Proposal Title: Activity Behavior and the Economic Value of EV Charging Infrastructure

Summary: In 2021, the Infrastructure Investment and Jobs Act (IIJA) allocated $7.5 bn for the construction of a national network of EV chargers. These are to be distributed to States according to a set of criteria which includes: "(…) meeting current and anticipated market demands for electric vehicle charging infrastructure, including with regard to power levels and charging speed, and minimizing the time to charge current and anticipated vehicles"[1]. Satisfying such a criterion naturally involves tradeoffs which must balance costs and benefits of a given charging deployment strategy. However, evaluating these tradeoffs when it comes to EV charging infrastructure is non-trivial and involves accounting for the interactions between multiple forces: activity scheduling, parking competition, and adoption dynamics. Our proposed research seeks to tackle that challenge and provide both theoretical and empirical insights into the efficient allocation of EV charging infrastructure funding.

1 Introduction

The basic question that this proposal seeks to answer—both theoretically and empirically—is: what is the economic value of EV infrastructure investment and its relationship to activity behavior? Indeed, with the resources of the IIJA in hand, policymakers must now plan and locate charging facilities in ways that effectively balance costs and benefits. However, evaluating the value of a given EV investment is non-trivial. **First**, the value of a given EV charger is intrinsically linked to individual scheduling behavior. Since charging time is often non-negligible, charging imposes scheduling costs on users which vary spatio-temporally. These costs emerge from drivers' desires to undertake activities that they value more relative to charging. These activities are also the point of departure for different trips whose completion depletes drivers' batteries. Thus, any model that aims to assess the economic value of EV infrastructure investment must integrate drivers' activity patterns and the value attached to these patterns. Researchers and practitioners alike have sought to incorporate such inherently dynamic patterns in transportation and economic models ((*1–15*))[2]. When of a theoretical bent, these works have usually considered scheduling trade-offs between at most two activities or the allocation of time across activities—regardless of schedule. While insightful, the simplified nature of these works limits their empirical application. When of a practical bent, these works have sought to capture granular details of individual human activity. While the output of these models is useful, their detailed structure makes them analytically intractable, hard to empirically validate, and hard to generalize. Thus, there remains an opening for an analytically tractable yet empirically suitable framework of dynamic travel behavior that can inform not only the theory of infrastructure investment but also specific investment decisions.

Second, the allocation of parking spaces to EV charging also introduces time costs on non-EV users by making parking resources scarcer. Thus, an appropriate measure of the costs and benefits of EV charging must also account for parking competition and costs on non-EV users. However, most studies on optimal charging and location do not capture and evaluate these costs (*16–31*).

Third, because EV adoption is still low, relying solely on EV owners for model estimation likely raises concerns about generalizability since early adopters likely differ from the rest of the population[3]. Thus, as a precursor to evaluating the value of EV investment, one must identify features that remain stable at an individual level even after EV adoption and can therefore be credibly used for inference. However, most models surveyed either a) assume that activity patterns will remain stable or b) rely on behavior data from EV adopters for calibration.

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[1] https://www.fhwa.dot.gov/bipartisan-infrastructure-law/nevi_formula_program.cfm

[2] Given the long literature on activity-based models in transportation and economics, we only provide here a representative subset of the references on the topic.

[3] See literature related to technology diffusion, dating back to (*32*) and before.

2 Proposed research and contributions

To tackle these challenges and quantify the economic value of charging infrastructure, we propose to develop and empirically validate a model of travel and charging demand. At the core of our model is the notion of marginal utility of time spent at a location ((*3*)). Individuals decide their spatio-temporal trajectory by comparing continuously over time the marginal utilities of time spent in each location. Additionally, they must account for several factors: travel time, parking and charger availability, their battery levels (if owning an EV). These decisions give rise to an undiscounted dynamic program for each individual and to competition over parking (both electric and non-electric) and charging resources in each location. While we are not the first to apply dynamic programming to evaluate demand in transportation systems, we notably differ from the rest of the activity-based literature in not capturing granular details of individual activity. Rather, we assume that the value of time spent in a location is a sufficient measure for the value of activities in that location[4] [5]. This simplification allows not only for the derivation of the spatio-temporal distribution of individuals (and their charge levels), but also of the Euler equations for the social planner and "user equilibrium" problem. From these, we hope to shed further light on the optimal allocation and pricing of charging and parking infrastructure. Moreover, we argue that, to a first order, the marginal utility of time spent in a location does not change with EV ownership. Rather, differences in behavioral patterns between EV and non-EV owners are due to charging considerations, not inherent differences in marginal utility (after controlling for relevant variables/characteristics). Thus, we can estimate the flow value in our dynamic program by relying on more abundant non-EV owner data and compute counterfactuals for different levels of adoption.

To estimate our proposed model, we require data in three categories: spatio-temporal behavioral patterns, parking locations and prices, and EV charging location and prices. To address the need for movement data, we have explored the utilization of data from Veraset Inc[6]. However, because of issues pertaining to the acquisition process, we have, for the moment, gained access to synthetic data from ReplicaHQ[7] for New York Metropolitan Area. This synthetic dataset is generated to match "ground truth" obtained from a combination of travel behavior and time use survey data, foot traffic data, and travel time information. The use of such a synthetic dataset allows identification of the flow values in our model through a) observation of the choice probabilities of synthetic agents b) and observation of the spatio-temporal distribution of the synthetic population as in (*33*). Our estimation strategy then relies on solving a mathematical program with equilibrium constraints whose basic outline is in the vein of (*34–36*). Because a subset of the synthetic population also uses EV, we can test for our assumptions that the marginal values of activity are the same for EV and non-EV owners.

We have additionally collected data on travel times, public and private parking locations, and EV charging locations and prices across NYC, combining information from various sources such as: NYC Departments of Transportation, Buildings, Information Technology and Communication; Google Maps; and the National Renewable Energy Laboratory.

We expect that our work will contribute to three key strands of literature. First, to the growing literature evaluating transportation systems and infrastructure investment ((*37–41*, *15*, *15*, *42*, *43*)). Especially, we hope to link the optimality and value of transportation policies more tightly to activity and scheduling behavior. Second, the literature on dynamic markets with frictions and their efficiency, of which two recent works are (*33*, *44*). Indeed, we recognize that the value of infrastructure is linked to the spatio-temporal dynamics of human activity and provide a framework that explicitly incorporates

[4] In a discrete-choice framework, this could be rationalized by noting that the value of time in a given location would represent the inclusive value of the set of activities available in said location.

[5] One will likely see parallels here with (*14*), whose value of waiting time savings on a trip depends on the marginal values at the origin and at the destination.

[6] Veraset Inc: https://www.veraset.com/

[7] ReplicaHQ: https://www.replicahq.com/

this aspect to inform the efficiency of infrastructure investment allocation. Moreover—and more related to the question of frictions—our model incorporates parking-related search frictions and quantifies their impact on welfare. Third, the literature on EV charging location optimization ((*16–31*)) and EV policy ((*45*)). Especially, in contrast to the existing optimization literature, our determination of optimal charger allocation depends on spatio-temporally varying scheduling costs for both EV and non-EV owners. We are able to capture changes in behavior resulting from adoption while also relying on measures that can be estimated even before adoption. This will allow us to more accurately quantify social costs and benefits associated with EV charging infrastructure.

3 Research team

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4 Conflict of Interest Statement

There is no conflict of interest to report.

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