Who Receives the Environmental Benefits from Driving Electric Vehicles?

Yucheng Wang
Cornell University
University of Sydney

NBER Distributional Consequences of New Energy Policies
Fall 2024

Motivation - Who Benefits from EVs?

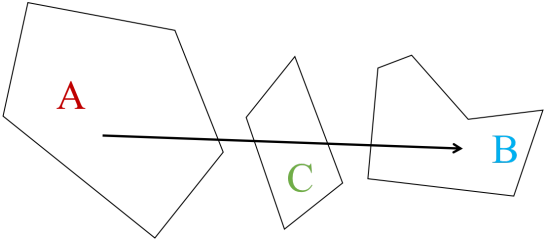
- EV can reduce local pollutants from on-road transportation: tailpipe emissions $\downarrow$.

Motivation - Who Benefits from EVs?

- EV can reduce local pollutants from on-road transportation: tailpipe emissions $\downarrow$.
- Equity and Environmental justice concern: Do EV adoption and policies mostly benefit the rich?
  - Higher-income and less polluted neighborhoods adopt more EVs (Jacqz and Johnston, 2024); top income quintile received about 80% of all EV credits (Borenstein and Davis, 2024).

Motivation - Who Benefits from EVs?

- EV can reduce local pollutants from on-road transportation: tailpipe emissions $\downarrow$.
- Equity and Environmental justice concern: Do EV adoption and policies mostly benefit the rich?
    - Higher-income and less polluted neighborhoods adopt more EVs (Jacqz and Johnston, 2024); top income quintile received about 80% of all EV credits (Borenstein and Davis, 2024).
- New perspective: Who owns EVs $\neq$ Who receives the benefits.
    - Vehicles move $\rightarrow$ spatial spillover effects.



Research Questions and Preview

- Question 1: How to measure very localized EV environmental benefits?
  - Real-time EV route data is difficult to access.

Research Questions and Preview

- Question 1: How to measure very localized EV environmental benefits?
  - Real-time EV route data is difficult to access.
  - This paper provides a model-based approach: demand model + simulated routes.

Research Questions and Preview

- Question 1: How to measure very localized EV environmental benefits?
  - Real-time EV route data is difficult to access.
  - This paper provides a model-based approach: demand model + simulated routes.

- Question 2: How are the environmental benefits from EV driving spatially distributed in CA?

Research Questions and Preview

- Question 1: How to measure very localized EV environmental benefits?
  - Real-time EV route data is difficult to access.
  - This paper provides a model-based approach: demand model + simulated routes.

- Question 2: How are the environmental benefits from EV driving spatially distributed in CA?
  - Higher-income communities benefit more.
  - However, positive spillover effects to lower-income communities.

Research Questions and Preview

- Question 1: How to measure very localized EV environmental benefits?
  - Real-time EV route data is difficult to access.
  - This paper provides a model-based approach: demand model + simulated routes.
- Question 2: How are the environmental benefits from EV driving spatially distributed in CA?
  - Higher-income communities benefit more.
  - However, positive spillover effects to lower-income communities.
- Question 3: Do investments in public charging infrastructure work better than purchase subsidies?

Research Questions and Preview

- Question 1: How to measure very localized EV environmental benefits?
  - Real-time EV route data is difficult to access.
  - This paper provides a model-based approach: demand model + simulated routes.

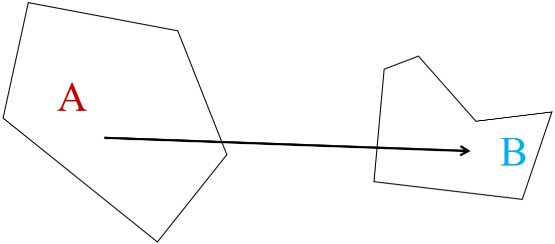
- Question 2: How are the environmental benefits from EV driving spatially distributed in CA?
  - Higher-income communities benefit more.
  - However, positive spillover effects to lower-income communities.

- Question 3: Do investments in public charging infrastructure work better than purchase subsidies?
  - More cost-effectively in generating environmental benefits; More equitable.

Empirical Methods and Data

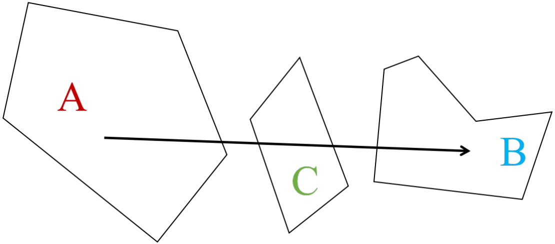
Intuition of the Method

- **Consider pollution from trip A to B:**



Intuition of the Method

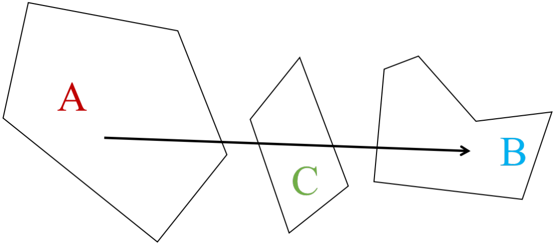
- **Consider pollution from trip A to B:**



1. Route AB: Spillover to C

Intuition of the Method

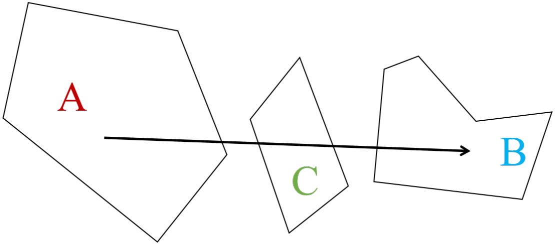
- **Consider pollution from trip A to B:**



1. Route AB: Spillover to C
2. Which vehicle to drive, EV or non-EV?

Intuition of the Method

- **Consider pollution from trip A to B:**

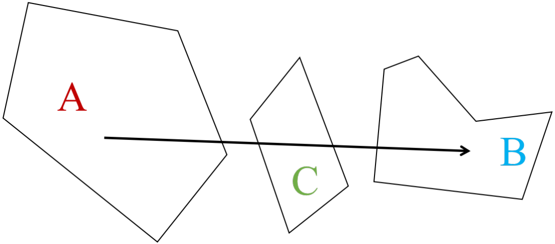


1. Use Google Map to determine the most common routes.

2. Which vehicle to drive, EV or non-EV?

Intuition of the Method

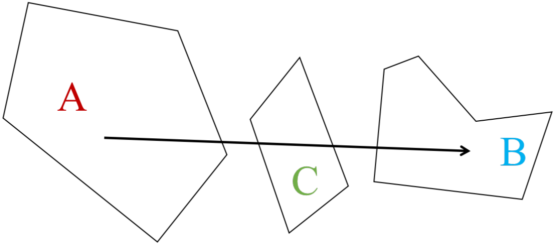
- **Consider pollution from trip A to B:**



1. Use Google Map to determine the most common routes.
2. $Pr(EV_{AB}^{Driving})$.

Intuition of the Method

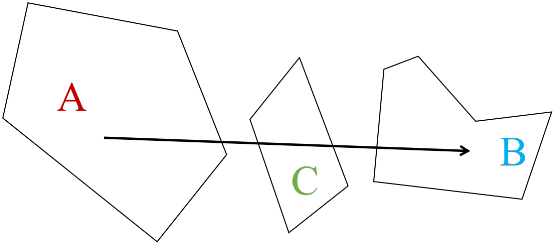
- **Consider pollution from trip A to B:**



1. Use Google Map to determine the most common routes.
2. $Pr(EV_{AB}^{Driving})$.
   - $Pr(EV_A)$: Adoption
   - $Pr(EV_{AB}^{Driving} \mid EV_A)$: Usage

Intuition of the Method

- **Consider pollution from trip A to B:**



1. Use Google Map to determine the most common routes.
2. $Pr(EV_{AB}^{Driving})$.
   - $Pr(EV_A)$: Adoption
   - $Pr(EV_{AB}^{Driving} \mid EV_A)$: Usage

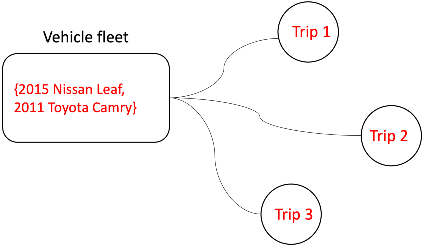
Intuition of the Method

3. A Nested and Sequential Demand Model: back out and combine the two probabilities. ▸ Model Structure

Intuition of the Method

3. A Nested and Sequential Demand Model: back out and combine the two probabilities. ▸ Model Structure

  - $Pr(EV_{AB}^{Driving} \mid EV_A)$:
    e.g. {Toyota Camry, Nissan Leaf},
    which one to drive?

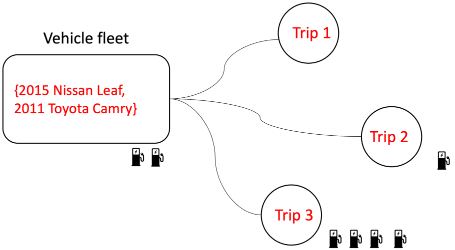


Multiple Choice +
Random Coefficient Logit (BLP)

Intuition of the Method

3. A Nested and Sequential Demand Model: back out and combine the two probabilities. ▸ Model Structure

- $Pr(EV_{AB}^{Driving} \mid EV_A)$ is a function of:
  $Nstation^A$, $Nstation^B$.

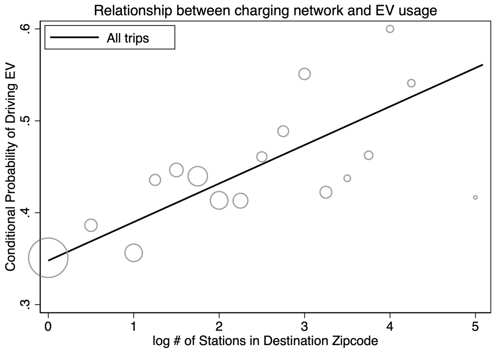


Multiple Choice +
Random Coefficient Logit (BLP)

Intuition of the Method

3. A Nested and Sequential Demand Model: back out and combine the two probabilities. ▸ Model Structure

- $Pr(EV^{Driving}_{AB} \mid EV_A)$ is a function of: $Nstation^A$, $Nstation^B$.

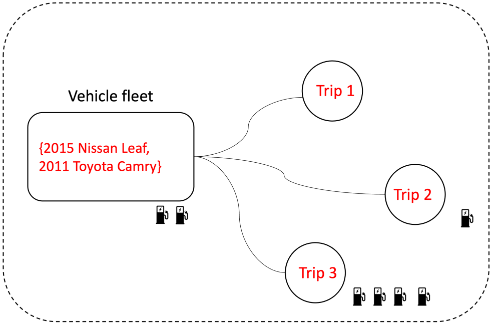


Intuition of the Method

3. A Nested and Sequential Demand Model: back out and combine the two probabilities. ▸ Model Structure

 - $Pr(EV_{AB}^{Driving} \mid EV_A)$ is a function of: $Nstation^A$, $Nstation^B$.

   $\Rightarrow$ Inclusive value



Multiple Choice +
Random Coefficient Logit (BLP)

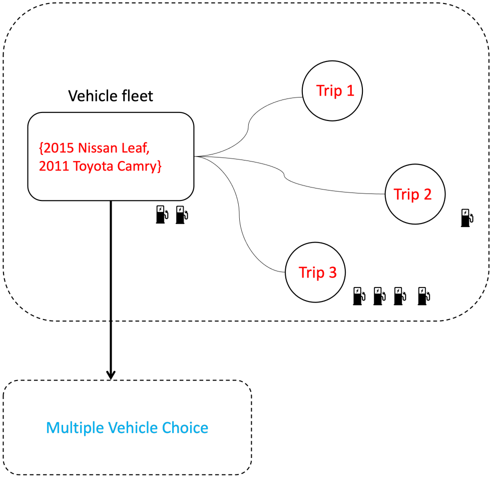
Intuition of the Method

3. A Nested and Sequential Demand Model: back out and combine the two probabilities. ▸ Model Structure

- $Pr(EV_{AB}^{Driving} \mid EV_A)$ is a function of:
  $Nstation^A$, $Nstation^B$.

  $\Rightarrow$ Inclusive value

- $Pr(EV_A)$ is a function of:
  $\underbrace{Pr(EV_{AB}^{Driving} \mid EV_A)}_{\text{Inclusive value}}$, $Subsidies$.



Intuition of the Method

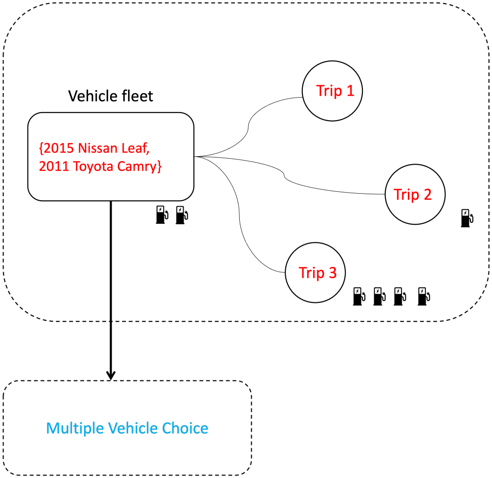
3. A Nested and Sequential Demand Model: back out and combine the two probabilities. ▸ Model Structure

- $Pr(EV_{AB}^{Driving} \mid EV_A)$ is a function of: $Nstation^A$, $Nstation^B$.

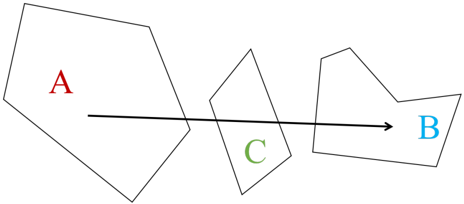
  $\Rightarrow$ Inclusive value

- $Pr(EV_A)$ is a function of: $\underbrace{Pr(EV_{AB}^{Driving} \mid EV_A)}_{\text{Inclusive value}}$, $Subsidies$.

- Intuition: more likely to adopt EV if expect to use it more.



Intuition of the Method

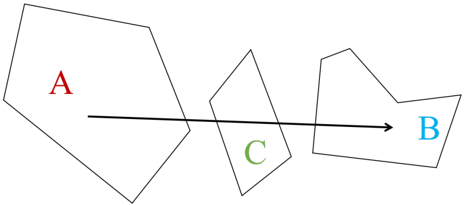


4. The role of policies.

- $Pr(EV_{AB}^{Driving}) \quad = \quad Pr(EV_A) \quad \cdot \quad Pr(EV_{AB}^{Driving} \mid EV_A)$

  is a function of: $Subsidies, Nstation^A$, $Nstation^B$.

Intuition of the Method



4. The role of policies.

- $Pr(EV_{AB}^{Driving}) \quad = \quad Pr(EV_A) \quad \cdot \quad Pr(EV_{AB}^{Driving} \mid EV_A)$

  is a function of: $\underbrace{Subsidies, Nstation^A}_{\text{Conventional framework}}, \underbrace{Nstation^B}_{\text{New!}}$.

Data

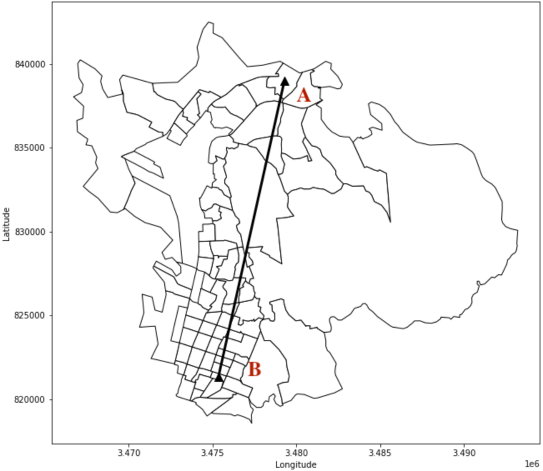
- **Individual data on EV adoption and usage behaviors in CA.**
  - 2017 National Household Travel Survey + Spatial data supplementary.
  - Vehicle Portfolio (vehicles to own)
  - Trip diary (which vehicle to drive for a specific trip).

Data

- **Individual data on EV adoption and usage behaviors in CA.**
  - 2017 National Household Travel Survey + Spatial data supplementary.
  - Vehicle Portfolio (vehicles to own)
  - Trip diary (which vehicle to drive for a specific trip).
- **Aggregate data on the automobile market in CA.**
  - Quarterly, MSA level new vehicle sales from 2016 to 2019, from IHS Automotive. (market-share data)
  - Vehicle attributes from Wards Automotive and manually collected from EPA.

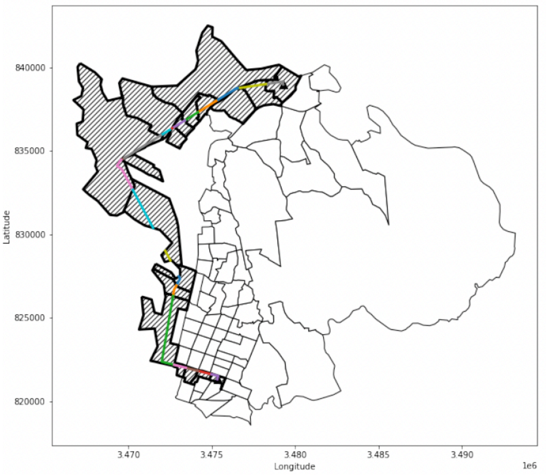
Spatial Distribution of Environmental Benefits

Environmental Benefits of A Single Trip



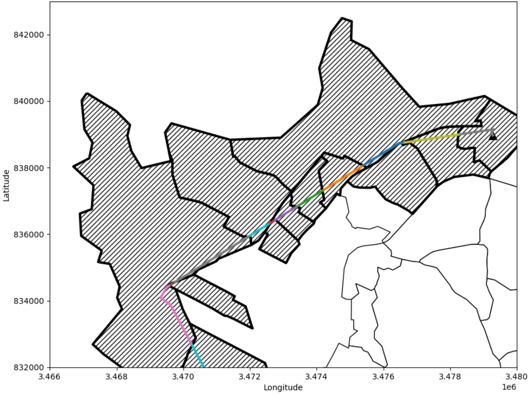
- **Model:** $\hat{P}r(EV_{AB}^{Driving})$.

Environmental Benefits of A Single Trip



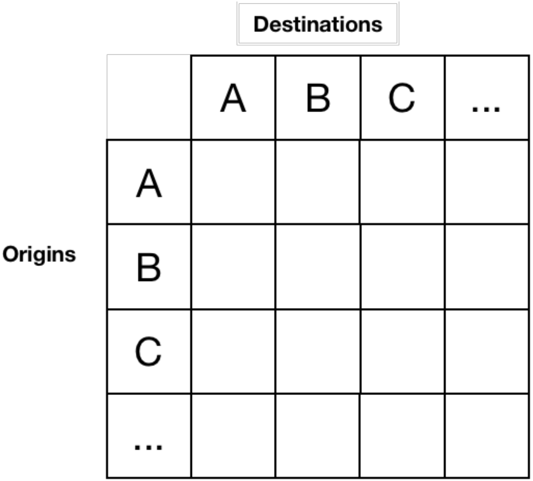
- **Model:** $\hat{P}r(EV_{AB}^{Driving})$.
- **Google Map**: Route AB.

Environmental Benefits of A Single Trip



- **Model:** $\hat{Pr}(EV_{AB}^{Driving})$.
- **Google Map**: Route AB.
- **Overlap with specific areas**: EV mileage = length of overlaid road segment.

Total Environmental Benefits



- **Simulation**:
  - Millions of routes from commuting matrix based on *Census Transportation Planning Products*.

Total Environmental Benefits

Destinations

Origins

	A	B	C	...
A				
B				
C				
...				

- **Simulation**:
  - Millions of routes from commuting matrix based on *Census Transportation Planning Products*.
- **Aggregation**:
  - Total EV mileage traveling through census tract.

Total Environmental Benefits

Destinations

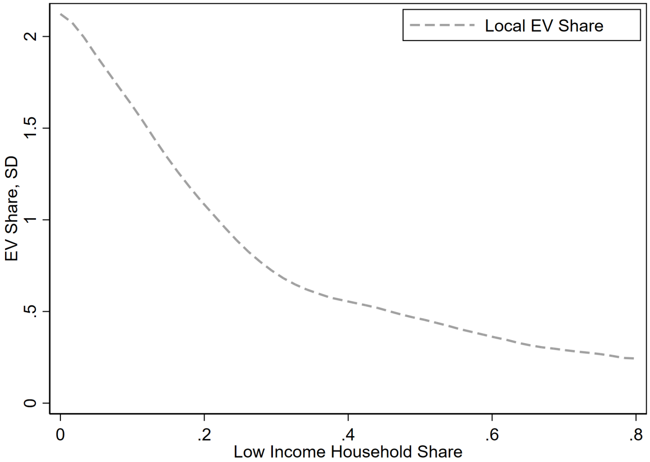
Origins	A	B	C	...
A				
B				
C				
...				

- **Simulation**:
  - Millions of routes from commuting matrix based on *Census Transportation Planning Products*.
- **Aggregation**:
  - Total EV mileage traveling through census tract.
- **Assumption**:
  - $EB_c = \rho \cdot \text{Total EV mileage}_c$

Inequality of Environmental Benefits across Census Tract

- Estimate the relationship between census tract-level low-income share and: (1) EV share; (2) Model-based EB measures.
  - Slope $\Longrightarrow$ Inequality

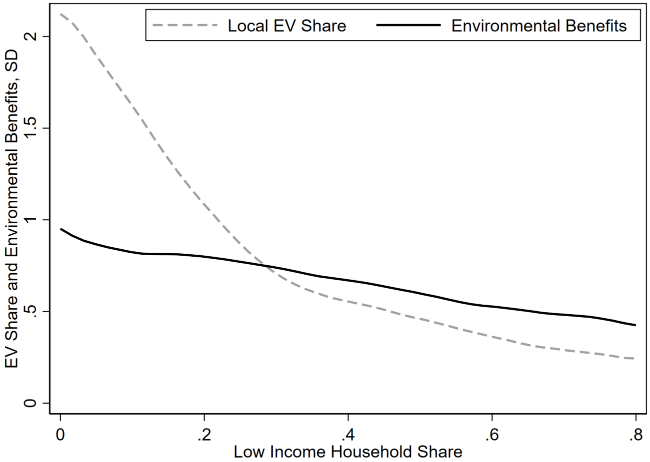
Inequality of Environmental Benefits across Census Tract



- Slope $\Longrightarrow$ Inequality
- Local EV share:
  Higher-income communities buy more EVs (Jacqz and Johnston, 2024).

▸ Spatial Distribution

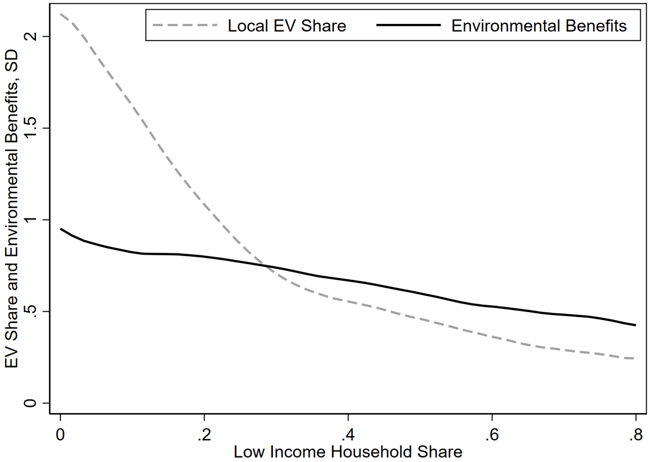
Inequality of Environmental Benefits across Census Tract



- Slope $\Longrightarrow$ Inequality
- Model-based environmental benefits:
  Positive environmental spillover

▸ Spatial Distribution

Inequality of Environmental Benefits across Census Tract



▸ Spatial Distribution

- Slope $\Longrightarrow$ Inequality
- Model-based environmental benefits:
  Positive environmental spillover
- Key results:
  The wealthiest 20% of zipcodes receive 30% of the environmental benefits but purchase 60% of the electric vehicles.

Counterfactual Experiments

- Question: What would have happened if purchase subsidies were invested in charging infrastructure?

Counterfactual Experiments

- Question: What would have happened if purchase subsidies were invested in charging infrastructure?
  - Step 1: Remove federal and local purchase subsidies. ▸ EV subsidy by group
  - Step 2: Use the same financial expenditure to fund new charging stations.
- Scenarios:
  - Scenarios 1: Deploy evenly across space.
  - Scenarios 2: Deploy based on population density.
  - Scenarios 3: Deploy disproportionately (50%) to disadvantaged communities (DAC).

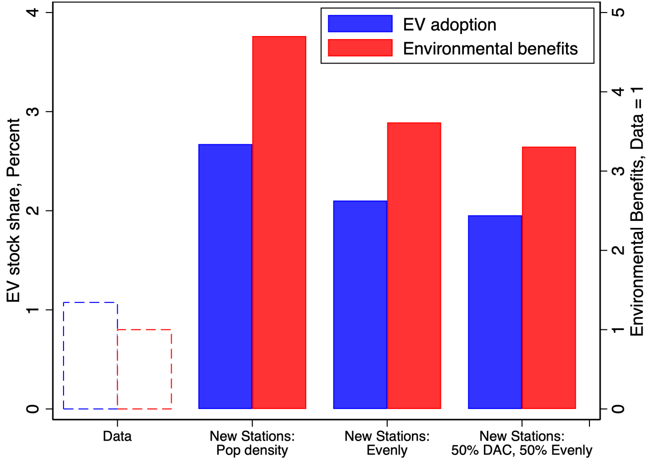
▸ Intuition: Subsidy ▸ Intuition: Station ▸ Charging infrastructure ▸ Counterfactual Algorithm

Counterfactual Outcomes - Efficiency

- Environmental benefits: $Pr(EV^{Driving}) = \underbrace{Pr(EV)}_{\text{adoption}} \cdot \underbrace{Pr(EV^{Driving} \mid EV)}_{\text{usage}}$

Counterfactual Outcomes - Efficiency

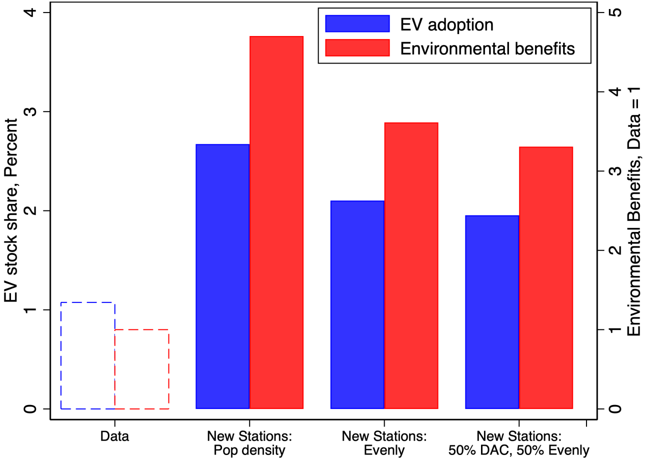
- Environmental benefits: $Pr(EV^{Driving}) = \underbrace{Pr(EV)}_{\text{adoption}} \cdot \underbrace{Pr(EV^{Driving} \mid EV)}_{\text{usage}}$



- Add charging stations outperform purchase subsidies.

Counterfactual Outcomes - Efficiency

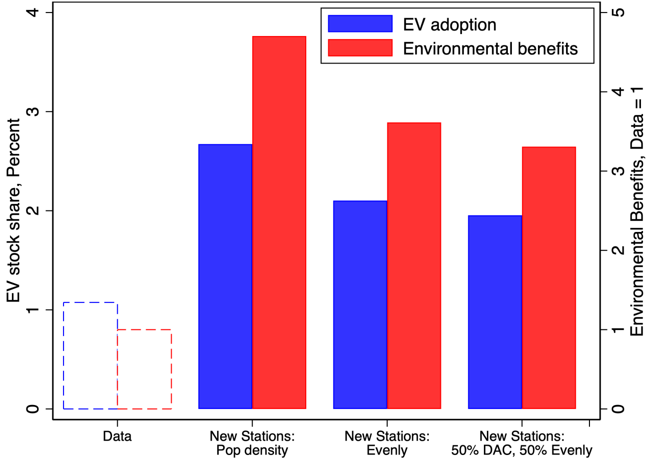
- Environmental benefits: $Pr(EV^{Driving}) = \underbrace{Pr(EV)}_{\text{adoption}} \cdot \underbrace{Pr(EV^{Driving} \mid EV)}_{\text{usage}}$



- Add charging stations outperform purchase subsidies.
- Deploying based on Pop density is the most efficient.

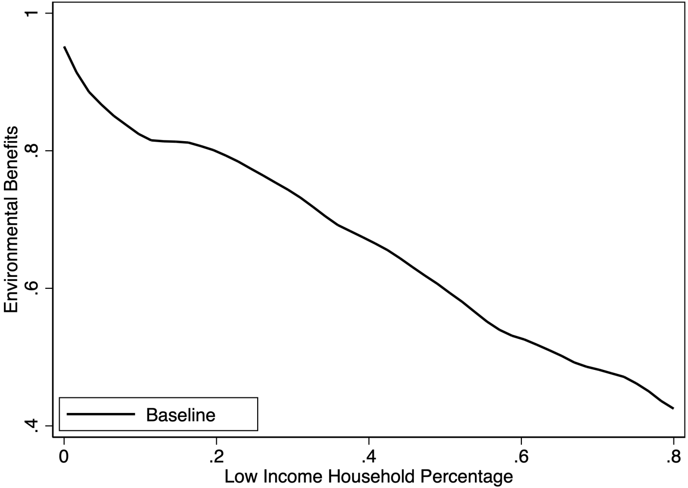
Counterfactual Outcomes - Efficiency

- Environmental benefits: $Pr(EV^{Driving}) = \underbrace{Pr(EV)}_{\text{adoption}} \cdot \underbrace{Pr(EV^{Driving} \mid EV)}_{\text{usage}}$



- Add charging stations outperform purchase subsidies.
- Deploying based on Pop density is the most efficient.
- Larger effects on environmental benefits.

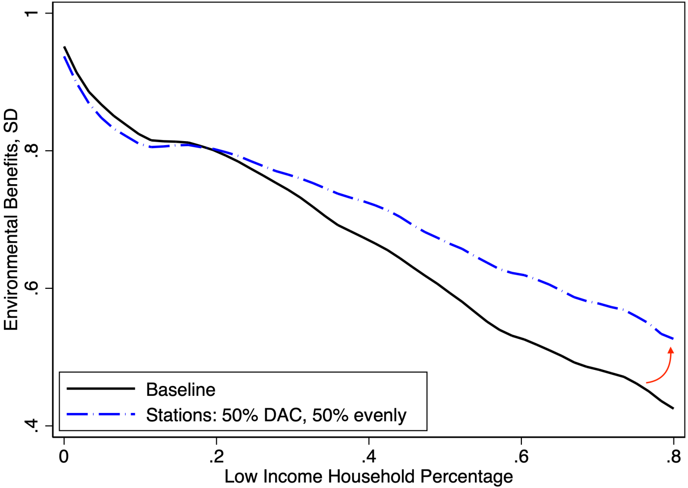
Counterfactual Outcomes - Inequality



- Slope $\Longrightarrow$ Inequality

▸ Charging infrastructure

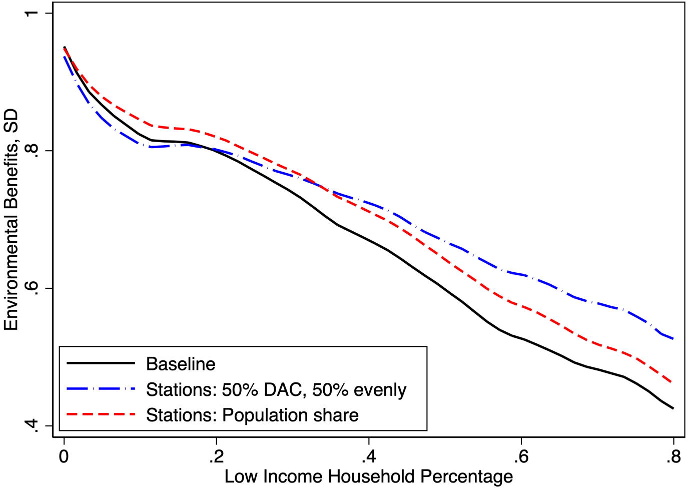
Counterfactual Outcomes - Inequality



- Slope $\Longrightarrow$ Inequality
- New charging stations targeting to DAC reduce the slope by nearly 1/3.

▸ Charging infrastructure

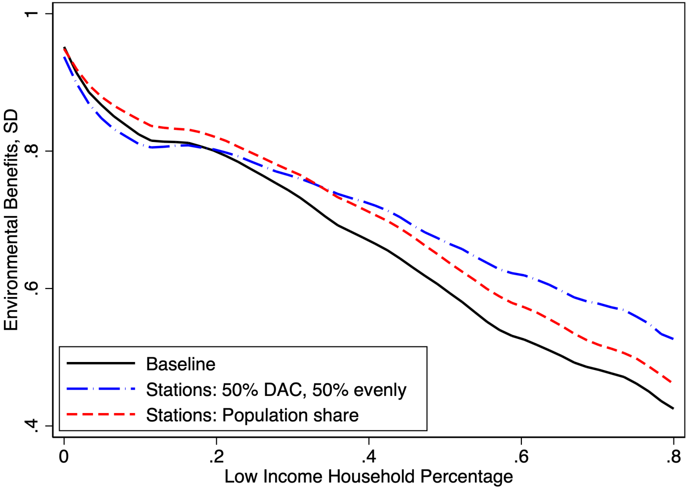
Counterfactual Outcomes - Inequality



- Slope $\Longrightarrow$ Inequality
- New charging stations targeting to DAC reduce the slope by nearly 1/3.

▸ Charging infrastructure

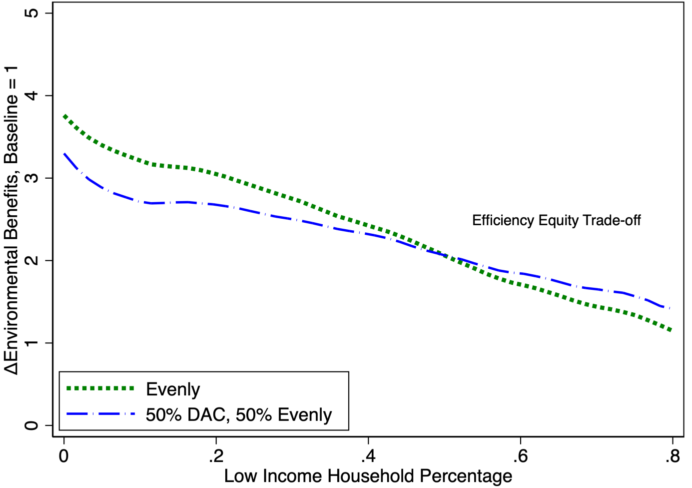
Counterfactual Outcomes - Inequality



- Slope $\Longrightarrow$ Inequality
- New charging stations targeting to DAC reduce the slope by nearly 1/3.
- Charging station policies could be more equitable.

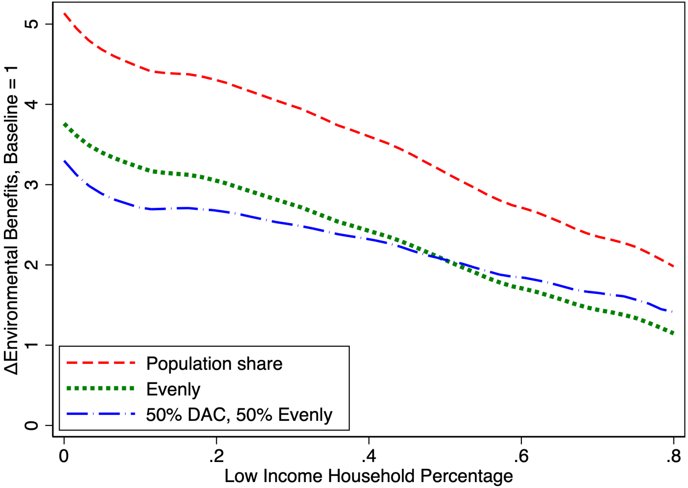
Charging infrastructure

Counterfactual Station Policies - Efficiency Equity Trade-off



- Slope $\Longrightarrow$ Inequality
  Level $\Longrightarrow$ Efficiency
- Comparison 1: Trade-off

Counterfactual Station Policies - Efficiency Equity Trade-off



- Slope $\Longrightarrow$ Inequality
  Level $\Longrightarrow$ Efficiency
- Comparison 1: Trade-off
- Comparison 2: no Trade-off

Decompose Effects of New Station Policies

- A simple framework: for environmental benefits in DAC.

$$
\begin{aligned}
EB_{DAC} &= EB_{O \in DAC} + EB_{O \notin nonDAC} \\
&= Pr(EV_{O \in DAC}) \cdot Pr(EV^{Driving}_{O \in DAC} \mid EV) + Pr(EV_{O \notin DAC}) \cdot Pr(EV^{Driving}_{O \notin DAC} \mid EV)
\end{aligned}
$$

Decompose Effects of New Station Policies

- A simple framework: for environmental benefits in DAC.

$$
\begin{aligned}
EB_{DAC} &= EB_{O \in DAC} + EB_{O \notin nonDAC} \\
&= Pr(EV_{O \in DAC}) \cdot Pr(EV^{Driving}_{O \in DAC} \mid EV) + Pr(EV_{O \notin DAC}) \cdot Pr(EV^{Driving}_{O \notin DAC} \mid EV)
\end{aligned}
$$

- Decomposition

	DAC	Non-DAC	Relative to Baseline
	Panel A: by Trip Origin		
Origin from	45.9%	54.1%	3.3

Decompose Effects of New Station Policies

- A simple framework: for environmental benefits in DAC.

$$\begin{aligned} EB_{DAC} &= EB_{O\in DAC} + EB_{O\notin nonDAC} \\ &= Pr(EV_{O\in DAC}) \cdot Pr(EV^{Driving}_{O\in DAC} \mid EV) + Pr(EV_{O\notin DAC}) \cdot Pr(EV^{Driving}_{O\notin DAC} \mid EV) \end{aligned}$$

- Decomposition

	DAC	Non-DAC	Relative to Baseline
	Panel A: by Trip Origin		
Origin from	45.9%	54.1%	3.3

Decompose Effects of New Station Policies

- A simple framework: for environmental benefits in DAC.

$$
\begin{aligned}
EB_{DAC} &= EB_{O \in DAC} + EB_{O \notin nonDAC} \\
&= Pr(EV_{O \in DAC}) \cdot Pr(EV^{Driving}_{O \in DAC} \mid EV) + Pr(EV_{O \notin DAC}) \cdot Pr(EV^{Driving}_{O \notin DAC} \mid EV)
\end{aligned}
$$

- Decomposition

	DAC	Non-DAC	Relative to Baseline
	Panel A: by Trip Origin		
Origin from	45.9%	54.1%	3.3
	Panel B: by Adoption and Usage		
$Pr(EV)$	68.9%	26.3%	
$Pr(EV^{Driving} \mid EV)$	31.1%	73.7%	
Total	100.0%	100.0%	

Conclusion

Conclusion

- **Key results:**
  - Spatial spillover effects could make EV policies less regressive.
  - Public funding might go further if invested in charging infrastructure than in purchase subsidies.

Conclusion

- **Key results:**
  - Spatial spillover effects could make EV policies less regressive.
  - Public funding might go further if invested in charging infrastructure than in purchase subsidies.

- **A new method:** Structural model + transportation big data.
  $\Longrightarrow$ Extrapolate unobserved route data.

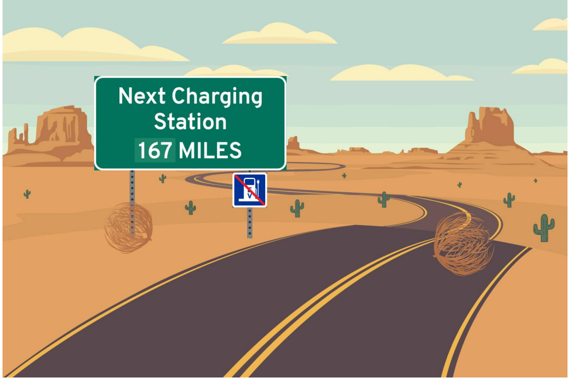
Conclusion

- **Key results:**
  - Spatial spillover effects could make EV policies less regressive.
  - Public funding might go further if invested in charging infrastructure than in purchase subsidies.

- **A new method:** Structural model + transportation big data.
  $\Longrightarrow$ Extrapolate unobserved route data.

- **A new perspective:** Who receives the environmental benefits $\neq$ Who adopts EV.
  $\Longrightarrow$ Add spatial dimension to the EV literature.

- Thank you!



Model Results

- A 10% expansion in charging network:

  $\Longrightarrow \uparrow$ the probability of driving EV by 3.8%;
  $\Longrightarrow \uparrow$ the benefits of "having an EV" by 3.5%;
  $\Longrightarrow \uparrow$ EV stocks by 5%.

- Heterogeneity in price elasticity of demand;

  Average elasticity $\approx$ -3; Consistent with previous studies.

- Consumer surplus.

  Lifetime (10-15 years) value from driving is about $32441.

- Model fit: model predicts well the **magnitude** and **heterogeneity** of EV adoption.

▸ Model Fit - Income ▸ Model Fit - Racial ▸ Model Fit - CBSA ▸ Model Fit - Out Sample

A Nested and Sequential Demand Model

- Stage 1: Vehicle Portfolio ▸ Evidence

  $\{\emptyset\}, \{EV\}, \{ICE\}, \{EV, ICE\}, \{ICE, ICE\}, \{EV, ICE, ICE\}, \{ICE, ICE, ICE\}$.

  Model yields: $Pr_i(EV_A)$.

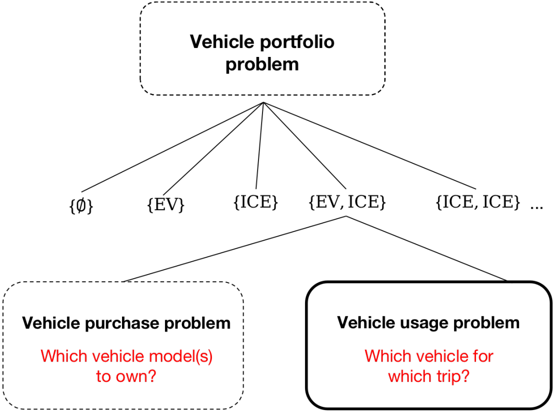
- Stage 2: Vehicle Purchase

  e.g. {Nissan Leaf, Toyota Camry} or {Tesla Model 3, Chevrolet Equinox}?

- Stage 3: Vehicle Usage ▸ Evidence

  e.g. {Nissan Leaf, Toyota Camry}, which one to drive?

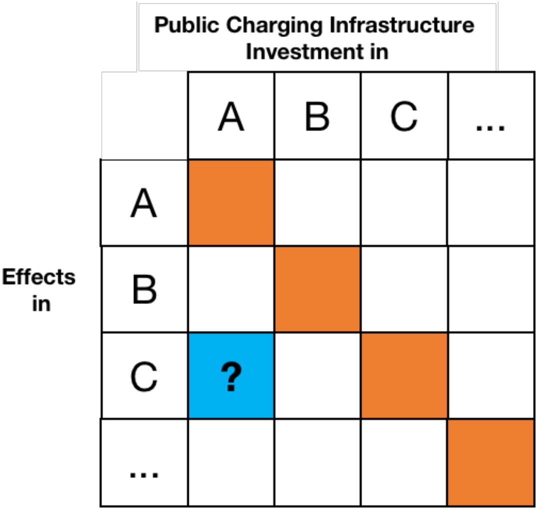
  Model yields: $Pr_i(EV_{AB}^{Driving} \mid EV_A)$.



▸ Intuition ▸ Solving Model S2&3 ▸ Solving Model S1

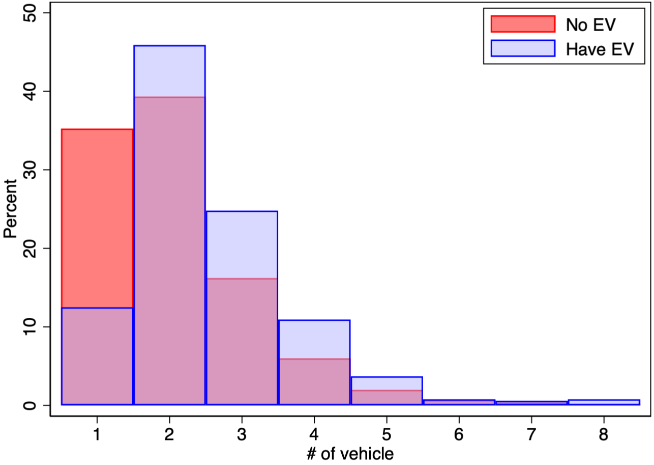
Challenge

- **If we want to simulate the effect of public charging stations:**



- Too many parameters to be estimated...
- Existing literature assumes zero off-diagonal elements.
- I explicitly model the EV usage problem as a function of spatial charging networks.

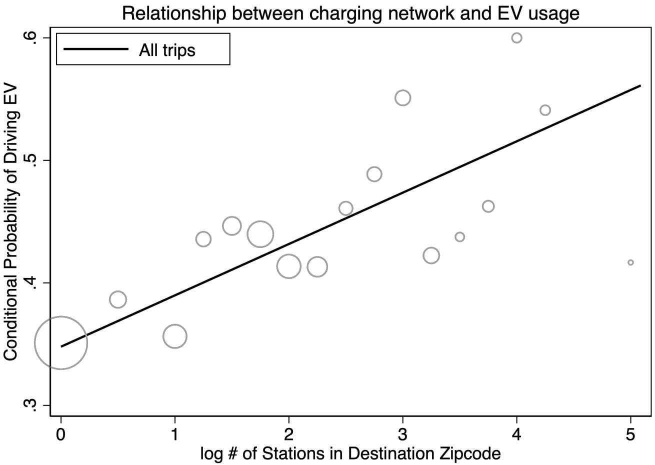
Evidence - It Is Important to Model Multiple Vehicles



- 89% (65%) of EV (non-EV) households have more than one vehicle.
- Implications:
  EVs are less likely to serve as the first and only vehicle.

Model Structure

Evidence - Public Charging Accessibility Promotes EV Usage



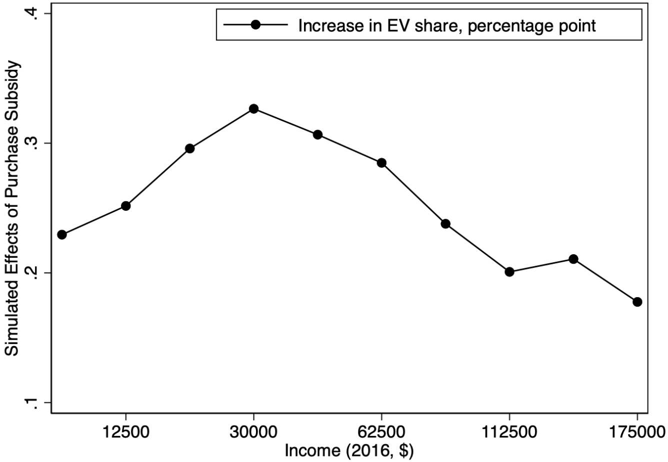
- The probability of EV usage increases with the number of public chargers available at the destination.

- Implications:
  The probability of driving is a function of charging networks.

▸ Model Structure

Simulated Effects of EV Purchase Subsidies by Income Group

- Difference between: data and No purchase subsidies scenarios.



- Subsidies are most effective for middle-income households.
- Implications:

  HHs buy an EV if:

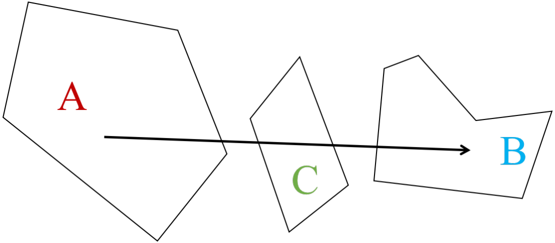
  (1) Have one ICE, want to buy the second vehicle.

  (2) Have two ICEs, want to replace one.

  Why a multiple-vehicle model.

▸ Counterfactual Scenarios ▸ Decompose Choice Probability

Intuition - Purchase Subsidy



- **Purchase subsidy.**
  - e.g. EV purchasing subsidy in area A
  - *"Direct" effect*:

$\Longrightarrow$ 1. EV cheaper in A;

$\Longrightarrow$ 2. EV adoption in A $\uparrow$;

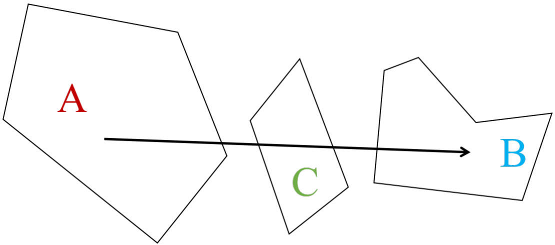
$\Longrightarrow$ 3. $Pr(EV_A) \uparrow$;

$\Longrightarrow$ 4. $Pr(EV_{AB}^{Driving}) \uparrow$;

$\Longrightarrow$ 5. EB $\uparrow$ in A,B,C;

▸ Counterfactual Scenarios

Intuition - Station Policy



- **Charging Infrastructure.**
  - e.g. investing in charging infrastructure in area B
  - *"Indirect" effect*:

    $\Longrightarrow$ 1. More EV usage in route A,B;

    $\Longrightarrow$ 2. $Pr(EV_{AB}^{Driving} \mid EV_A) \uparrow$;

    $\Longrightarrow$ 3. EV usage value in A $\uparrow$;

    $\Longrightarrow$ 4. $Pr(EV_{AB}^{Driving}) \uparrow$;

    $\Longrightarrow$ 5. EB $\uparrow$ in A,B,C;

▸ Counterfactual Scenarios

Literature

1. Environmental benefits of EV (Graff-Zivin et al., 2014; Holland et al., 2016; 2019; Nehiba, 2024): This study focuses on
   - (1) Emission from driving instead of electricity grid;
   - (2) Local pollutant instead of Greenhouse Gas;
   - (3) Higher geo-resolution.

2. EV literature with industrial organization framework (Beresteanu and Li, 2011; Li et al., 2017; Springer, 2021, Muehlegger and Rapson, 2023; Shaldon, 2022): This study extends the demand-side analysis by
   - (1) Multiple Vehicles and more realistic substitution patterns.
   - (2) Spatial Dimension.
   - (3) Studying the effect of charging network on travel.

3. Urban transportation (Redding and Turner, 2015) and pollution (Currie and Walker, 2011; Jacobsen et al., 2023): This study shows
   - (1) Travel route matters and measure it using Google Map.

Solving Model Stage-by-Stage

- Stage 3: Vehicle Usage ▸ Vehicle Usage Problem
  - Vehicle-trip matching problem + Individual data.
  - Model yields:
    - $Pr_i(EV_{AB}^{Driving} \mid EV_A)$.
- Stage 2: Vehicle Purchase
  - Discrete choice problem + market share data.
  - Random coefficients, demographic heterogeneity. (BLP)

▸ Model Structure

Solving Model Stage-by-Stage

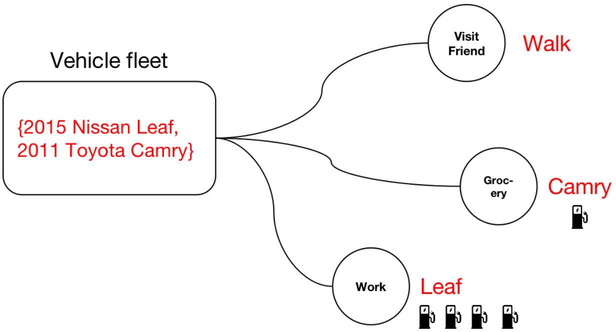
- Stage 1: Vehicle Portfolio ▸ Vehicle Portfolio Problem
  - Why do I prefer $\{EV, ICE\}$ than $\{ICE\}$?
    - Costs: pay for a new car.
    - Benefits: gain availability and flexibility
  - The value from a portfolio, e.g. $\{EV, ICE\}$, are decomposed into:
    - Stage 2: Inclusive value of "Attribute-adjusted price" $\longrightarrow$ Costs.
    - Stage 3: Inclusive value of "having an EV" $\longrightarrow$ Benefits.
  - Model yields:
    - $Pr_i(EV_A)$.

▸ Model Structure

Model - Vehicle Usage Problem

- Given vehicle portfolio S_i, household i's utility from trip d using vehicle v

$$\max_{v \in S_i} U_{idv} = F\Big(FuelCost_{idv}, Nstation^{O}_{id}, Nstation^{D}_{id}, Purpose_{id}, EV_v, ...,\Big) + \varepsilon_{idv}$$



- Mixed-logit model:
  - Vehicle-trip matched data.
  - Observed vehicle choice + MLE.
- Identification:
  - Evidence - public charging accessibility promotes EV usage.
- Model yields:
  - $Pr_i(EV^{Driving}_{AB} \mid EV_A)$.

▸ Solving Model

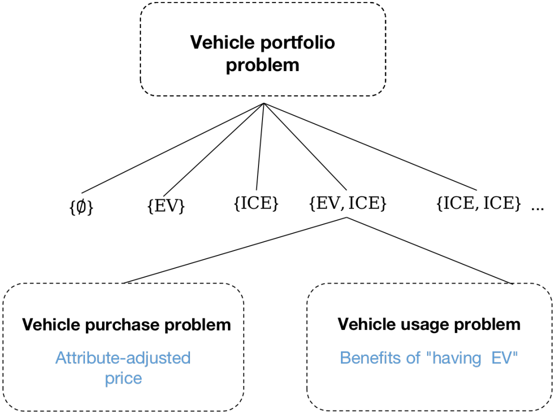
Model - Vehicle Portfolio Problem

- The utility for household i choosing vehicle portfolio $\mathcal{S}_i$, eg., $\{2; EV, ICE\}$

$$\max_{\{\mathcal{S}_i \in \mathbb{S}_i\}} V_i(\mathcal{S}_i) = \widetilde{V_i(\mathcal{S}_i)} + \varepsilon_i(\mathcal{S}_i)$$

$$\widetilde{V_i(\mathcal{S}_i)} = \lambda_i(\mathcal{S}_i) + \rho_1 \cdot IVV_i(\mathcal{S}_i) + \rho_2 \cdot IVU_i(\mathcal{S}_i)$$

- IVU: Value of "able to choose" $\rightarrow$ Benefits of "having an EV".
- IVV: Attribute-adjusted price $\rightarrow$ Cost.
- $\varepsilon_i(\mathcal{S}_i)$ is from T1EV distribution.
- $\lambda_i(\mathcal{S}_i)$ is portfolio fixed effects.



▸ Solving Model ▸ Portfolio Problem Math

Model - Vehicle Portfolio Problem

- The utility for household i choosing vehicle portfolio $\mathcal{S}_i$, eg., $\{2; EV, ICE\}$

$$\max_{\{\mathcal{S}_i \in \mathbb{S}_i\}} V_i(\mathcal{S}_i) = \widetilde{V_i(\mathcal{S}_i)} + \varepsilon_i(\mathcal{S}_i)$$

$$\widetilde{V_i(\mathcal{S}_i)} = \lambda_i(\mathcal{S}_i) + \rho_1 \cdot IVV_i(\mathcal{S}_i) + \rho_2 \cdot IVU_i(\mathcal{S}_i)$$

$$IVV_i(\mathcal{S}_i) = \sum_{g \in \mathcal{S}_i} \phi^T \cdot IVV_i(g)$$

  - Parameter set $\rho_1, \rho_2, \phi\}$
- $\lambda_i(\mathcal{S}_i)$ is fixed effects that capture utility not captured by either attribute and usage.
- Adjust dynamic value of IVV based on vehicle ages T using parameter ϕ. ϕ is estimated by maximizing LR.

▸ Vehicle Portfolio Problem

Inequity Problem - EV Adoption

- Inequality of EV adoption

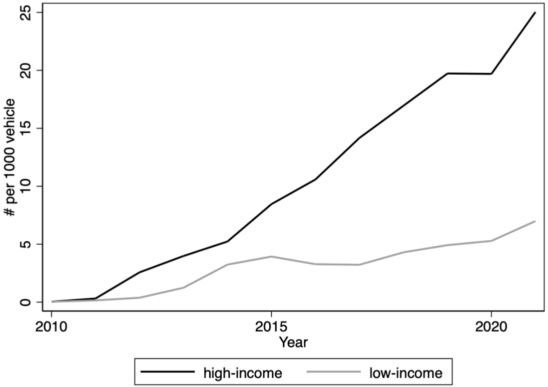


Figure: EV adoption in high- and low-income communities in CA

▸ Motivation

Inequity Problem - Charging Network

- EV charging network is unevenly distributed.

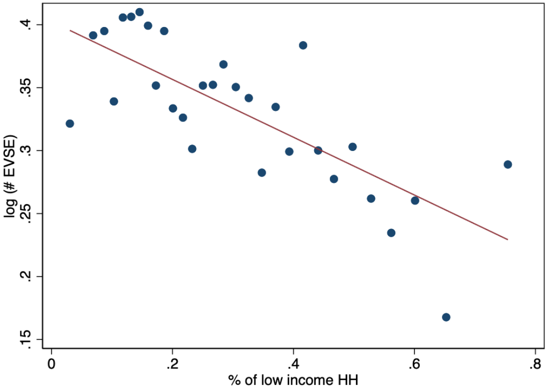
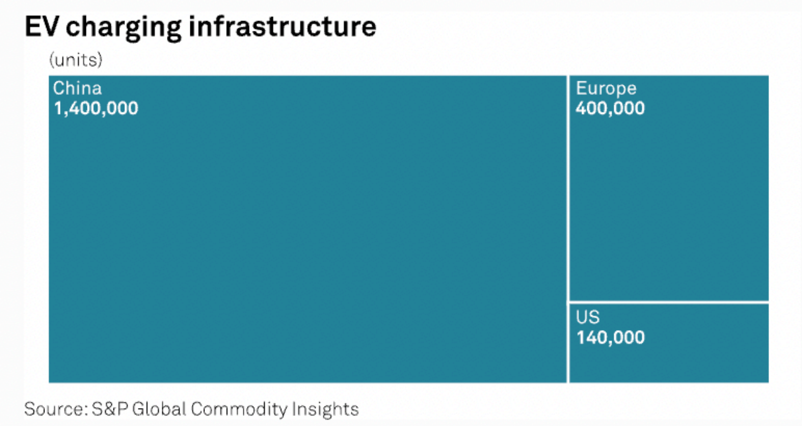


Figure: Relationship between income and charging network deployment

Insufficient Public Charging Infrastructure in US



- The number of charging ports is much smaller in the US than EU and China.

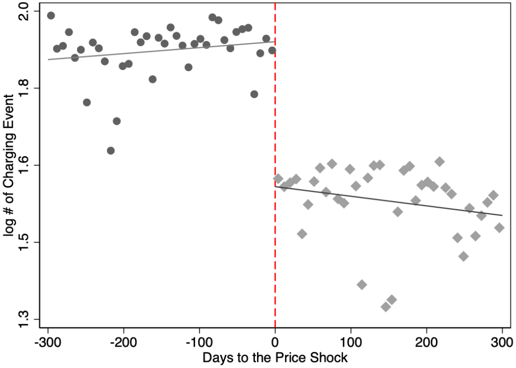
What are "Charging Infrastructures"

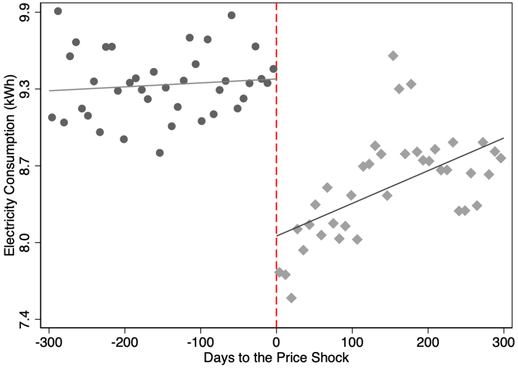
- Infrastructure Investment and Jobs Act subsidies:
  - $5 BN along highways, $2.5 BN in communities.
  - Subsidies cover 80 percent of the private cost to build and install a new EV charger.
- Utilities (public or private), Automakers (Tesla), Charging Networks (EVgo, ChargePoint)...
- Curbside chargers of public utility (Left) or Chargers on alternative fuel corridors (Right)

EJ Results Counterfactual Scenarios

Charging Rate Elasticity (Wang, companion paper)

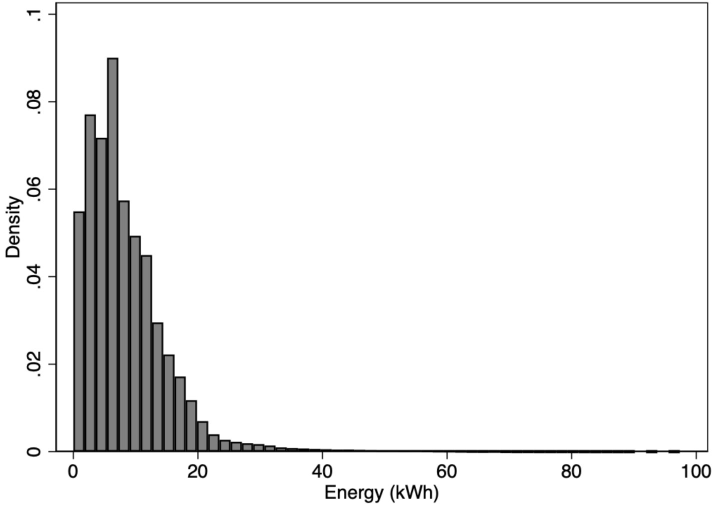
- A price shock: from \$0 to \$0.23 per kWh
- A clear (re)scheduling behavior $\rightarrow$ public charging station matters



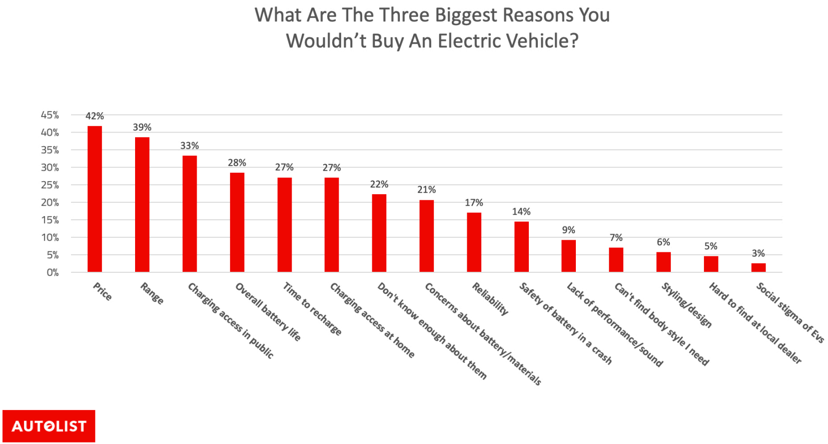


Charging Rate Elasticity (Wang, companion paper)

- Very few fully charged events

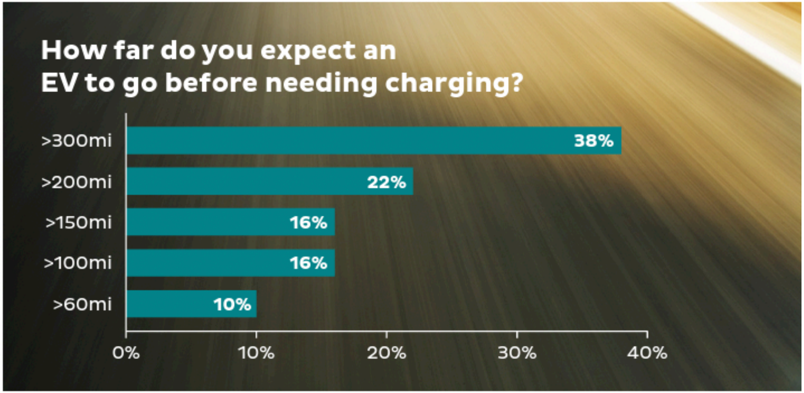


Survey Evidence 1



- Autolist's survey was conducted between February and July 2023, and it surveyed 3,104 car shoppers using autolist.com and its iOS and Android app.

Survey Evidence 2



- Source: Verra Mobility 2023

Survey Evidence 3

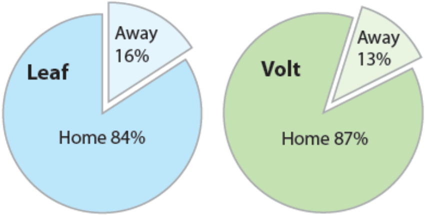


Figure 3.
Leaf and Volt drivers performed most of their charging at home.

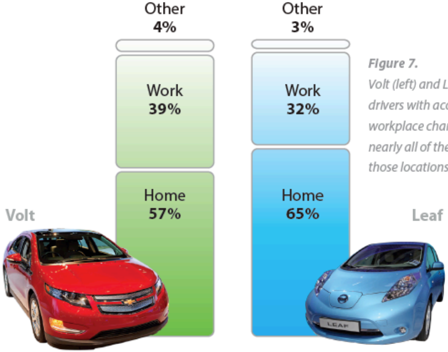


Figure 7.
Volt (left) and Leaf (right) drivers with access to home and workplace charging performed nearly all of their charging at those locations.

- Source: Idaho National Laboratory.
- Most EV owners charge at home. However, for owners who have access to both home and workplace charging, 32-39% of them charge at the workplace.

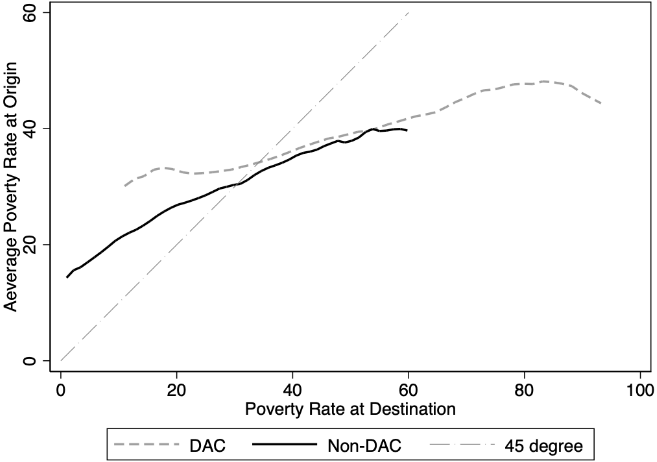
Why California is a Good Context to Study

- EV share is high (2.5%, 2021): California has the greatest number of vehicles, approximately 37% of vehicles nationwide (AFDC)
- The environmental benefits of EVs are high (Holland et al., 2016):

State	EB, \$/miles
California	1.856
Utah	0.726
Colorado	0.601
Arizona	0.593
Washington	0.577
Nevada	0.485
Oregon	0.432
New Mexico	0.347
Texas	0.337
Idaho	0.333
Wyoming	0.137

Stylized Facts

- **Fact 3: Many higher-income HH drive to low-income areas**



- **Data:** Commuting matrix from Census Transportation Planning Products (CTPP)
- The relationship between origin and destination income level.
- The gradient of the O-D income relation is much smaller than one.
- **Commuting flows and routes matter.**

▸ Data ▸ Environmental Benefits

Empirical Evidence

Why Model-Based Approach is An Improvement?

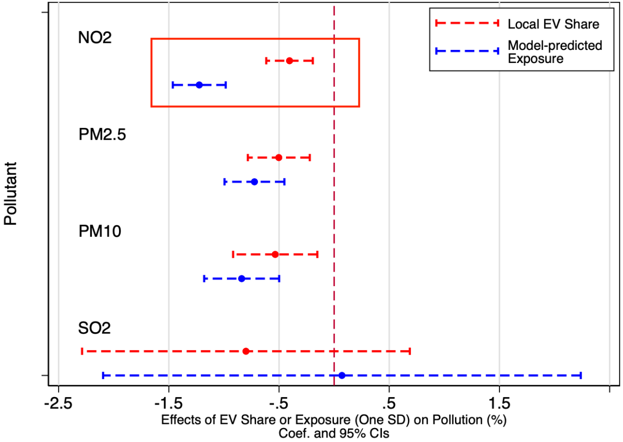
- Questions: Which measurements can better capture pollution reduction?
- Methods: Two-way fixed effects model; Monthly, Zipcode-level analysis.

$$\log(\mathit{Pollution}_{it}) = \beta_1 \, \mathit{EVshare}_{it} + \mathbf{X_{it}}\Gamma + \lambda_i + \eta_t + \varepsilon_{it}$$

$$\log(\mathit{Pollution}_{it}) = \beta_2 \, \mathit{ModelBasedEB}_{it} + \mathbf{X_{it}}\Gamma + \lambda_i + \eta_t + \varepsilon_{it}$$

  - Standardize *EVshare* and *ModelBasedEB*.
  - Compare β_1 and β_2.
- Data:
  - US Environmental Protection Agency air pollution monitor data.
  - Vehicle registration data from California Department of Energy.

Why Model-Based Approach is An Improvement?



- $EVshare_{it} = \#EV/\#Veh$ (existing approach)
- $ModelBasedEB_{it} =$ model-based environmental benefits (new approach)
- The EV share measurement is biased as failing to capture the spillover effects.

▸ Environmental Benefits

Full Model

- The complication of the problem arises from combining stock and flow data.
- To close the model and calculate the full market equilibrium, need to specify the used car market (Bento et al., 2009)
- The full mean utility equation for the new vehicle market.

$$\delta_j = X_j \bar{\beta} - \bar{\alpha}\, ln(p_j) + \kappa\, 1(g_i \in EV) + \xi_j$$

- Different from BLP and nested Logit model, κ is assumed to be identified from the portfolio problem (stock data).
- Used vehicle market is described by a reduced-form function $U(\cdot)$ that maps from EV share in new vehicle sales (s_g) and in vehicle stock (A_g). Eg, in 2023, s_{EV} $\approx$ 10%,$\text{A}_{EV} \approx$ 2%.

$$s_g = U\Big(A_g\,;\; \bar{Q}_{new}, \bar{Q}_{used}\Big), \quad g \in \{\text{EV, ICE}\}$$

▸ Vehicle Portfolio Problem

Model - Vehicle Usage Problem

- Given vehicle portfolio S_i, household i's utility from trip d using vehicle v

$$\max_{v \in S_i} U_{idv} = \gamma_{0v} + \sum_{l \in \{O,D\}} C_{idv}\left(\Psi^l_{iv}, Nstation^l_{id}, Purpose_{id}\right) + \gamma_{1v} \cdot Distance_{id}$$
$$+ \gamma_{2v} \cdot Purpose_{id} + FuelCost_{idv} + X_{idv} \cdot \Gamma_v + \varepsilon_{idv}$$

- Heterogeneous parameters

$$\gamma_{kv} = \bar{\gamma}_k + \gamma_k \cdot 1_v(EV), \quad \Gamma_v = \bar{\Gamma} + \Gamma \cdot 1_v(EV)$$

- Charging conveniences function

$$C_{idv}(\cdot) = \Psi^l_{1,iv} Nstation^l_{id} + \Psi^l_{2,iv} Nstation^l_{id} \times Purpose_{id}$$

- Heterogeneous parameters

$$\Psi^l_{iv} = (\bar{\psi}^l + \sum_{r=1}^{R} z_{ir}\psi^l_r + v^l_i \psi^u) \cdot 1_v(EV)$$

Model - Vehicle Usage Problem

- The inclusive value of use (IVU) (Barwick et al., 2022) is,

$$IVU_i(\mathcal{S}_i) = \begin{cases} \mathbb{E}_{D(d)}\left(I_{id}(S_i)\right) & \text{if } S_i \in \mathcal{S}_i \\ \mathbb{E}_{D(d)}\mathbb{E}_{G(\widetilde{S}_i|\widetilde{\mathcal{S}}_i)}\left(I_{id}(\widetilde{S}_i)\right) & \text{if } \widetilde{S}_i \notin \mathcal{S}_i \end{cases}$$

- where,

$$I_{id}(S_i) = E_{\epsilon_{idv}}\left(\max_{v\in S_i} U_{idv}\right)$$

$$I_{id}(\widetilde{S}_i) = E_{\epsilon_{idv}}\left(\max_{v\in \widetilde{S}_i} U_{idv}\right)$$

- $\mathbb{E}(\cdot)$ is calculated over (1) trip distribution (2) potential vehicle portfolios (matched neighbors)

▸ Vehicle Usage Problem

Model - Vehicle Model Choice Problem (BLP)

Portfolio *{2; EV, ICE}* ...

Choice occasion 1

Choice occasion 2

Fuel type *EV* *ICE* *EV* *ICE*

Make-Model-Year

2016 Tesla Model S

2015 Nissan Leaf

2016 Chevrolet Bolt

2016 Ford Fusion

⋮

524 model

BLP utility framework

- Price parameters interact with demograpics
- Random coefficients in preference
- Endogenous price

▸ Vehicle Portfolio Problem

Model - Vehicle Model Choice Problem (BLP)

- For HH i with demographic z_{ir} and vehicle model j,

$$\begin{aligned} u_{ij} &= \delta_j + \mu_{ij} + \epsilon_{ij} \\ \delta_j &= X_j \bar{\beta} - \bar{\alpha}\, log(p_j) + \xi_j \\ \alpha_i &= \bar{\alpha} + \alpha_1 \cdot log(income_j) + \sigma \cdot v_i \\ \mu_{ij} &= \alpha_i log(p_j) + \sum_{k=1}^{K} \left(\sum_{r=1}^{R} \boldsymbol{z}_{ir} \beta_{kr} + v_{ik}\, \beta_k^u \right) \end{aligned}$$

- Aggregate demand

$$s_j = \int_{\Omega_i} \frac{\exp(\delta_j + \mu_{ij})}{1 + \sum_{j'} \exp(\delta_{j'} + \mu_{ij'})} \, dG(\Omega_i)$$

- The fuel-type-specific inclusive value of the vehicle group, eg., EV; Large ICE; Small ICE;

$$IVV_{im}(g|\boldsymbol{z_i}) = \mathbb{E}_{\mathbf{v}_i} \left\{ \ln \left[\sum_{j \in g} \exp\Big(\delta_{jm} + \mu_{ijm}(\boldsymbol{z_i})\Big) \right] \right\}, \quad g = \text{EV, ICE}$$

▸ Vehicle Portfolio Problem ▸ BLP Problem

Results - Vehicle Usage Problem

‣ Model Results

	Logit	Logit-Random coef.
Vehicle age	-0.0487	-0.0488
	(0.001)	(0.001)
Fuel cost	-0.0107	-0.0107
	(0.001)	(0.001)
EV $\times$ distance	-0.00236	-0.00371
	(0.001)	(0.001)
EV $\times$ $log(Nstation^O)$	0.136	0.136
	(0.026)	(0.064)
EV $\times$ $log(Nstation^D)$	0.0784	0.0297
	(0.027)	(0.070)
EV $\times$ $log(Nstation^D)$ $\times$ work	0.222	0.523
	(0.051)	(0.270)

Random Coefficients: EV $\times$ Stations variables
Controls: Fuel type FE, Body style FE, EV $\times$ demographics

Results - Vehicle Model Choice Problem (BLP)

▸ Model Results

	(1) Logit		(3) BLP-Logit	
Variable	Coefficient	SE	Coefficient	SE
Parameters in mean utility				
log(price)	-0.840	0.008	-19.455	0.048
EV × log(price)	0.221	0.021	0.237	0.059
EV × log(# station)	-0.038	0.024	0.075	0.018
Dollars per mile (DPM)	-3.919	0.154	-3.875	0.648
Horsepower/weight	4.778	0.200	3.073	1.081
Liter	0.097	0.004	0.198	0.015
Displacement × EV	-0.196	0.011	-0.388	0.034
log(range)	0.081	0.005	0.074	0.011
Parameters in the household-specific utility				
log(price) × log(income)			3.304	0.091
log(income)			-6.742	0.308
log(income) × EV			0.638	0.036
EV × White			0.085	0.089
EV × Black			-2.137	1.185
EV × Asia			1.959	0.214
Random Coefficients				
σ(log(price))			1.921	0.037
σ(EV)			0.205	0.934
σ(Const)			0.391	1.597
Fixed Effects: Time, CBSA, CBSA × EV, Segment				

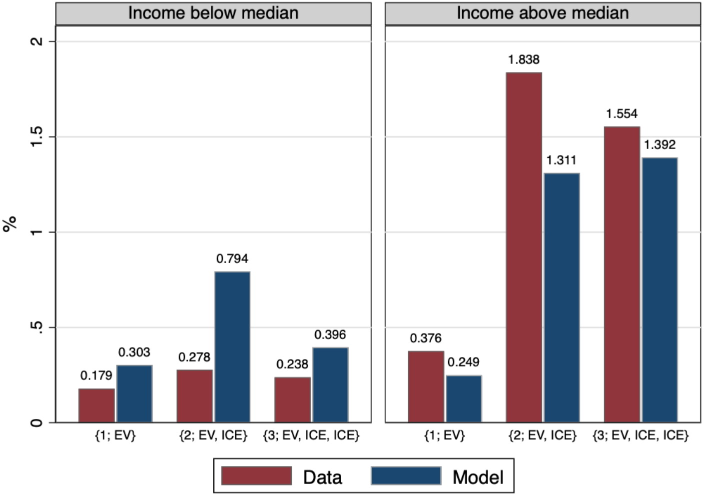
Results - Vehicle Portfolio Problem

	(1) Logit	(2) Logit	(3) Logit	(4) Logit Random coef.
IVU - Usage	0.187	0.878	1.152	1.541
	(0.023)	(0.045)	(0.066)	(0.070)
IVV - Attribute: BLP-Logit		0.222	0.122	0.224
		(0.005)	(0.005)	(0.009)
Portfolio FE	No	No	Yes	Yes
Portfolio-by-CBSA FE	No	No	No	Yes
Log-likelihood	-38615.42	-33593.95	-24719.78	-24542.87
Random Coefficients: Portfolio dummies				

Model Results

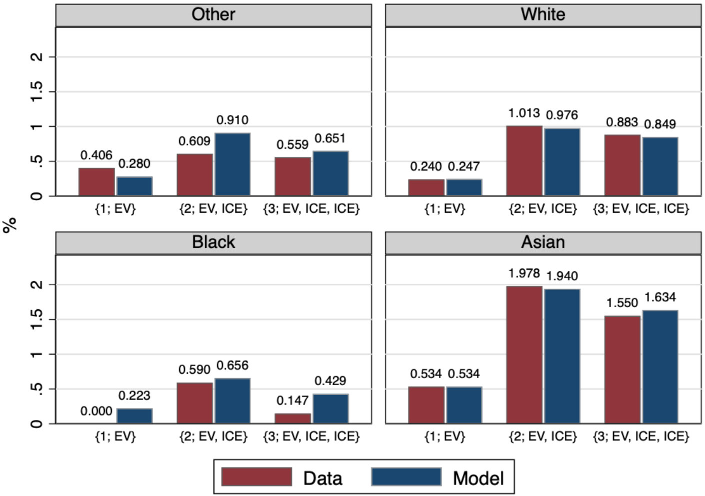
Model Fit - Within Sample

- Data vs Model: choice probability for each income group ▸ Model Results



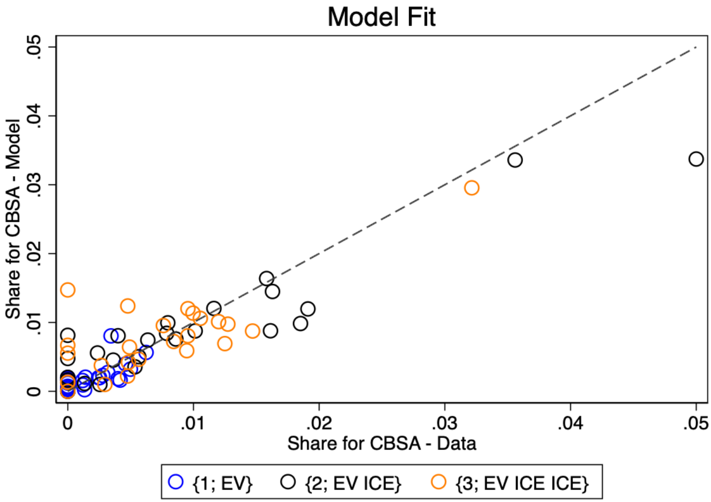
Model Fit - Within Sample

- Data vs Model: choice probability for each racial group ▸ Model Results

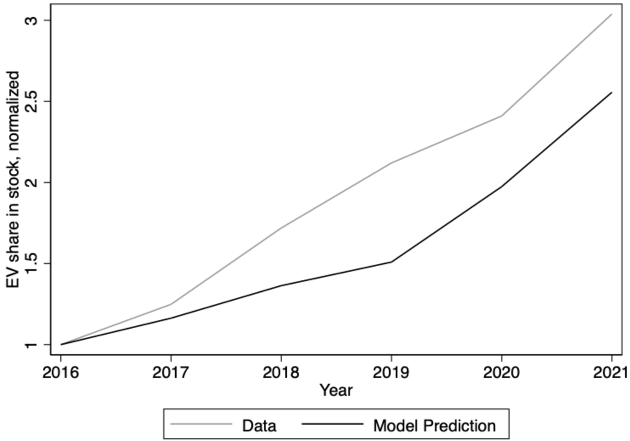


Model Fit - Within Sample

- Data vs Model: choice probability for each CBSA ▸ Model Results



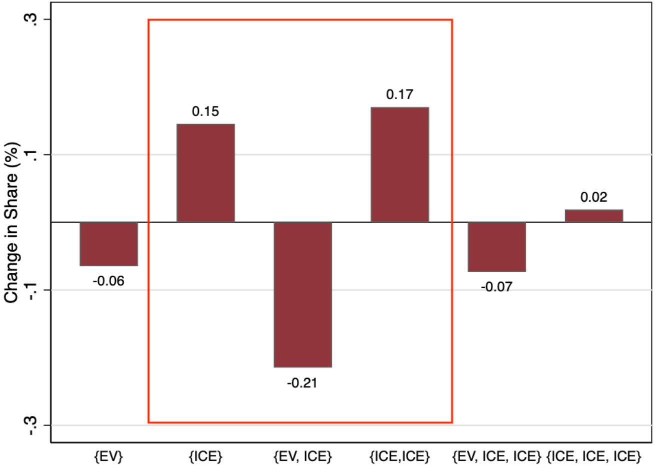
Out-of-Sample Prediction



- For each out-of-sample year, feed the model:
  - Data on charging networks.
  - Data on the new vehicle market.

▸ Model Results ▸ More EV Model ▸ EV Cheaper ▸ Counterfactual Algorithm

Decompose Change in Choice Probability

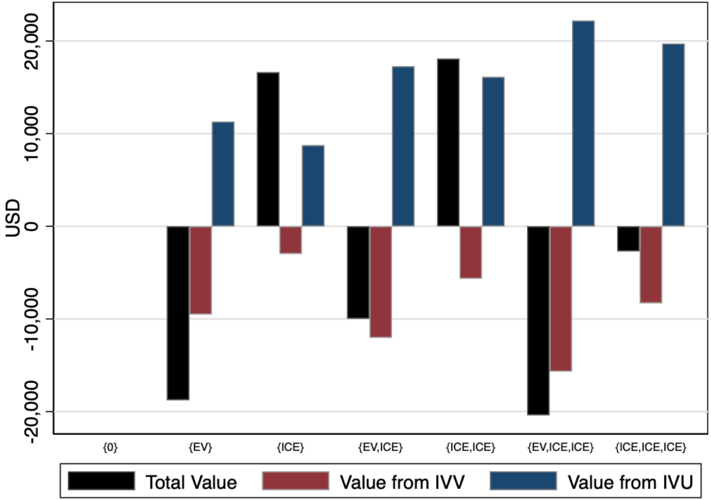


- The impacts of eliminating EV purchase subsidies

▸ Effect of EV Adoption

Analysis of the Model - Value Decomposition

▸ Model Results



Analysis of the Model - Model Results by Income Group

- Consumer surplus:

$$CS(\boldsymbol{y}) = \mathbb{E}_{i \in \boldsymbol{y}} \left\{ \frac{1}{\bar{MU}_i} \left[\ln \left(\sum_{\{\mathcal{S}_i \in \mathbb{S}_i\}} \exp(\widetilde{V_i(\mathcal{S}_i)}) \right) \right] \right\}$$

	Price Elasticity		Welfare	Travel Behaviors
	EV	Non-EV	CS ($)	% EV Trips
Blow $30000	-7.119	-7.302	7602.34	48.578
$30000 to 62500	-4.512	-4.667	14793.37	46.799
$62500 to 112500	-2.963	-3.111	27706.65	44.694
$112500 to 175000	-1.812	-1.952	51754.99	40.316
Above $175000	-0.427	-0.558	1138524.38	38.966
Median	-3.282	-3.431	23244.42	46.352

- Interpretation: lifetime (10-15 years) value from driving about $23244.42.

▸ Model Results

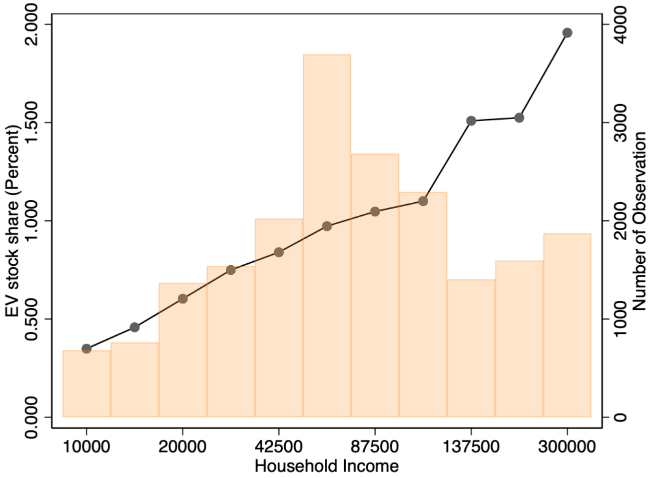
Counterfactual Algorithm

- Step 0: New policies
- Step 1: Counterfactual changing networks and equilibrium vehicle price
- Step 2: Counterfactual IVV and IVU
- Step 3: Re-simulate counterfactual Portfolio $\mathcal{S}_i$ (Adoption) and $Pr(EV_{OD}^{Driving})$
- Step 4: Re-simulate counterfactual EV route and environmental benefits

▸ Model Fit -Out Sample

▸ Counterfactural Scenarios

EV Share in NHTS Data



▸ Effect of EV Adoption

Counterfactual Results - Welfare

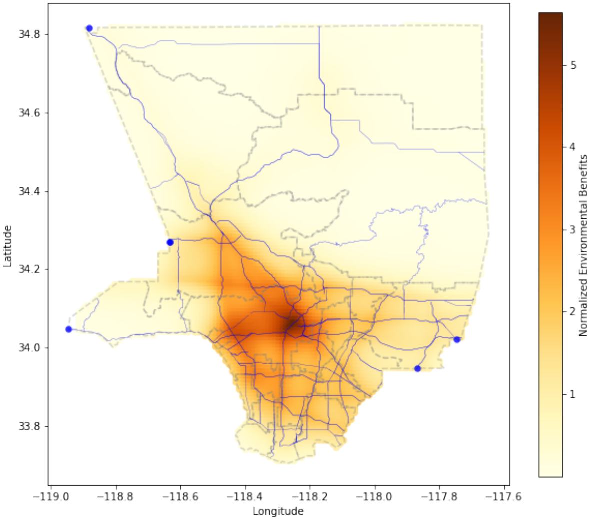
▸ CF EV Share

- Station Policy 1: proportional to the current charging network.
- Station Policy 2: based on population share.
- Station Policy 3: evenly.
- Station Policy 4: disproportionately to (DAC).

Income Groups	Subsidy Low	Station Policy 1	Station Policy 2	Station Policy 3	Station Policy 4
			$\triangle$ EV Stock Shares (%)		
Blow \$ 30000	0.172	0.092	0.402	0.167	0.177
\$ 30000 to 62500	0.150	0.507	1.098	0.619	0.577
\$ 62500 to 112500	-0.232	0.905	1.758	1.116	0.964
\$ 112500 to 175000	-0.222	1.169	1.994	1.300	1.088
Above \$ 175000	-0.127	1.355	2.362	1.690	1.381
Average	-0.026	0.846	1.598	1.027	0.879
			$\triangle$ Consumer Surplus (\$ per Household)		
Blow \$ 30000	8.1	13.4	28.2	16.1	16.9
\$ 30000 to 62500	12.3	61.7	105.2	62.7	60.0
\$ 62500 to 112500	-7.1	155.9	265.1	168.7	148.9
\$ 112500 to 175000	-46.0	348.7	518.7	333.7	304.6
Above \$ 175000	-172.0	7558.3	12124.9	8583.8	7764.3
Average	-37.4	1443.3	2314.6	1623.7	1468.9

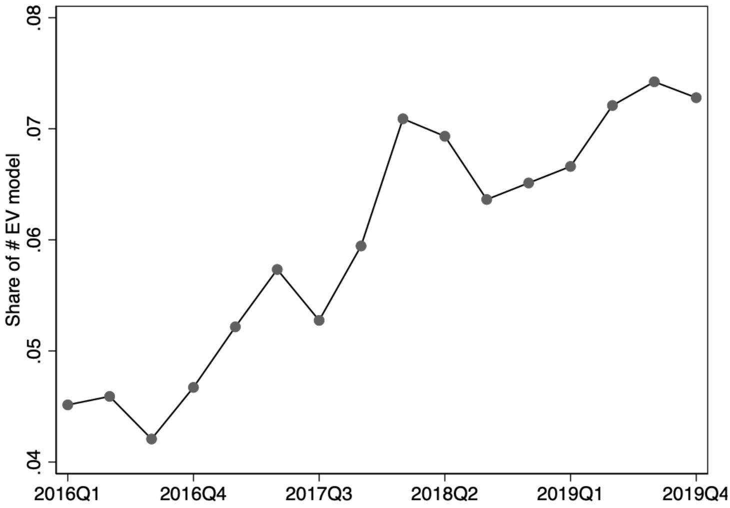
Appendix - EV Exposure, LA

▸ Environmental Benefits



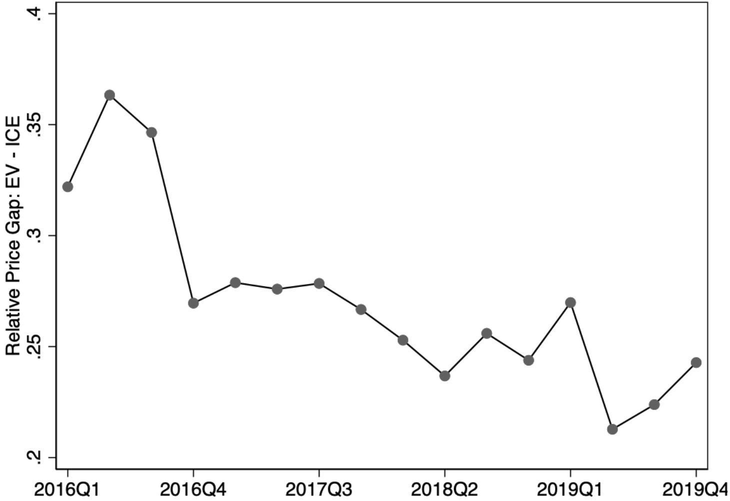
Appendix - Attribute Change Over Time, More EV Model

▸ Model Fit -Out Sample



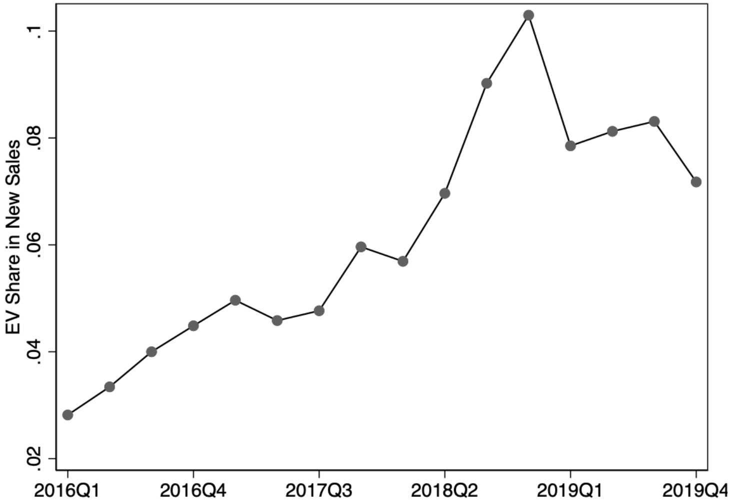
Appendix - Attribute Change Over Time, Small Price Gap

Model Fit -Out Sample



Appendix - Attribute Change Over Time, Higher EV Share

Model Fit -Out Sample



Appendix - EJ Regression

	Baseline	Subsidy Low Income	Station Policy DAC
Pct. Low Income (<2X poverty line)	-0.777***	-0.720***	-0.548***
	(0.102)	(0.103)	(0.099)
Pct. Minority Population	-0.0985**	-0.0797	0.163***
	(0.049)	(0.049)	(0.051)
PM 2.5 Concentration Score	0.0519***	0.0541***	0.0819***
	(0.006)	(0.006)	(0.006)
Controls	Y	Y	Y
Observation	7864	7864	7864

▸ Environmental Justice