Final Report

Impact of Charging Infrastructure on Electric Vehicle Adoption: A Synthetic Population Approach

Cinzia Cirillo
University of Maryland
Phone: 301-405-6864; Email: ccirillo@umd.edu

Lavan Teja Burra
University of Maryland
Email: burra1@purdue.edu

Mohammad Bilal Mohammad Al-khasawneh
University of Maryland
Email: mbmk2020@umd.edu

Date
March 2026

Prepared for the Safety and Mobility Advancement Regional Transportation and Economics Research Center, Morgan State University, CBEIS 327, 1700 E. Coldspring Lane, Baltimore, MD 21251

ACKNOWLEDGMENT

This research was supported by the Safety and Mobility Advancement Regional Transportation and Economics Research Center at Morgan State University and the University Transportation Center(s) Program of the U.S. Department of Transportation.

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<table>
<tr><td>1. Report No. SM25</td><td>2. Government Accession No.</td><td colspan="2">3. Recipient's Catalog No.</td></tr>
<tr><td colspan="2" rowspan="2">4. Title and Subtitle
Impact of Charging Infrastructure on Electric Vehicle Adoption: A Synthetic Population Approach</td><td colspan="2">5. Report Date</td></tr>
<tr><td colspan="2">6. Performing Organization Code</td></tr>
<tr><td colspan="2">7. Author(s)
Cinzia Cirillo, 0000-0002-5167-0413
Lavan Teja Burra 0000-0002-8507-6076
Mohammad Bilal Mohammad Al-khasawneh, 0000-0003-4725-3067</td><td colspan="2">8. Performing Organization Report No.</td></tr>
<tr><td colspan="2" rowspan="2">9. Performing Organization Name and Address
University of Maryland
1179 Glenn M. Hall
College Park, MD 20742</td><td colspan="2">10. Work Unit No.</td></tr>
<tr><td colspan="2">11. Contract or Grant No.
69A3552348303</td></tr>
<tr><td colspan="2" rowspan="2">12. Sponsoring Agency Name and Address
US Department of Transportation
Office of the Secretary-Research
UTC Program, RDT-30
1200 New Jersey Ave., SE
Washington, DC 20590</td><td colspan="2">13. Type of Report and Period Covered
Final,</td></tr>
<tr><td colspan="2">14. Sponsoring Agency Code</td></tr>
<tr><td colspan="4">15. Supplementary Notes</td></tr>
<tr><td colspan="4">16. Abstract
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<tr><td colspan="2">17. Key Words: Electric vehicle, Charging infrastructure, Synthetic population, DC fast charging</td><td colspan="2">18. Distribution Statement</td></tr>
<tr><td>19. Security Classif. (of this report) :
Unclassified</td><td>20. Security Classif. (of this page)
Unclassified</td><td>21. No. of Pages</td><td>22. Price</td></tr>
</table>

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Abstract

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Introduction

Traditional household travel surveys available regionally or nationally often lack sufficient data on households with electric vehicles (EVs), limiting their utility in providing a nuanced understanding EV adoption. Consequently, researchers often rely on stated-preference survey data, which capture hypothetical choices rather than the actual decisions (revealed preferences) of respondents. These data limitations pose a challenge for policymakers; understanding micro-level EV adoption rates is crucial for informing targeted policies, infrastructure development, and investment decisions.

Most studies in the literature rely on choice experiments or stated-preference survey data to investigate the potential role of infrastructure (see [1] for an overview of such studies). More recent studies use aggregate car registration data to analyze the effect of financial incentives and access to public charging stations on EV sales (A review of such studies can be found in [2] and [3]). Only a few studies utilize revealed preference data that includes socio-demographic information on households (e.g., [4, 5, 6]). Acquiring such granular datasets can be expensive, and collecting them directly is resource-intensive [7,8].

To investigate this, researchers can use household travel survey data, which typically includes information about the vehicle holdings of households in the sample. The latest travel survey data were collected before 2020, however—prior to a historic increase in EV adoption in the US[1]. These existing datasets therefore limit the development of reliable transportation models or statistics for policymakers. To overcome this limitation, we propose an integrated synthetic population approach that provides detailed sociodemographic and socioeconomic information at individual and household levels, preserving the dependency structure between variables of interest and the aggregated statistics of the actual population. This technique has been successfully used in transportation microsimulation systems, such as activity-based models [9, 10, 11].

Through this, the proposed research aims to address the following questions in the context of EV ownership. First, what factors influence households' decision to own an EV, and how does access to public charging stations influence EV ownership rates? Second, how does increasing the availability of public charging stations influence EV adoption? These questions are addressed by using Maryland as the case study.

Maryland's geographical proximity to major metropolitan areas, its households covering a wide range of socioeconomic backgrounds—from affluent urban areas to rural communities—and the unique mix of urban, suburban, and rural regions, present an opportunity to study EV ownership in this diverse landscape.

[1] In the 2017 National Household Travel Survey, less than 1% of surveyed vehicles are EVs.

Literature Review

There is a growing body of literature that has examined the factors important to plug-in electric vehicle (PEV) consumers. Several studies, based on consumer surveys and PEV sales data, have highlighted inadequate access to charging infrastructure and longer battery charging times as significant barriers to large-scale EV adoption, among other reasons [1, 12, 13, 14, 15, 16, 17, 18, 19, 20] [21, 22, 23].

Specifically, studies focused on consumer preferences reveal that regular charging options, such as home or workplace charging, play a critical role in PEV ownership during the early phase of adoption [1, 4, 14, 21]. Hardman et al. [1] find that, on average, 50-80% of EV charging occurs at home[2]. Funke et al. [14] in a meta-analysis of studies across different countries, find that home charging alone is sufficient for early EV buyers who have access to parking and can charge their car overnight.

Research on the EV market in the US [24, 25], Norway [26, 27], Germany [28], and China [29], using revealed preference or vehicle registration data, has shown a positive effect of charging infrastructure on EV adoption rates. However, most of these studies do not differentiate between different levels of charging, with Sommer and Vance [28] being the exception. It is important to consider nuances between different levels of public charging (mainly level-2 and DC fast charging) to better understand EV adoption rates [30]. Li et al. [24] highlights the indirect network effects between EVs and public charging infrastructure using EV registration data aggregated at the Metropolitan statistical areas. Studies based on GPS data/real-world car usage data find that among public charging stations, access to DC fast charging has a greater impact on PEV adoption than level-2 or other slower charging stations [31, 32, 33].

All else being equal, access to charging infrastructure at home is the most important factor for determining EV ownership, followed by workplace charging, and the public charging stations [1, 21, 34, 35, 36].

The majority of these studies either utilize stated-preference consumer survey data or aggregated vehicle registration data, which do not provide information on household demographics. The present study, however, utilizes household travel survey data from the state of Maryland to understand factors influencing households' choice of owning an EV. This data enables us to evaluate how their EV ownership changes across different area types and demographic groups with increased accessibility to public charging.

Data Description

The data used in this study is constructed from different sources that provide information on EV ownership at the household level, public charging station location and characteristics, household sociodemographic, and travel patterns in the state of Maryland, USA.

[2] "The state of EVs in America", Volvo Car USA

Maryland Regional Travel Survey

The primary data source is the Regional Travel Survey (RTS) conducted by the Metropolitan Washington Council of Governments (MWCOG), covering the DMV regions from October 2017 to December 2018. For this study, we focus only on the state of Maryland. Additionally, the study is complemented by the Maryland Travel Survey (MTS) conducted by the Baltimore Metropolitan Council (BMC), spanning from April 2018 through May 2019.

During these surveys, travel diary information was collected from 17,152 households that own 31,186 vehicles, providing detailed insights into household composition, residential locations, vehicle holdings, and their characteristics. Furthermore, the surveys recorded a one-day travel diary of the household residents, which includes information about the start and end time of each trip, trip length, and mode of transport. The data encompasses households from various area types, making it highly relevant to our study. Moreover, the survey includes valuable information about the possibility of charging EVs at work (if the households own any) and the time spent teleworking.

The final dataset used for analysis consists of 16,757 households after the cleaning process.

Table 1. Summary statistics of households and location attributes

Variable	N. of valid Obs	Mean	Std. Dev.	Min	Max
Household size	16,757	2.19	1.18	1	8
Number of workers	16,757	1.17	0.90	0	7
Household income	16,757	5.67	1.99	1	8
Number of vehicles	16,757	1.85	1.08	0	12
Average daily trips per person	16,757	3.44	2.14	0	41
Number of daily transit trips	16,757	0.76	1.82	0	28
Home office dummy	16,757	0.32	0.47	0	1
Home ownership	16,757	0.75	0.43	0	1
Single-family house dummy	16,757	0.77	0.42	0	1

Notes: *Household Income: 01=Less than $15,000; 02=$15,000 to $24,999; 03=$25,000 to $34,999; 04=$35,000 to $49,999; 05=$50,000-$74,999; 06=$75,000-$99,999; 07=$100,000-$149,999; 08=$150,000 or more; Home Ownership: 0=False (Rented); 01=True (Owned).

Table 1 presents the summary statistics of sociodemographic and location characteristics of the household sample in the survey data. On average, each household owns approximately two cars. Around 94% of Maryland's vehicles are powered by gasoline, with the remaining 6.3% distributed among other types. For the purposes of this study, we consider both battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEV) as EVs. Out of the households surveyed, only 169 own at least one EV, and among these, 15 households possess two EVs. These EVs constitute 0.59% of the total vehicles in the sample data. Interestingly, households with EVs tend to own more vehicles, with an average of 1.85 vehicles for households without EVs, compared to 2.33 vehicles for households with EVs. Among the households with EVs, 81% of households also had a non-electric vehicle in addition to the EV (consistent with the findings from [37]).

They tend to be larger, with an average of 2.47 members compared to 2.19 members for non-EV households. These findings provide valuable insights into the characteristics and demographics of households that own EVs in the study sample.

Charging Infrastructure

We utilized the electric vehicle charging station database provided by the U.S. Department of Energy (DoE) from the Alternative Fuels Data Center (AFDC). This publicly available national database contains comprehensive information about charging stations, including the number of charging ports based on charging speed, opening dates, geographic coordinates, and other relevant characteristics.

The database includes information about three types of charging ports: level-1, level-2, and DC fast chargers (DCFCs). Level-1 chargers are the slowest and, consequently, quite limited in public charging networks. On the other hand, level-2 chargers are more prevalent due to their higher power capacity and relatively affordable installation costs, making them a popular choice for public charging. DC fast chargers, being the fastest option as they employ high voltage, come with a higher usage cost. In Maryland, as of May 2019, there are a total of 1,203 public charging points available, with some stations having multiple charging outlets for different types of charging equipment. The distribution of these charging ports across the state includes 19 level-1, 967 level-2, and 217 DCFC ports.

Figure 1 illustrates the spatial distribution of public charging ports installed in Maryland from 2010 to 2019. A noticeable concentration of chargers is evident in the Baltimore and Montgomery County (close to Washington D.C.) regions. It's important to note that these charging stations do not include residential, workplace, or private charging facilities. We also observe that more charging stations were built in the latter years of the study.

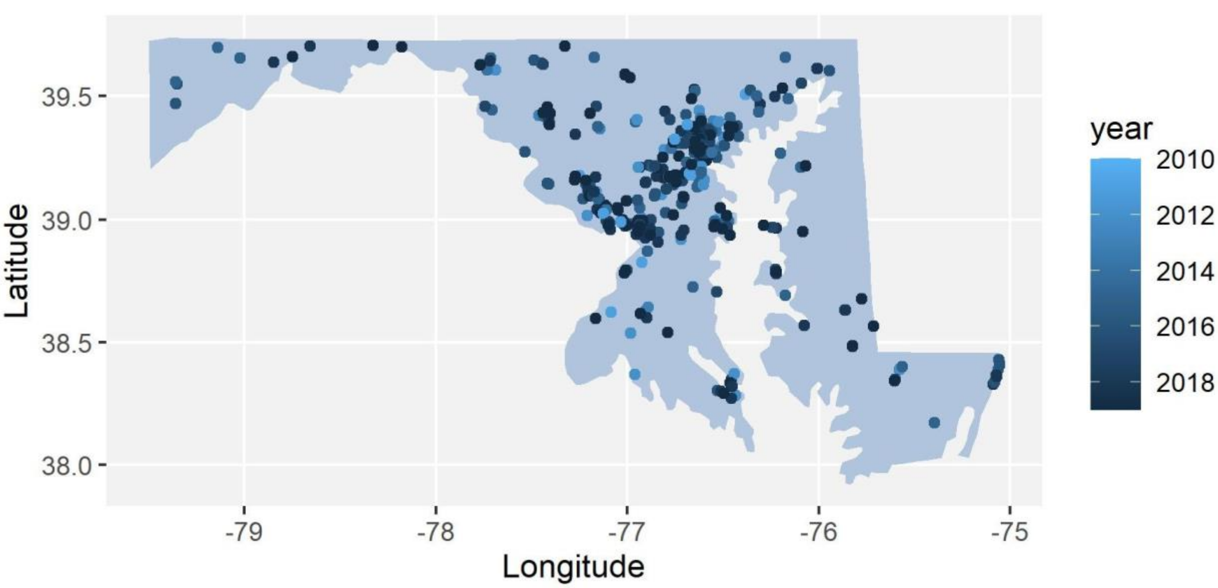


Figure 1. EV public charging port installation in Maryland from 2010 to 2019

In this report, we construct a measure of charging stations that calculates the total number of publicly accessible charging ports within a 5-mile radius from the centroid of each census tract, assuming no heterogeneity across households regarding access to charging within the census tract. The choice of the 5-mile buffer is based on the 50th percentile of the daily average car trip distances. Furthermore, we recognize that the availability of level-2 and DCFC stations impacts EV adoption among consumers differently [28]. Level-2 charging points, due to longer charging times, are primarily utilized for opportunity charging or at locations like offices or homes for parking [38]. To address this in the model, we create a measure of level-2 charging by counting the number of such ports within a 1,000-meter radius from the centroid of each census tract.

On the other hand, despite having to travel a bit further, consumers prefer to use DC fast charging stations due to their relatively fast charging speed. To incorporate this charging preference heterogeneity, we create a measure of DC fast charging by counting the number of such ports within a 5-mile radius from the centroid of each census tract. This approach helps us capture the varying effects of charging station types on EV adoption in the study area.

Figure 2 illustrates the 5-mile buffers created for two random census tracts. After constructing the data, on average, we find 45 level-2 charging ports and 4 DCFC ports within a 1,000-meter and 5-mile radius from the centroid of the census tract. Additionally, approximately 16% of the census tracts have no charging points available for public use.

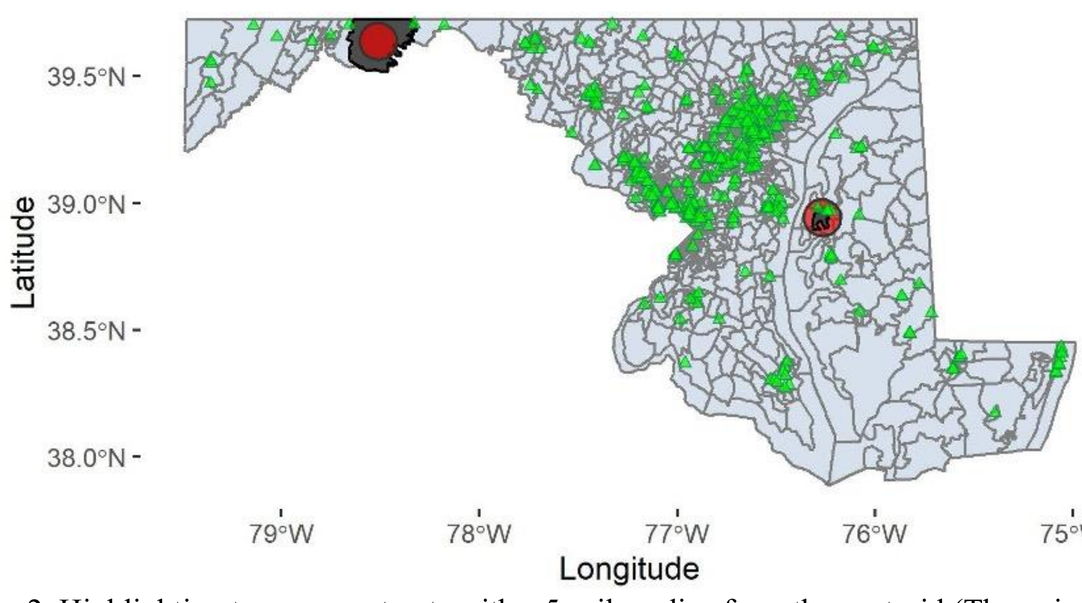


Figure 2. Highlighting two census tracts with a 5-mile radius from the centroid (The points in the map are the public charging station locations)

Methodology

We develop an integrated approach to examine the relationship between the growth of EVs and the increased deployment of public charging stations. We start by estimating a binomial logit model utilizing household survey data to help us understand the factors influencing the decision to own an EV. These estimates are subsequently applied to a synthetic population generated using a Bayesian network-based method, enabling us to determine the probability of households owning an EV. Finally, we test various scenarios of growth in public charging stations on this synthetic population to observe the changes in EV ownership levels, taking into account housing types and location characteristics.

Binomial Logit Model

Drawing on the microeconomic theory of consumer behavior, the decision to own an EV can be framed as a household maximizing its utility, taking into account charging considerations and various other constraints. In this study, the choice set comprises two alternatives: owning an EV (both BEV and PHEVs), represented as $j = 1$, and not owning any EV, represented as $j = 0$. We denote the observed EV ownership of a household i during a specific period as Y_{ij}.

To model the household's decision regarding the ownership of an EV, we employ a binomial logit model (BNL) with a set of predictors. This modeling framework assumes that the utilities (U_j) associated with the alternatives in the discrete model consist of two components: a systematic utility component (V_j), which is observable, and an error term (ϵ_j), which is not observable. Following the discrete choice theory [39], the probability that a household chooses EV ownership over not owning it, in terms of the binomial logit model, can be expressed by the following equation:

$$P_{i1} = \frac{1}{1 + \exp[V_{i1} - V_{i0}]} \tag{1}$$

Here, the utility of EV ownership can be written as $V_{i1} = \beta_0 + \beta_k X_k + \beta_c C$, where, X_k is a vector of consumer characteristics, location, and car characteristics, and C is the measure of public charging stations accessible to the consumer. β_k is a vector of parameters to be estimated and β_c reflects the role of public charging infrastructure. We assume households to be rational and choose to own an EV only if it maximizes utility.

The independent variables will include household income, the number of working persons in the household, whether they live in a single-family house, the number of bicycles owned by the household, the number of transit trips made during the travel day, the total distance traveled using a car during the travel day, whether they teleworked, and the possibility of charging at work. Additionally, the utility function of EVs will include a measure of level-2 and DCFC points that are available for public use in the corresponding census tract.

Synthetic Population

Even though the survey dataset accurately represents the entire population of Maryland, it does not provide disaggregated data for every single unit in the population. For this research study, the weighted sample provided by the survey dataset was used to obtain the cumulative distribution functions (CDFs), which would later be utilized in constructing the synthetic population.

We employ a Bayesian network (BN) approach to create the synthetic population, an artificial representation of the actual population. It is a probabilistic model that encodes the joint probability distribution of a set of random variables and represents them in a directed acyclic graph (DAG) [40]. The DAG contains nodes and directional links that represent the variables and their conditional dependencies; the link $A \rightarrow B$ indicates that B (the child) is dependent on A (the parent). Each node carries the probability of finding that node under a given condition. Sun and Erath [41] have used BN for creating a synthetic population for Singapore, and the study results showed that BN outperformed other population synthesizers such as Iterative Proportional Fitting (IPF) and Markov chain Monte Carlo algorithm (MCMC) in terms of overfitting, heterogeneity, and missing data. Moreover, the BN approach has been used in recent studies to generate disaggregated data using traditional survey data or open data for transportation models [42, 43].

A synthetic population was created, incorporating the necessary variables to accurately represent Maryland households in terms of income, household composition, travel behavior, and housing status. The sample observations for each census tract were converted to pseudo-observations ranging from 0 to 1 and used to learn the dependency structure among the selected variables of interest using Bayesian network learning techniques. To do so, we utilized a greedy search algorithm to determine the optimal network structure (see Figure 7), establishing dependencies among the selected variables. The optimal network structure was then used to synthesize n number of synthetic pseudo-observations, where n is equivalent to the total number of households. Finally, the synthetic population was obtained by transforming the synthetic pseudo-observations to the original values using inverse CDFs. For more information on the BN method used in this paper to generate the synthetic population, see [44].

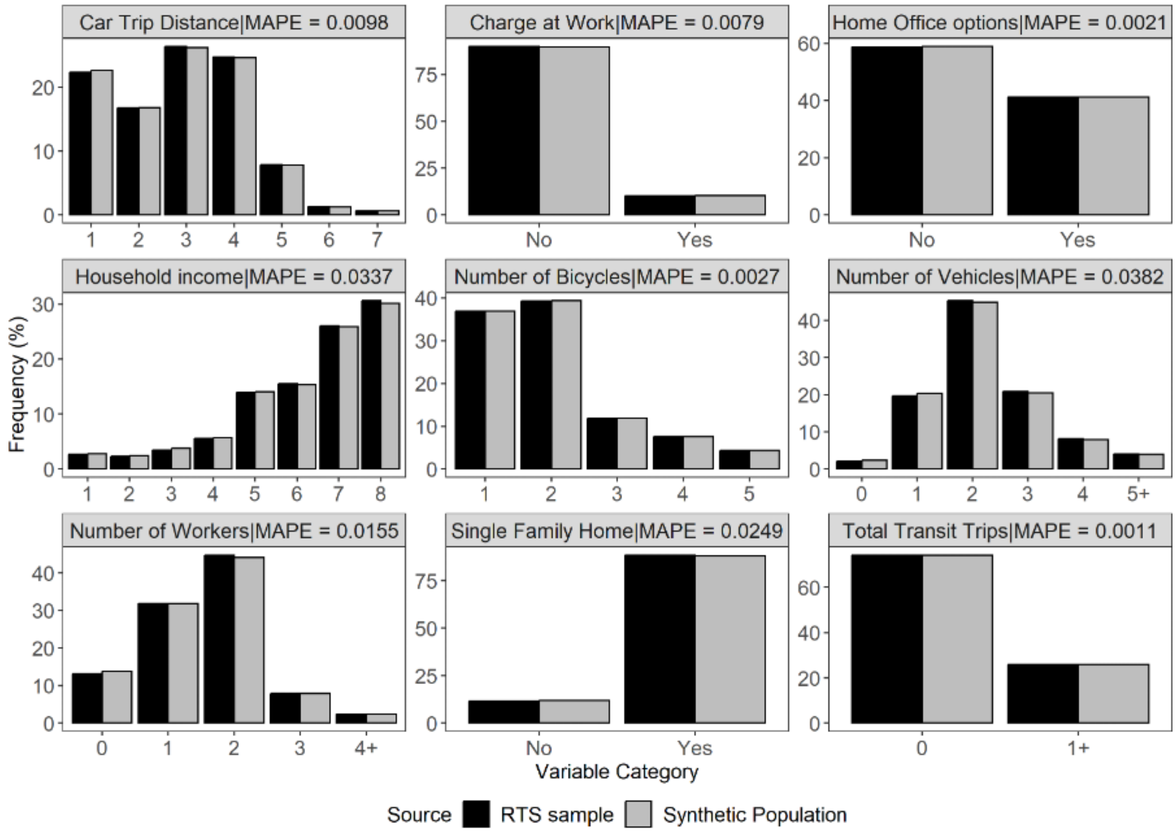


Figure 3. Comparison of synthetic population and decennial census data

As the sampling process may generate unfeasible samples, we incorporate a sanity check mechanism to exclude infeasible attribute combinations during the generation process. For example, we exclude any household sample if the number of workers exceeds the total number of people in that household or if the number of transit trips exceeds the total number of daily trips. By doing so, we ensure that the synthetic population remains realistic and representative of the underlying population. Our aim is to enhance the modeling process by synthesizing a population that encompasses a broader range of samples that might not be captured in the original survey data, thereby improving the robustness and generalizability of our models.

The Mean Absolute Percentage Error (MAPE) was used to compare the household attributes resulting from the synthetic population (synthesis estimates) with the weighted estimates from the RTS sample. MAPEs were found to be low for all variables, indicating a reliable synthetic population. Figure 3 shows the results of a comparison between the synthetic population and the RTS sample.

Results

We start by estimating a binomial logit model that includes the total number of public charging ports accessible for households based on their location. Motivated by the differential effects of charging points by charging speed as discussed before, we subsequently analyze the effect of level-2 and DC fast charging. We then apply the model to the synthetic population generated to arrive at the probability of a household owning an EV.

Table 2 summarizes the final statistical results of the estimated binomial logit model. As mentioned, the estimates indicate the choice of households owning an EV. Model 1 presents the estimates which include a measure of total public charging ports accessible for the households, whereas Model 2 distinguishes between different levels of charging. Overall, the coefficients' signs were as expected, and they were statistically significant in most cases.

A higher number of bicycles owned in the household has a positive influence on the ownership of an EV. The coefficient of the single-family house variable, which serves as a proxy for access to private charging at the home location, is positive but is statistically significant only at the 10% level. The coefficient of distance traveled using cars in the household is also significant, indicating that households with longer commutes are less likely to own an EV, reflecting concerns about the limited range of EVs.

Regarding charging infrastructure, the availability of public charging points is generally found to have a positive effect on EV ownership. In the model with only the total number of publicly accessible charging ports, the coefficient is positive but statistically insignificant. However, when differentiating between levels of charging stations, we observe that the availability of both level-2 and DC fast charging has a positive influence on EV ownership, while only the latter has a statistically significant influence. Specifically, the availability of DC fast charging has a stronger effect than level-2 charging (in line with the received literature [28]), indicating households' preference for accessibility to fast charging when owning an EV. A likelihood ratio test indicates that the specification with level-2 and DCFC variables (i.e., Model 2) in Table 2 provides a significantly better fit than the specification with omitting these variables[3].

[3] The likelihood-ratio (LR) test statistic equals 8.06 with a p-value of 0.01, indicating that the inclusion of level 2 and DCFC variables improves the model fit significantly.

Table 2. Estimates from the Binomial Logit model

	Model 1		Model 2	
	Coeff.	Std. Err.	Coeff.	Std. Err.
Household income	0.303***	(0.065)	0.305***	(0.065)
Single-family house dummy	0.443	(0.290)	0.479	(0.294)
Number of bicycles	0.133**	(0.056)	0.136**	(0.056)
Number of workers	-0.264**	(0.107)	-0.269**	(0.107)
Total no. of transit trips	-0.034	(0.046)	-0.044	(0.046)
Total distance traveled by car	-0.005***	(0.002)	-0.004***	(0.002)
Home office dummy	0.789***	(0.179)	0.783***	(0.179)
Charge at work	0.795***	(0.197)	0.799***	(0.197)
No. of public charging ports	0.002	(0.001)	–	–
No. of level 2 charging ports	–	–	0.011	(0.014)
No. of DC fast charging ports	–	–	0.032***	(0.012)
Constant	-7.542***	(0.461)	-7.676***	(0.464)
No. of observations	30,868		30,868	
Initial log-likelihood	-1084.88		-1084.88	
Log-likelihood at convergence	-1026.83		-1023.78	
R-square	0.053		0.056	

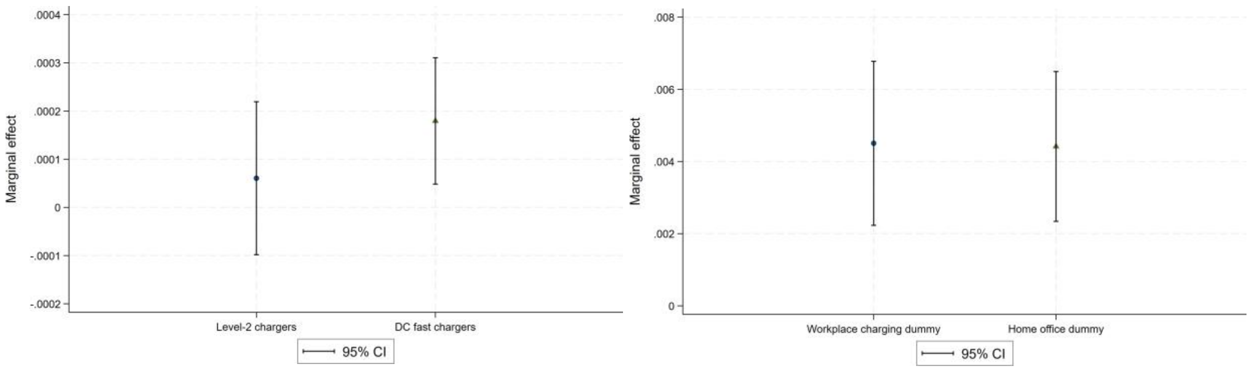
*Notes: Charging station variables in the model include: Level 2 charging ports within a 1,000- meter radius, DC fast charging ports within a 5-mile radius, and the total number of charging ports within a 5-mile radius from the centroid of the census tract. Additionally, the variable "charge at work" indicates the possibility of charging at the workplace for at least one person in the household. Household Income: 01=Less than $15,000; 02=$15,000 to $24,999; 03=$25,000 to $34,999; 04=$35,000 to $49,999; 05=$50,000-$74,999; 06=$75,000-$99,999; 07=$100,000-$149,999; 08=$150,000 or more; Home Ownership: 0=False (Rented); 01=True (Owned). Robust standard errors are reported in parenthesis. ***, **, *, and denote statistical significance at the 0.1%, 1 %, 5 %, and 10 % level, respectively.*

Interestingly, the possibility of teleworking and the possibility of charging at the workplace are both very significant and positively affect EV ownership. This suggests that households with access to teleworking options and workplace charging facilities are more likely to own an EV reflecting that flexibility in travel and convenience in access to charging is important. Notably, the most striking finding is that access to workplace charging has a stronger positive effect on EV ownership than publicly available DC fast charging, which is consistent with the findings from [1, 21].

Figure *4* presents the marginal effects of key variables from Model 2 in Table 2. Having an additional DC fast charger within a 5-mile radius of the census tract centroid increases the probability of a household owning an EV by about 0.02%. Similarly, an additional level-2 charging point within 1,000 meters increases the probability by 0.006%. Notably, access to workplace charging and the possibility of teleworking each independently increase the probability of EV ownership by 0.45%.

Furthermore, to provide a better understanding of the practical significance of these findings, we follow the recommendation of [45] and calculate the marginal effects scaled by the standard deviation of the corresponding variables (standardized marginal effects). These estimates reveal that a one standard deviation increase in level-2 chargers increases the probability of owning an

EV by 0.002%, while a one standard deviation increase in DC fast chargers increases the probability by 0.003%. Access to workplace charging and home office possibility have a more substantial impact, with standardized effects of 1.7% and 0.9% increase in ownership probability, respectively[4].



(a) Number of public charging points (b) Access to workplace charging and teleworking

Figure 4. Marginal effects of variables

Notes: The variables in Figure 4a are the number of public charging points (no. of leve-2 within 1000 meters and DCFC within a 5-mile radius from the centroid of the census tract) in our data, and the variables in Figure 4b are dummies indicating the access to workplace charging and the possibility of teleworking.

Due to the relatively low number of EVs in our survey data and the assumption of a symmetrical logistic distribution for the dependent variable in the logit model, we additionally estimated a skewed logistic model as a robustness check. While the point estimates from both models were similar, the standard errors differed slightly (see Table 3). This difference resulted in the effect of level-2 chargers becoming statistically significant in the skewed logistic model. The log-likelihood values between the two models were also quite comparable, as reported in the paper.

In the next step, using the estimates from Model 2, which distinguishes chargers by charging speed, we predict the probability of owning an EV for each household unit generated by the synthetic population. The predicted numbers of EVs are then aggregated for the entire state of Maryland and compared with the total number of EVs estimated from the survey to evaluate the accuracy of the results. The model predicts 15,809 EVs, compared to the 14,790 EVs reported in RTS, with a MAPE of 6.4%.

In Figure 5, the spatial distribution of the predicted number of EVs across Maryland at the census tract level is illustrated. Overall, we identify a certain nexus between the distribution of charging stations (by levels) from Figure 1, and the adoption of EVs among the synthetic population as shown in Figure 5.

[4] The mean and standard deviation of these key variables: level-2 chargers (0.496, 3.459), DC fast chargers (3.717, 5.958), workplace charging dummy (0.345, 0.475), and home office dummy (0.074, 0.261).

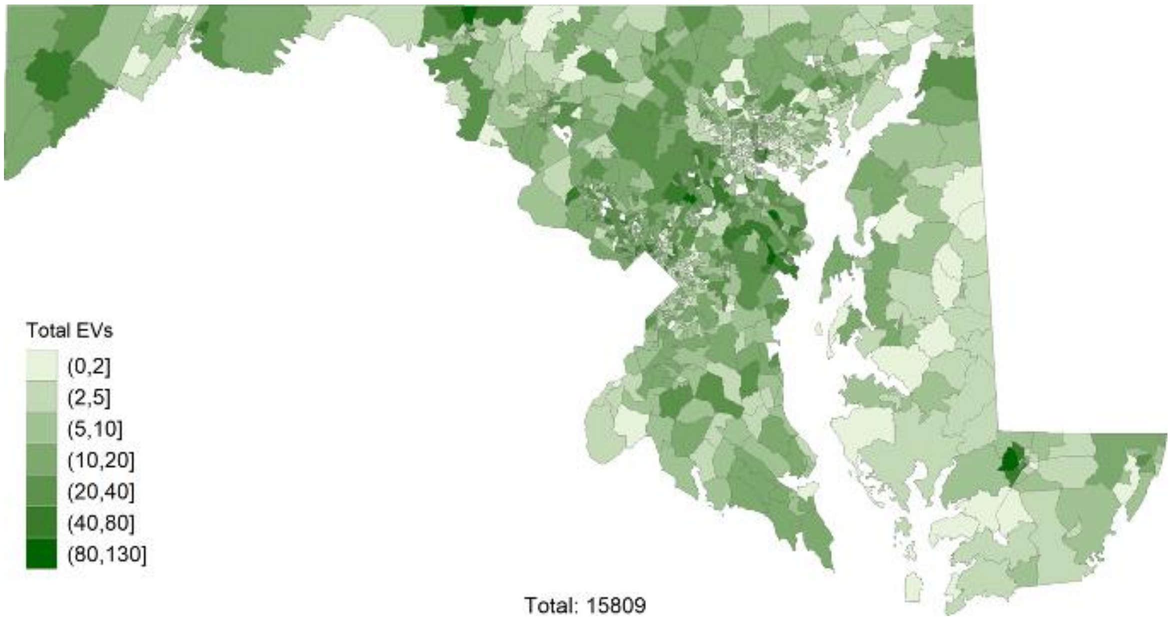


Figure 5. Spatial distribution of the predicted number of EVs

Scenarios of Growth in Public Charging Stations

Using the BNL model estimates and the synthetic population, we can evaluate different scenarios of charging station growth and assess their impact on EV ownership. Regardless of which deployment scenario tracks closest with reality in the coming years, understanding how the EV market will respond to a certain increase in public charging stations is of significant interest to policymakers, transport planners, and automobile companies.

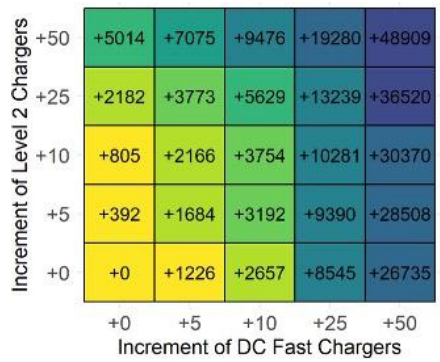
We start by classifying census tracts in Maryland into three area types: rural, suburban, and urban areas, based on household density (measured in households per square mile)[5]. Figure *6* presents the predicted change in EV ownership across these areas in Maryland with a change in the current number of Level 2 and DCFC stations, assuming that all other household characteristics will remain the same. Overall, the results highlight two important findings: the growth in DC fast charging stations will significantly drive the increase in EV ownership across all area types, and for the same growth in charging stations, we observe a strong rise in the ownership of EVs in suburban areas.

As shown in Figure *6*, a 50-unit increase in Level 2 charging points across all census tracts, while maintaining the same level of DCFC points, results in an overall increase of 5,014 EVs in suburban areas, 4,608 EVs in urban areas, and only 820 EVs in rural areas. Similarly, a 50-unit increase in DCFC points across all census tracts leads to an overall increase of 26,735 EVs in suburban areas, 24,504 EVs

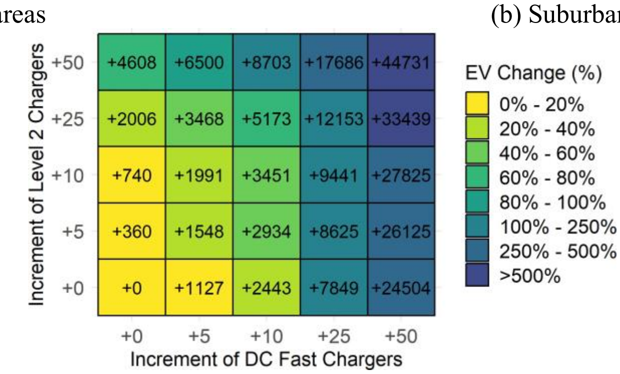
[5] This classification follows the categories defined by [47] as follows: rural area if the household density is less than 106, suburban area if the household density ranges from 106 to 1314, and urban area if the household density is greater than 1314. Based on this classification, the census tracts in Maryland are distributed as follows: 52% are categorized as urban areas, 37% as suburban areas, and 11% as rural areas.

in urban areas, and 4,406 EVs in rural areas. This indicates that for the same level of growth in charging stations, we observe more than a 5-fold increase in EV ownership levels across suburban and urban areas compared to rural areas.

(a) Rural areas



(b) Suburban areas



(c) Urban areas

Figure 6. Marginal effects of variables

The majority of the areas classified as urban are located in Baltimore and close to Washington D.C. (Montgomery and Prince George's County region) in Maryland, where reasonably significant public charging is available (see Figure 1). As a result, we observe a significantly higher increase in EV ownership among households residing there, although it remains relatively lower compared to suburban areas[6]. This difference in adoption rates could be attributed to the more extensive public transportation options available in these urban areas and the challenges of limited parking availability.

Regarding suburban areas, we find the highest increase in EV ownership levels with the growth in public charging stations, as accessible charging infrastructure can facilitate longer distance commutes for suburban residents. Conversely, due to longer commuting distances and sparsely distributed charging network, we observe relatively lower levels of EV ownership in rural areas.

[6] [46] also predicts stronger EV adoption levels in suburban levels across the US by 2030.

Conclusion

Due to the limited availability of revealed preference survey data on electric vehicle choices, and the significance of understanding demand at a finer geographic level to better direct investments in public charging infrastructure, we propose an integrated approach of discrete-choice modeling and synthetic population generation through a Bayesian network-based approach. Using this method, we analyze the impact of public charging stations on electric vehicle ownership at the census tract level in Maryland. We differentiate between the effects of level-2 and fast chargers. Initially, we estimate a binomial logit model based on a regional travel survey to assess the likelihood of households owning an EV, while controlling for household demographics and nearby charging infrastructure.

Our findings align with existing literature, demonstrating a positive and significant effect of level-2 and DC fast chargers on EV ownership. Notably, the impact of access to fast charging was stronger, reflecting its importance in facilitating longer-distance travel. Interestingly, access to workplace charging had a significantly positive effect, highlighting the crucial role of convenient charging options in influencing EV ownership. Additionally, the possibility of teleworking was found to be a positive factor for EV ownership, as it reduces the range anxiety for workers and provides for more flexibility in charging schedules.

Using our logit model estimates on the synthetic population, generated using a Bayesian network approach, we were able to predict EV ownership levels across various socio-demographic groups and residential environments. Interestingly, for the same increase in public charging stations across census tracts, suburban areas exhibited the highest projected growth in EV ownership, followed by urban areas.

By applying our model estimates to the state's synthetic population, we predicted a total of 15,809 EVs during the survey period. This approach crucially allowed us to capture the spatial distribution of EV adoption at the census tract level.

We acknowledge that including interaction terms between public chargers and regional groups might reveal even more nuanced results. However, due to the limited sample size of EVs in our survey data (only 176 vehicles), including interactions would leave too little variation to estimate the parameters reliably. However, our synthetic population incorporates demographic information. This allowed us to predict the increase in EV ownership levels across different groups with an increase in public charging points. However, for a more detailed analysis of the differential effects across demographic groups, a larger real-world data sample would be beneficial for future research.

Although our methodology enables us to analyze EV ownership across the entire population, we acknowledge the reliance on slightly older data. The EV market and public charging stations have developed considerably since the data was collected, prompting the need for analysis using more recent data. Despite these limitations, our study provides valuable insights into the impact of public charging stations on EV ownership across different demographics. Additionally, this methodology can be extended to other states or the United States if vehicle-type ownership models are available.

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APPENDIX

Table 3. Estimates from the Skewed Logistic (scobit) model

	Model 1		Model 2	
	Coeff.	Std. Err.	Coeff.	Std. Err.
Household income	0.303***	(0.073)	0.305***	(0.073)
Single-family house dummy	0.441	(0.291)	0.477	(0.296)
Number of bicycles	0.133**	(0.054)	0.135**	(0.054)
Number of workers	-0.263**	(0.114)	-0.268**	(0.114)
Total no. of transit trips	-0.034	(0.065)	-0.044	(0.065)
Total distance traveled by car	-0.005***	(0.002)	-0.004***	(0.002)
Home office dummy	0.786***	(0.176)	0.780***	(0.176)
Charge at work	0.791***	(0.194)	0.794***	(0.195)
No. of public charging ports	0.002	(0.001)	–	–
No. of level 2 charging ports	–	–	0.011*	(0.006)
No. of DC fast charging ports	–	–	0.031***	(0.010)
Constant	-16.715***	(0.828)	-16.923***	(1.996)
No. of observations	30,868		30,868	
Log-likelihood at convergence	-1026.78		-1023.76	

*Notes: Charging station variables in the model include: Level 2 charging ports within a 1,000- meter radius, DC fast charging ports within a 5-mile radius, and the total number of charging ports within a 5-mile radius from the centroid of the census tract. Additionally, the variable "charge at work" indicates the possibility of charging at the workplace for at least one person in the household. Household Income: 01=Less than $15,000; 02=$15,000 to $24,999; 03=$25,000 to $34,999; 04=$35,000 to $49,999; 05=$50,000-$74,999; 06=$75,000-$99,999; 07=$100,000-$149,999; 08=$150,000 or more; Home Ownership: 0=False (Rented); 01=True (Owned). Robust standard errors are reported in parenthesis. ***, **, *, and . denote statistical significance at the 0.1%, 1 %, 5 %, and 10 % level, respectively.*

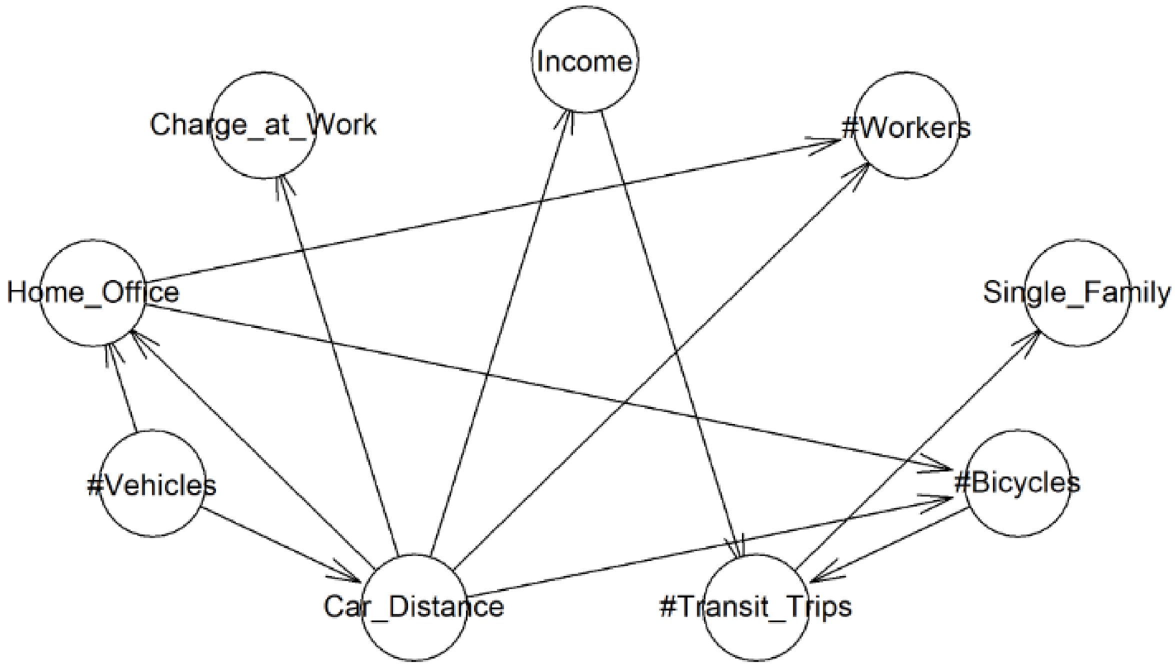

Figure 7. Optimal Bayesian network structure reflecting the dependency among the variables