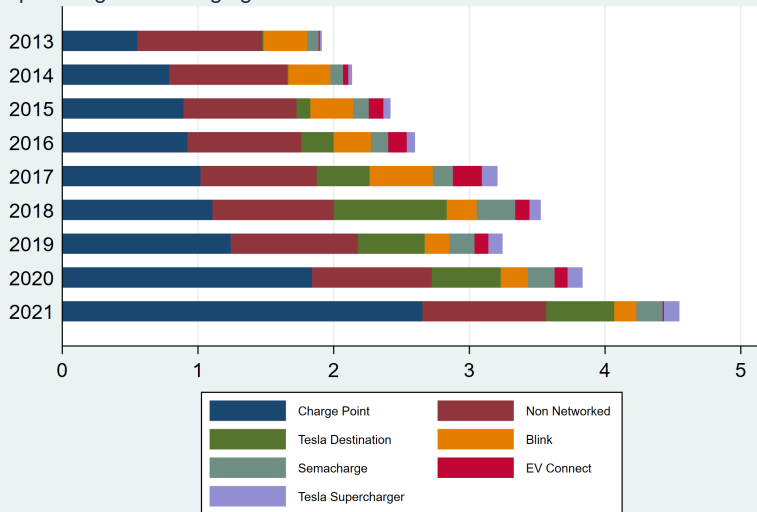
# Charging Facility Type in 2021

[▶ Back to Map](#)

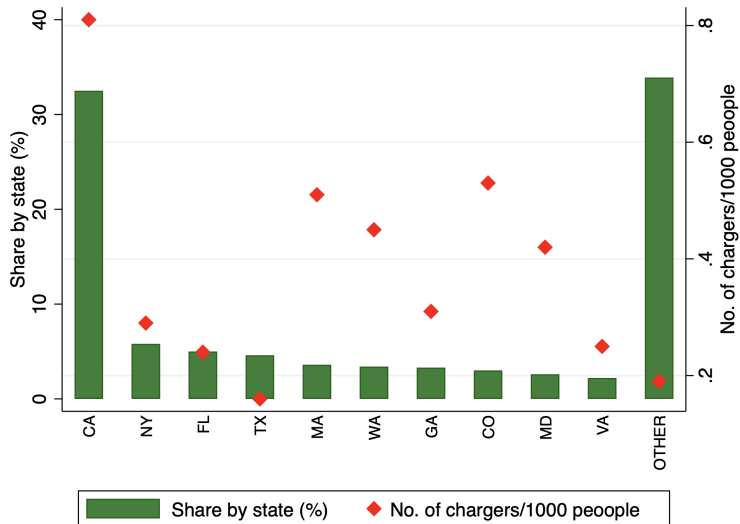
# Charging Network over Time

[▶ Back to Map](#)

Zip Average EV Charging Station Network over Year



# Charging Stations by State in 2021

[▶ Back](#)

- Consumers choose among a set of EV models and an outside good (e.g., a gasoline model) based on preferences and available choices
- Utility of consumer  $i$  from choice  $j$  in location  $m$

$$u_{ijm} = \alpha_i(p_j - s_{ij}) + x_j\beta_i + \gamma_i \sum_{l=1}^n \omega(z_l, d_{lm})k_l + \varepsilon_{ijm},$$

- $\alpha_i$ ,  $\beta_i$  and  $\gamma_i$ : heterogeneous consumer preference, f(income, VMT)

$$\alpha_i = -e^{\tilde{\alpha} + y_i\alpha_y^P + v_i^P\sigma^P}$$

$$\theta_i = \tilde{\theta} + y_i\theta_y + vmt_i\theta_{vmt} + v_i^\theta\sigma^\theta, \forall \theta \in \{\beta, \gamma\}$$

- $\sum_{l=1}^n \omega(z_l, d_{lm})k_l$  characterizes station density in a location.  $d_{lm}$ : distance;  $k_l$ : station count



- Free-entry condition: indifferent between entering at  $t$  and  $t + 1$  for type  $\tau$

$$\pi_m^\tau \begin{matrix} \geq \\ \leq \end{matrix} C_t^\tau - \delta C_{t+1}^\tau$$

- Period-profit function from providing charging and/or being an ancillary service:

$$\pi_m^\tau = q_m^\tau r_m^\tau + \varepsilon_{r_m}$$

- ▶  $q_m^\tau$ : total charging at a type- $\tau$  station in  $m$
- ▶  $r_m^\tau$  markup per kWh:  $\frac{\lambda_1}{1+\lambda_2 \bar{k}_m}, \bar{k}_m = \sum_{j=1}^n \frac{k_j}{d_{jm}+1}$

# Empirical Model: Charging Investment

- $q_m^\tau = \sum_{l=1}^n Q_l S_{lm}^\tau$ : charging at  $m$  come from many locations
  - ▶  $Q_l$  is total charging from EVs in  $l$
  - ▶  $S_{lm}^\tau$  is the share allocated to charging type  $\tau$  at  $m$

$$Q_l = \frac{vmt_l \times EVstock_l}{fuelefficiency_l}$$

$$S_{lm}^\tau = \frac{\exp[\psi^1 \times foot_l + \psi^2 \times d_{lm} + \psi^3 \log(\sum_{s \in T_m} \exp(\varphi_0^s + \varphi_1^s k_m^s))]}{\underbrace{\sum_{j=1}^n \exp[\psi^1 \times foot_j + \psi^2 \times d_{lj} + \psi^3 \log(\sum_{s \in T_j} \exp(\varphi_0^s + \varphi_1^s k_j^s))]}_{\text{Prob. of charging at } m}} \times \underbrace{\frac{\exp(\varphi_0^\tau + \varphi_1^\tau k_m^\tau)}{\sum_{s \in T_m} \exp(\varphi_0^s + \varphi_1^s k_m^s)}}_{\text{Prob. of charging at type } \tau} \times \underbrace{\frac{1}{k_m^\tau}}_{\text{Prob. of charging at a given station}}.$$

# Estimation Strategy: GMM

- Moment conditions for EV demand:
  - ▶ BLP IVs: of EV models, battery capacity, driving range, vehicle size
  - ▶ Micro-moments: shares by income group among EV buyers; shares of EV buyers by income group among new vehicle buyers; shares by VMT group among EV buyers
- Moment conditions for station entry:
  - ▶ Interaction of national EV stock with: (1) share of college degree or higher by zip, (2) foot traffic by zip, (3) foot traffic within 20 miles, (4) annual VMT per driver by zip
  - ▶ Interactions of foot traffic by zip with: (1) national stations, and (3) national L3 stations

▶ First stage

# Estimation Results: EV Demand

► Back

	Para.	S.E.
<b>Linear para.</b>		
Range	0.173	(0.042)
HP/Weight	-0.001	(0.010)
Vehicle Size	0.436	(0.136)
<b>Non-linear para.</b>		
Price ( $\bar{\alpha}$ )	5.252	(0.028)
Price*Income ( $\alpha_y^P$ )	-1.564	(0.004)
Station density	17.463	(0.128)
Station density*VMT	-0.127	(0.002)
<b>Random Coefs. (<math>\sigma</math>)</b>		
Price ( $\sigma^P$ )	3.330	(0.019)
Constant	9.338	(0.112)

$$\alpha_i = -e^{\bar{\alpha} + y_i \alpha_y^P + v_i^P \sigma^P}$$

Notes: unit of observation for the GMM objective function is model by commuting zone by year. Zone-year FEs, fuel type (BEV/PHEV) FEs, and Firm FEs included.

	Para.	S.E.
<b>Markup (in \$/kWh)</b>		
Constant ( $\lambda_1$ )	0.320	(0.012)
Competition effect ( $\lambda_2$ )	0.046	(0.003)
<b>Charging Location Choice</b>		
Foot traffic ( $\psi^1$ )	0.805	(0.030)
Distance ( $\psi^2$ )	-1.430	(0.081)
Expected Utility of Charging ( $\psi^3$ )	1.594	(0.055)
<b>Charging Type Choice</b>		
L3 Stations FE ( $\varphi_0$ )	1.065	(0.038)
Number of Stations ( $\varphi_1$ )	0.071	(0.004)

Notes: unit of observation is zip by year. Zip FEs included.

# Simulation Assumptions [▸ Back](#)

Parameters	Value	Notes
<b>Fixed costs</b>		
Level 2	\$20,000 (4 ports)	4% decline/yr
Level 3	\$200,000 (4 ports)	4% decline/yr
<b>Charging at home vs. outside</b>		
Charging at home	80%	
<b>Environmental benefit</b>		
Carbon and local pollutants	\$700-1974	

Note: the environmental benefit is the lifetime benefit of an average EV relative to a gasoline vehicle in NY. The lower bound is from “Benefit-Cost Analysis of Electric Vehicle Deployment in New York State,” NYSERDA (2019). The upper bound is based on author’s calculation. Results in the slides are based on the lower bound.

# Impact Heterogeneity w.r.t. Population Size

► Income

- Correlation between zip-level population size with outcomes

