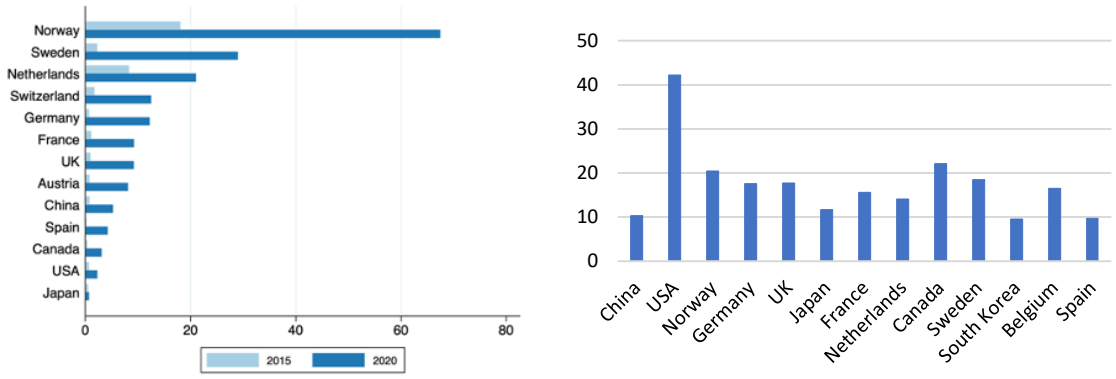
Optimal Charging Infrastructure for Electric Vehicles

Panle Barwick, Christopher Knittel, Shanjun Li, and James Stock[1]

1. Background and Research Questions:

The US is lagging behind in EV adoption and charging infrastructure among major economies (Figure 1). In 2020, the share of EV among new vehicle sales was only about 2%, compared to over 5% in China and 70% in Norway. The Biden administration announced a goal of raising EV shares to 50% by 2030. As the US and countries across the world deploy policies to accelerate the pace to electrify transportation, a central question in effective policy design is the role of charging infrastructure. The US bipartisan infrastructure bill includes $7.5 billion to fund charging stations in order to build out a national network of EV chargers, the first-ever national investment in EV charging infrastructure in the US. Simulation evidence in Cole et al. (2021) points to the importance of charging stations in expediting EV adoption, both to make adoption possible for those who do not have the property rights needed to install a home charger and for all EV owners who wish to make long-distance trips that require fast charging.

Figure 1: EV Market Share and EV-Charging Ratio in Top 13 EV Countries



(a) EV share (%) in new vehicle sales (b) EV stock to charging station ratio as of 2020

Note: The 13 countries in the list accounted for 95% of worldwide EV sales by 2020. Authors' own calculation.

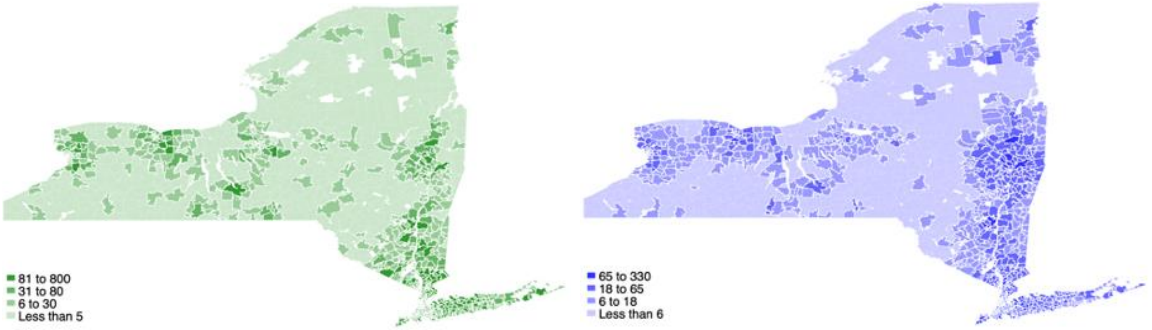
Despite both the political interest in and economic importance of supporting national charging infrastructure, to date there has been very little study of even the most basic questions that would shape the details of charger cost-share programs. What would the optimal charging network look like in terms of the number of stations and the spatial pattern from the perspective of EV adoption? How can a given charger subsidy budget be used most effectively to promote EVs? The EV market is a two-sided market with the classical indirect network effect: the demand for EV's depends on the availability of publicly-accessible charging stations and the supply of charging stations depends on the installed base of EV's (Zhou and Li 2018). To answer these questions, we need to understand the decision processes on each side of this two-sided markets: (1) the EV purchase on the EV side and in particular the role of charging access in these decisions; and (2) the charging station entry decisions by different types of investors (e.g., gasoline stations and grocery stores) on different charging types (slow or fast charging).

[1] Barwick: Cornell University, pjb28@cornell.edu; Knittel: MIT, knittel@mit.edu; Li: Cornell University, SL2448@cornell.edu; Stock: Harvard University, james_stock@harvard.edu. COI Statement: the authors declare no relevant material or financial interests related to the research described in this proposal.

2. Data Description

We use detailed data on EV sales at the zip code level, geo-referenced charging stations, visitation at geo-referenced consumer points-of-interest (to capture traffic flow), together with rich data on demographics and road networks to understand the decision processes and the interactions between the two sides of the market. For illustration, Figure 2 depicts the EV stock and public charging infrastructure density in New York as of April 2021.

Figure 2: EV Stock and Charging Density by April 2021 in New York State

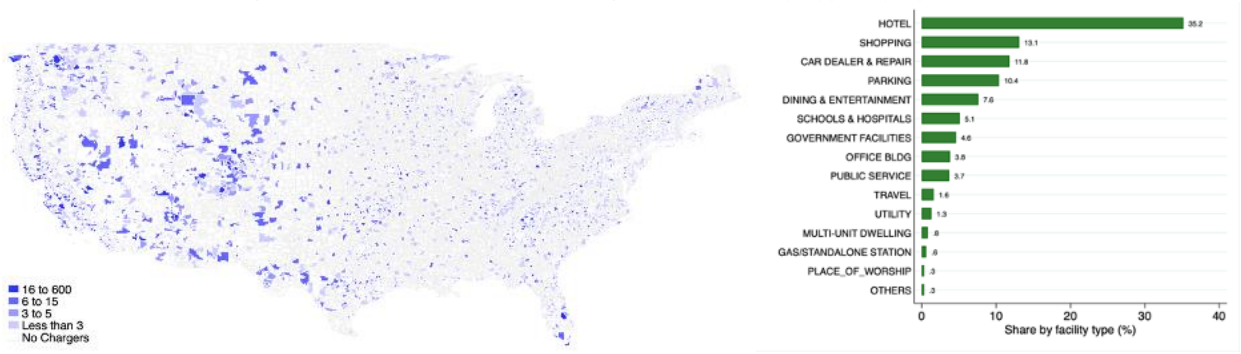


(a) EV stock by zip code (b) Charging density by zip code

Note: Charging density is defined as the inverse distance weighted sum of the No. of public chargers within a 50-mile radius of a zip code. the Source: DOE Alternative Fuel Data Center, New York DMW, and Authors' calculations.

Figure 3 shows the number of public chargers by zip codes in the US as of April 2021 in panel (a) and the facility type in panel (b). Hotels account for over one third of charging stations while shopping malls and grocery stores account for about 13%. The accessibility and availability of ancillary services on site are important factors in the investment decisions. In addition, there are significant differences in the charging speed and installation costs across level 2 (slow) and level 3 (fast) chargers, currently accounting for 83% and 17% of public chargers, respectively. The fast chargers can charge a typical EV under one hour but cost about $50,000 to install while the slow chargers need about 8 hours of charging time but cost only $2,000 to install.

Figure 3: Number of Public Chargers and Facility Type by April 2021



(a) No. public chargers by zip code (b) Shares by facility type

Source: DOE Alternative Fuel Data Center and authors' calculations.

3. Research Framework

We develop and estimate an equilibrium model of a two-sided market with a focus on charging station locations at the granular level. The model specifies the EV purchase decisions and

charging investment decisions. For the purpose of illustration, we consider a static framework which will be extended to a dynamic framework to take into account the forward-looking behaviour. There are M sites (m={1, 2,…M}) within a region (e.g., a commuting zone or MSA) where consumers live and work and investors can choose to build charging stations.

EV adoption decision and EV stock:

EV demand is specified as a discrete choice model with consumer preference heterogeneity. The utility of consumer i at location *m* from choosing a vehicle model j (j=1,..J, including both gasoline and electric vehicle) is defined as:

$$u_{ij} = \alpha_i(p_j - s_j) + x_j\beta_i + \gamma cs_m \mathrm{I}(j \in EV) + \varepsilon_{ij} = \bar{u}_{ij} + \varepsilon_{ij}, \quad (1)$$

where p_j is the retail price of vehicle model j and s_j is consumer subsidy which is zero for gasoline models. x_j is a vector of product attributes such as vehicle size, fuel economy and driving range. cs_m is a measure of the availability of public charging stations that is defined for consumers located in *m*:

$$cs_m = \sum_{l=1}^{M} d_l * f(\tau_{lm}, x_l, x_m), \quad (2)$$

where d_l is an indicator for whether location l has a charging station. f(.) is a function of the travel cost (τ_{lm}) between locations l and m and locational attributes x_l and x_m that affect the attractiveness of the locations for charging. We characterize x_l and x_m using observed locational attributes as well as foot traffic data at points-of-interest. A simple measure of charging availability for location m could be the inverse-distance weighted sum of charging stations within a certain radius. Our measure allows us to incorporate the heterogenous impact of charging station of different facility types on EV demand.

Assuming the type I extreme value distribution for the error term ε_{ij}, EV sales in location m is:

$$q_m = \sum_{j \in EV} I_m * \frac{\exp(\bar{u}_{ij})}{\sum_h \exp(\bar{u}_{ih})}, \quad (3)$$

where I_m is the number of potential vehicle buyers (i.e., market size) in location m. The EV stock in location m, Q_m, is the new EV sales plus the existing stock Q_{mo}.

$$Q_m = Q_{mo} + q_m. \quad (4)$$

Charging Station Investment:

Investors make entry decision based on the total expected profit, which depends on the number of customers from different locations. The profit of a charging station in location m is defined as:

$$\pi_m = \gamma_m * (\sum_l Q_l * \lambda_{lm}) - c_m + \tilde{s}_m, \quad (5)$$

Where γ_m is the per-unit profit of charging and could be affected by the pricing decision of charging station m. λ_{lm} , micro-founded by a charging-demand model, is the share of EVs in location l going to location m for charging service:

$$\lambda_{lm} = \frac{\exp[(f(\tau_{lm}, x_l, x_m)] * d_l}{\sum_k \exp[(f(\tau_{lk}, x_l, x_k)] * d_k}. \quad (6)$$

c_m is the installation cost which could be affected by land price, permits, and utility upgrade. $\tilde{s}_m$ is the government subsidy for charging station investment.

Equations (1) and (5) illustrate the indirect network externality in this market: building a charging station in location m could increase the EV sales in location m and elsewhere through Equation

(1), while the increase in EV stock would increase the profitability of charging stations and increase the entry. The network size of the charging infrastructure (one side of the market) affects the size of the EV stock (the other side). Subsidies on either side of the market could help the diffusion of the technology, but the cost-effectiveness of EV purchase subsidies and charging investment subsidies may not be the same. Empirical studies using data from earlier years of EV diffusion in China, US, and Norway have shown that subsidizing charging infrastructure is at least twice as effective as subsiding EV purchases (Li et al. 2017, Springel 2020, Li et al. 2021).

The equilibrium outcomes include EV sales $Q = (q_1, q_2 \dots q_M)$ and charging-station entry decisions $D = (d_1, d_2 \dots d_M)$ at each location. Under reasonable assumptions, the equilibrium exists but is not guaranteed to be unique as is typical in the market with positive spillovers.

Social Planner as Charging Station Investors:

We use this as a benchmark against which private solutions is compared to. The welfare maximization problem can be cast as:

$$\max_{d_m=\{0,1\},\forall\, m} W(D) = \sum_m d_m * [\alpha_m * (\sum_l Q_l * \lambda_{lm}) - c_m], \quad (6)$$

where α_m is the marginal social benefit of charging, different from the private benefit to charging investors denoted by γ_m in Equation (5). Let the socially optimal investment decisions be denoted as $D^* = (d_1^*, d_2^*, \dots d_M^*) =$ argmax $W(D)$. In general, the optimal investment decision from (6) is a combinatorial problem that is computationally demanding to solve. To make it feasible, we utilize the following condition: the optimality of D^*implies that the welfare at D^* must be (weakly) higher than the welfare at any one-location deviation.

$$W(d_1^*, \dots, d_m^* \ \dots d_M^*) \geq W(d_1^*, \dots, d_m, \dots d_M^*), \forall\, m. \quad (7)$$

This condition implies the following decision rule of investment:

$$d_m^* = \mathbb{I}\left(sb_m = \underbrace{\alpha_m * (\sum_l Q_i^* * \lambda_{lm}) - c_m}_{w_m^* = \text{direct benefit}} + \underbrace{\sum_{l \neq m} d_l^* * \alpha_l * \left(\sum_j \kappa_{mj} * \lambda_{jl}\right)}_{\mu_m^* = \text{indirect benefit}} \geq 0 \right), \quad (8)$$

where $\mathbb{I}(.)$ is an indicator function, Q_m^* is the EV stock under D^*. The quantity in the parenthesis, $sb_m = w_m^* + \mu_m^*$, is the marginal contribution of station m to the aggregate welfare, i.e., the social marginal benefit. w_m^* is the direct benefit of station m (holding EV stock constant), i.e., the benefit from the single side of the market. μ_m^* captures the benefit from the indirect network effect: building a station in location m increases EV stock in location j by κ_{mj}, increasing the service demand in all locations. The benefit from the increase in EV stock in all locations will bring benefits to all charging stations by $\mu_m^* = \sum_{l \neq m} d_l^* * \alpha_l * \left(\sum_j \kappa_{mj} * \lambda_{jl}\right)$.

The socially optimal decision rule is to invest if and only if the social marginal benefit of station m is positive. The social marginal benefit includes the spillovers from one side of the market to the other side. The maximization problem can be transformed into searching for the fixed points of the necessary conditions (8). This translates the problem from a set of 2^N elements to the set of

fixed points of the necessary conditions, which has a much smaller dimension. A similar problem was solved in Barwick (2008) in the context of location choices of chain stores and in Yu et al. (2016) for charging locations.

Private Investment Decisions with Government Subsidies:

The current administration's charging investment plan with a fixed budget entails the following constrained optimization problem:

$$\max_{s_m,\forall\, m} W(S) = \sum_m d_m * \left[\alpha_m * \left(\sum_l Q_l * \lambda_{lm}\right) - c_m\right], \qquad s.t.$$
$$d_m = \mathbb{I}\left(\pi_m = \gamma_m * \left(\sum_l Q_l * \lambda_{lm}\right) - c_m + \tilde{s}_m \geq 0\right),$$
$$\text{Equation (3), and } \sum_m \tilde{s}_m = \bar{S}. \tag{9}$$

In the presence of the budget constraint, the socially optimal investment decision D^* and the corresponding social welfare $W(D^*)$ may not be realized. The goal is to get as close to the welfare outcome as possible with a fixed budget $\bar{S}$.

4. Expected Outcomes

We plan to estimate preference parameters in EV purchases and charging demand, as well as cost parameters in investment decisions using granular data discussed above. Importantly, the estimation allows for rich heterogeneity in both preference across consumers and cost and revenue considerations across facility types and locations. In addition, the model takes into account the critical differences between private and social benefits as well as the indirect network effects in this two-sided market. We then conduct counterfactual simulations to compare the cost-effectiveness of different policy designs in implementing the $7.5 billion Bipartisan Infrastructure Deal and consumer EV subsidies discussed in the $3.5 trillion reconciliation packages. We will disseminate our findings broadly and engage policy makers to adopt an effective path toward the decarbonization of the transportation sector.

References:

Panle Jia Barwick, "What Happens When Wal-Mart Comes to Town: An Empirical Analysis of the Discount Retail Industry," *Econometrica*, 76(6): 1263-1316, November 2008.

Cassandra Cole, Michael Droste, Christopher Knittel, Shanjun Li, and James H. Stock, "Policies for Electrifying the Light-Duty Vehicle Fleet in the United States," NBER Working Paper, 2021.

Shanjun Li, Lang Tong, Jianwei Xing and Yiyi Zhou, "The Market for Electric Vehicles: Indirect Network Effects and Policy Impacts," *Journal of the Association of Environmental and Resource Economists*, 4(1): 89-133, 2017.

Katalin Springel, "Network Externality and Subsidy Structure in Two-Sided Markets: Evidence from Electric Vehicle Incentives", *American Economic Journal: Economic Policy*, 2020.

Zhe Yu, Shanjun Li, Lang Tong, "Market dynamics and indirect network effects in electric vehicle diffusion," *Transportation Research Part D*, 47: (336-356), 2016.

Yiyi Zhou, Shanjun Li, "Dynamics of Technology Adoption and the Critical Mass in the Market for Electric Vehicles," *Journal of Industrial Economics*, 2: 423-480, 2018.