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Exploring Workplace or Public Charging Demand for Electric Vehicles (EVs) in Califronia

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Executive Summary

This study aims to explore the out-of-home charging demand in California with a focus on electric vehicle (EV) commuting. Using regression techniques, we first develop a method to estimate destination-based car commuters by considering other modes so that we estimate EV commuters at destinations (Census block group level). We then estimate the total number of daily EV charging events and energy demand for charging at commute destinations using charging demand models with multiple scenarios. Some key findings from charging demand models are as follows. First, the statewide commute charging demand is 2,462 MWh/day for a total of 581,710 EVs within the state in 2020. Second, we observe a significant positive relationship between free workplace charging and charging demand at commute destinations. Third, a decrease in home-based charging accessibility increases out-of-home charging demand. Lastly, increases in the range of electric vehicles (EVs) are less critical in altering charging behavior, which may imply that the average range of the current EV fleet is already sufficient for commuting.

Keywords: Electric Vehicles (EVs), EV commuting, public charging demand, daily charging events, California charging infrastructure

1 Introduction

Over the past few years, the penetration of electric vehicles (EVs) into a conventional internal combustion engine vehicles (ICEVs) market has been considered a great opportunity to reduce greenhouse gas (GHG) emissions and cope with increasing oil prices (Liu et al., 2019; Sun et al., 2019; Chakraborty et al., 2022). Many countries and the U.S. have tried to reach higher rates of EV ownership (Chakraborty et al., 2019; Jia and Chen, 2022), especially, California has the most aggressive EV plan in the U.S. which achieve 100 percent zero-emission vehicle sales by 2035 (California Air Resources Board (CARB), 2022).

In recent years, EV adoption has accelerated, but limited charging infrastructure has still been considered one of the significant barriers to the penetration of EVs (Greene et al., 2020; Fachetta and Noussan, 2021; Shi et al., 2021). Although many current EV owners conduct charging at home (Hardman et al., 2022; Iravani, 2022), not every owners can access home-based charging. In particular, EV owners of multi-unit dwellings that lack proper access to home charging and those with parking spaces that lack access to electricity have to rely on out-of-home charging such as workplace or public charging stations (Davis, 2019). In addition, reasonable access to charging infrastructure allows EV drivers to travel long distances (Csonka and Csiszár, 2017; Iravani, 2022). Therefore, out-of-home charging infrastructure will be beneficial for EV owners, as this can be a primary source of charging or an optional way to extend driving range.

As the demand for out-of-home charging infrastructure continues to increase, it has been a significant challenge for planners and policymakers to distribute charging stations in the right numbers and places (Davis, 2019; Xu et al., 2021; Carlton and Sultana, 2022). Although it may seem obvious to deploy charging stations where EVs are expected to be charged, it can be challenging to accomplish in practice because it completely depends on current and future demand forecasting. Many existing studies have utilized EV sales or adoption rates to estimate the demand for charging infrastructure. However, most studies are based on residential locations and use large geographical scales, and tend to ignore commuting. Since most out-of-home charging occurs at or near the workplace (Xu et al., 2021), it is important to focus on car commuters to estimate out-of-home charging demand. In this context, this study identifies the commute charging demand with a focus on destination-based commuting, such as commuters and their mode share.

This study can be divided into two analysis parts: (1) estimating EV commuters and (2) estimating their charging demand. This study mainly utilizes data from American Community Survey (ACS) and LEHD (Longitudinal Employer-Household Dynamics) Origin-Destination Employment Statistics (LODES). Using regression techniques, we first develop a method to estimate destination-based commuting such as commuters and their mode share at the Census block group level. We then employ a charging demand model (Chakraborty et al., 2019; Davis and Tal, 2021) to estimate the total number of daily charging events and energy demand for charging at destinations.

2 Data, Descriptive statistics, and Methods

This study mainly utilizes the data from the 2015-2019 American Community Survey (ACS) 5-year estimates conducted by the U.S. Census Bureau, which provide information on demographic, socio-economic, and housing characteristics (U.S. Census Bureau, 2020). The ACS data also include information on means of transport to work, which is destination-based but only at the county level. Figure 1 shows mode share at the county level in California.

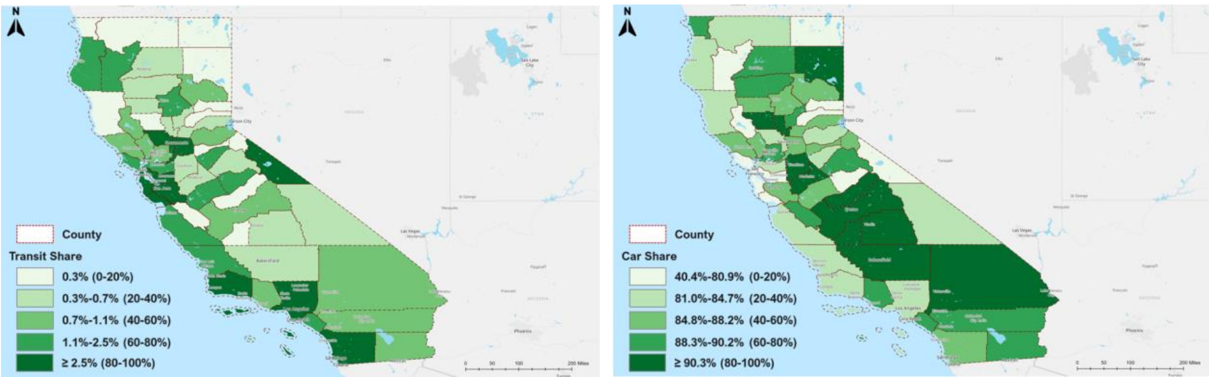

Figure 1. Commute mode share (public transit (left) and car (right) in California

This study consists of two analysis parts to estimate commute charging demand at the Census block group level. Figure 2 provides a schematic overview of commute charging demand models.

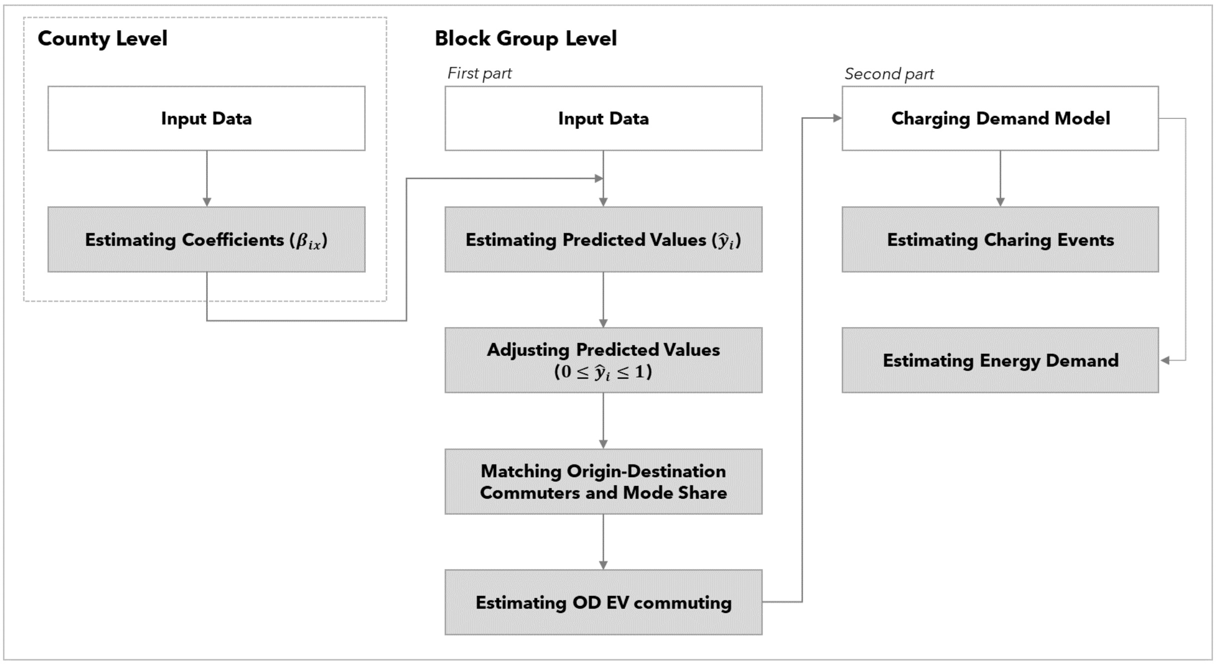

Figure 2. Schematic overview of the commute charging demand models

To estimate destination-based commuters and mode share at the census block group level, we first develop a method using regression models based on mode share from the ACS data at the county level. We combine ACS data with the LEHD (Longitudinal Employer-Household Dynamics) Origin-Destination Employment Statistics (LODES), National Land Cover Database, and OpenStreetMap (OSM) data to generate input variables.

Table 1 shows the definition and descriptive statistics of input variables used in the county and block group level models.

Table 1. Definition and descriptive statistics of input variables

Variables	Definition	County	Block Group
		Mean (Std. Dev.)[a]	Mean (Std. Dev.)[a]
Mode Share: Car	The proportion of car commuting at destination-based	84.56%	.
Mode Share: Transit	The proportion of transit commuting at destination-based	2.43%	.
Mode Share: Other	The proportion of walk or other commuting and work from home at destination-based	13.01%	.
Population Density	The number of people per square mile of land area	404.3 (775.8)	9359.1 (10199.5)
Employment Density	The number of employees per square mile of land area	207.7 (520.3)	2868.9 (11545.0)
Intersection Density	The number of intersections per square mile of land area	91.1 (143.3)	1130.7 (1095.9)
Land: Water	The proportion of areas of open water	7.65%	0.98%
Land: Open Space	The proportion of areas of open space, impervious surfaces account for less than 20% of total cover	2.97%	6.59%
Land: Low Intensity	The proportion of areas of developed area, impervious surfaces account for 20% to 49% of total cover	1.94%	15.74%
Land: Medium Intensity	The proportion of areas of developed area, impervious surfaces account for 50% to 79% of total cover	2.94%	47.01%
Land: High Intensity	The proportion of areas of developed area, impervious surfaces account for 80% to 100% of total cover	1.11%	15.34%
Land: Barren	The proportion of areas of bedrock, desert pavement, scarps, sand dunes, etc.	1.93%	0.22%
Land: Forest	The proportion of areas dominated by trees	24.89%	2.68%
Land: Shrubland	The proportion of areas dominated by shrubs	41.42%	7.43%
Land: Cultivated Crop	The proportion of areas of grasses, legumes, or used for the production of crops	13.70%	3.56%
Land: Wetland	The proportion of areas where soil or substrate is periodically saturated with or covered with water	1.44%	0.45%
Number of observations	The number of counties in the study area (CA)	58	23,212

[a] Mean or Percentage. For continuous variables, we report the mean values. Standard deviations are reported in parenthesis. We report the percentage for categorical (dummy) variables

As can be seen in Table 1, the first part aims to estimate predicted values of commute mode share at the census block group level using regression analysis techniques. To illustrate, we estimate parameters affecting mode share at the county level. As independent variables, we use population density, employment density, intersection density, and proportion of land use which are classified into 10 categories.

We then utilize estimated parameters to measure predicted values (commute mode share) at the census block group level. Since the predicted values can deviate between 0 and 1, we adjust the values using the normalization formula and county's average mode share. The LODES data include information on the number of origin and destination employees. It is used to measure destination-based car commuters through destination-based estimated car share multiplied by the number of employees as follows:

$$\text{Car Commuters}_{\text{BG}_\text{i}} = \text{Car}\ \widehat{\text{Mode Share}}_{\text{BG}_\text{i}} \times \text{Number of employees}_{\text{BG}_\text{i}}$$

The sum of commuters in census block groups by county is the same as county commuters. However, since mode share in each census block group is based on mode share in its county, rural areas' mode share tends to be under-estimated. To revise this problem, we classify census block groups into urban and rural areas using the 2019 Urban Areas data from Census Bureau. Urban Areas are defined as densely developed territories encompassing urban land uses (Census Bureau, 2020). Figure 3 shows the Urban Areas and census block groups.

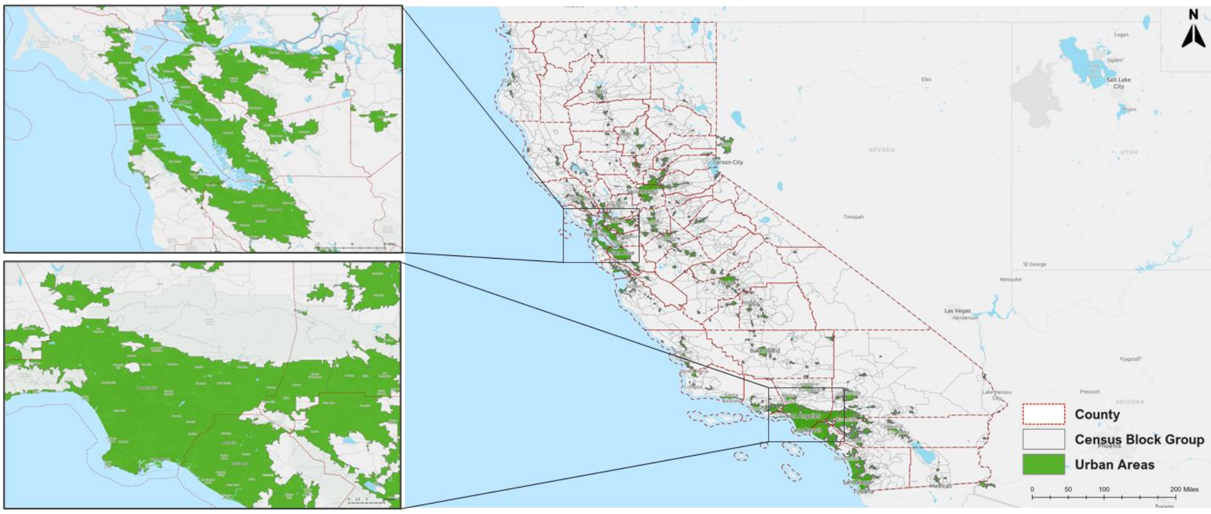

Figure 3. Urban areas and census block group

To classify block groups into urban and rural areas, we measure each block group's overlapping rate of urban areas. Based on population density and land use, block groups with less than 10 percent overlap are selected as rural areas. In rural block groups, the average population density is around 145 per square mile, and about 85 percent of areas are dominated by shrubland, cultivated crops, and forest. The number of rural block groups is 1,661 out of 23,212, accounting for 7.2 percent of the total block groups. We assume that cars are used 100 percent for commuting in rural block groups and manually assign them. We then recalculate the adjusting ratio considering rural areas' car share and each county's average mode share. We then re-estimate the destination-based mode share and car commuters at the census block group level.

We check the validity of our predicted mode share at the census block group level by comparing them with estimates used in the travel demand model in MPOs such as the Southern California Association Government (SCAG) and Sacramento Area Council of Government (SACG). Their activity-based travel demand model tends to overestimate car mode share since they do not consider work-from-home commuters. However, it is worthwhile to compare the share of public transit share and overall spatial distribution patterns of mode share. As a result, we find that the differences between our predicted public transit share and MPO's share range from 0.09 to 0.5 percent, which indicates our predicted mode share is well-estimated.

We match predicted destination-based commuters with origin commuters from LODES data to generate Origin-Destination (OD) matrix of commuters. Since we cannot control out-of-state commuters, we adjust the total origin commuters based on total destination commuters. Using destination-based mode share, we generate OD fractions of car commuters. We also measure the proportion of EVs at the census block group level using the 2020 vehicle registration data from the Department of Motor Vehicles (DMV) in California. Finally, we estimate Origin-Destination EV commuters using OD fractions of car commuters and origin-based EV fractions. In addition, we also generate an Origin-Destination network distance matrix based on census block group centroids and OpenStreetMap (OSM) road data using QGIS.

As can be seen in Figure 2, we estimate charging events and energy demand using charging demand models in the second analysis part. Based on the above regression models, we are able to estimate the number of electric vehicles (EVs) that are used for commuting at each commute destination. We then investigate the charging demand at commute destinations by utilizing a charging demand model developed in a previous study (Chakraborty et al., 2019), which provides predictions of charging probability at work and aggregate expected number of charging events per day for commute routes. Attributes that affect charging behavior include the cost of charging, access to charging infrastructure, and vehicle characteristics like electric range. Electric vehicle network commute distance eVMT_(BG_i) and share of charging at work are used to calculate the energy demand for charging at work with the equation below:

$$\mathrm{ChargingDemand}_{\mathrm{BG_i}} = \text{share of charging at work}_{\mathrm{BG_i}} \times \mathrm{eVMT}_{\mathrm{BG_i}}$$

To better capture the variability of fleet composition and charging behaviors, we tested a base case scenario and three sensitivity scenarios. The assumptions of the scenarios are shown in Table 2.

Table 2. Assumptions of charging characteristics

Scenarios	Long range fraction	Home charge fraction	Workplace charge free
Base case	0.85	0.90	FALSE
Free workplace charging	0.85	0.90	TRUE
Low home charging	0.85	0.64	FALSE
High long-range fraction	0.95	0.90	FALSE

Since our estimation of charging demand is based on the total registered electric vehicles in California in 2020, our base case scenario is defined based on the characteristics of current EV fleet. Since there are uncertainties on charging behaviors of EV commuters, we also tested two sensitivity scenarios – low home charging and free workplace charging scenarios. In the charging demand model, BEVs range over 220 miles are defined as long-range vehicles. According to the information from the Alternative Fuels Data Center, the ranges of EVs on the road are from 50 -361 miles, and the average weighted range is 240 mi in 2020.

Therefore, we assume that the long-range electric vehicles account for 85% in our base case scenario, and 95% in the high long-range fraction scenario. Data from the 2019 California Vehicle Survey is used to establish the assumptions for home charge fraction. The base case scenario assumes that almost all (90% in this study) vehicles have access to charging at home. But in the future when EVs are broadly adopted, the home charge access fraction will be lower considering that there is only a total of 64% of the vehicles in this survey are owned by households that can park at least one car in a garage with potential for charger installation. Finally, we also define a scenario with free workplace charging since charging cost plays a vital role in changing charging behaviors.

3 Model Results and Discussion

3.1 EV Commuting

Table 3 shows the mode share in ACS data at the county level and our predicted mode share at the census block group level. Overall, mode share between county and block group levels is similar, but slight differences may be due to the control for rural areas.

Table 3. Mode Share results

	N	Mean	Std. Dev.	Minimum	Maximum
ACS Mode Share (County)					
Car	58	0.8456	0.0841	0.4042	0.9276
Public Transit	58	0.0243	0.0600	0.0000	0.4104
Others (walk, other, work from home)	58	0.1301	0.0498	0.0652	0.3097

Predicted Mode Share (Block Group)					
Car	23,156	0.8653	0.1006	0.2359	1.0000
Public Transit	23,156	0.0261	0.0451	0.0000	0.5722
Others (walk, other, work from home)	23,156	0.1086	0.0669	0.0000	0.5142

As can be seen in Table 3, California has an average car commute mode share of 86.5 percent, public transit of 2.6 percent, and others of 10.7 percent. We measure car commuters and EV commuting using the car commute mode share and LODES data.

Figure 4 shows the spatial distribution of our predicted car share and EV commuting at the census block group levels. Urban areas have lower car share than suburban and rural areas. On the other hand, more EV commuters are concentrated in urban areas (along the west coast).

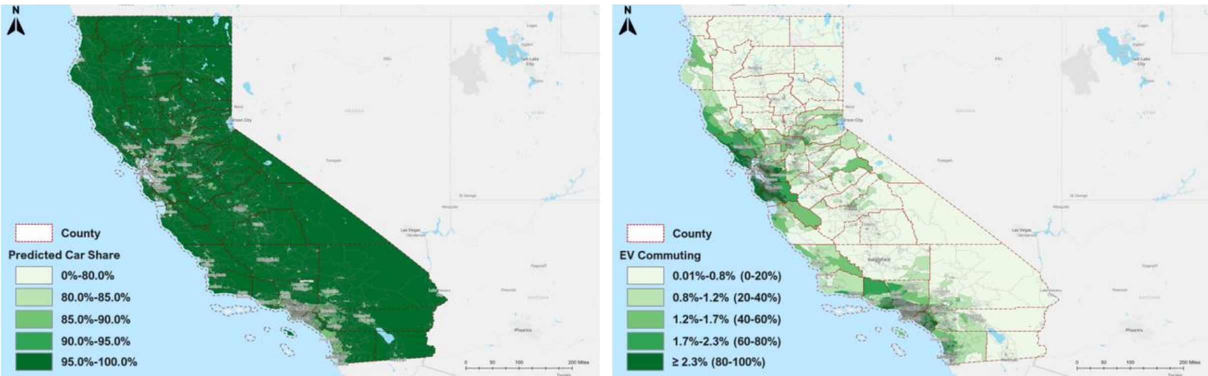

Figure 4. Predicted car share (left) and EV commuting (right)

3.2 Charging Demand

Figure 5 shows the spatial distribution of charting demand at commute destinations in terms of eVMT in the base case. We observed a high disparity of charging demand in urban areas, especially big cities like San Francisco Bay areas and Los Angeles. Compared with past studies, our model provides a higher resolution estimation for charging demand at work (census block group level), and a better accuracy estimation for cities with transit systems such as San Francisco Bay areas and Los Angeles since our model eliminates the impact from transit commute and only considers the commute trips by electric vehicles.

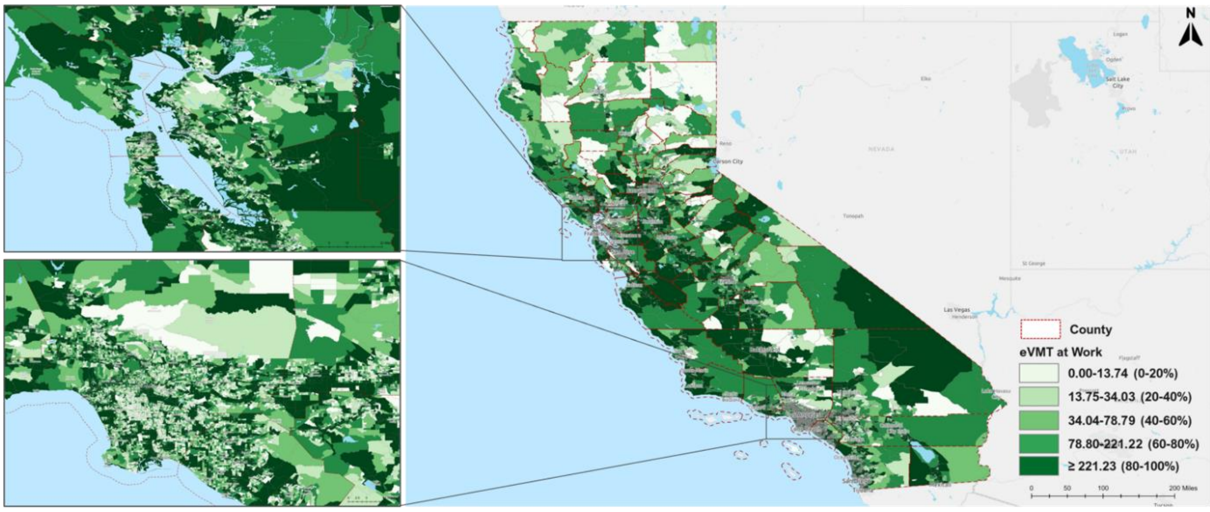

Figure 5. Charging demand at commute destination in terms of eVMT

In sum, the daily statewide charging demand for EV commute is over 7.1 million eVMT for a total of 581,710 electric vehicles and 270,462 EV commuters in the base case. Assuming an average energy efficiency of 0.346 kWh/mile, the statewide charging demand at commute destinations is 2462 MWh/day. In the scenario that the workplace charging is free, the charging demand at commute destinations will increase by 43%. The charging demand at work will increase by 28% if home charge accessibility decreases from 90% to 64%.

However, when the portion of long-range electric vehicles increases from 85% to 95%, the charging demand at work only increases by 0.14%, indicating that the range of electric vehicles plays a less important role in altering charging behaviors since the average range of current EV fleet is already sufficient for commute trips.

Table 4 shows the distribution of total number of charging activities at work destinations among all block groups in California. We find that the average charging demand is low for most block groups while some "hotspot" regions with extremely high charging demand exist, indicating the areas with very high public or workplace fast charging infrastructure requirement.

Table 4. Daily numbers of charges at work destinations for commute trips

Scenarios	**Mean**	**Std Dev**	**Min.**	**Max.**	**Lower Quartile**	**Median**	**Upper Quartile**
Base case	3.87	20.21	0	817.90	0.33	0.87	2.38
Free workplace charging	5.70	29.68	0	1192.22	0.48	1.28	3.51
Low home charging	4.97	25.92	0	1048.09	0.42	1.12	3.06
High long-range fraction	3.82	19.93	0	805.16	0.32	0.85	2.35

4 Conclusions

This study explores the out-of-home charging demand in California with a focus on electric vehicle (EV) commuters. Using multiple data sources such as American Community Survey (ACS), LEHD (Longitudinal Employer-Household Dynamics) Origin-Destination Employment Statistics (LODES), National Land Cover Database (NLCD), and OpenStreetMap (OSM), we measured destination-based car commuters by considering other modes (transit, walking, cycling, and working from home). We then estimated EV commuting at commute destinations (census block group level) through fractions of origin-destination car commuters and registered EVs at residential locations. Lastly, we estimated the total number of daily charging events and energy demand for charging at commute destinations using charging demand models with multiple scenarios.

The results of our predicted destination-based mode share at the census block group level show similar proportions with actual mode share in ACS at the county level. In particular, the proportion of public transit is almost the same, and our predicted outcomes are more reasonable estimates because we controlled the car share in rural areas. In addition, the results of the spatial distribution of our predicted car commuters and EV commuting show that urban areas have lower car commuters than suburban and rural areas, while more EV commuting are concentrated in urban areas.

Key findings from our charging demand models are as follows. First, the statewide commute charging demand is 2,462 MWh/day. There should be at least 97,845 level 2 public charger if assuming a charging speed of 7 kW, or 25,735 DC fast chargers within a charging speed of 50 kw to fulfill the charging demand. Second, the charging demand at commute destinations will increase by 43 percent if the workplace charging is free. Third, a decrease in home-based charging accessibility increases out-of-home charging demand. For instance, the charging demand at work will increase by 28 percent if home charging accessibility decreases from 90 to 64 percent. Lastly, increases in the range of electric vehicles are less critical in altering charging behavior, which may imply that the average range of the current EV fleet is already sufficient for commuting.

Focusing on destination-based EV commuting is important for a better understanding of out-of-home charging demand. Since most out-of-home EV charging takes place at or near the workplace (Nicholas et al., 2017; Xu et al., 2021), demand outcomes from based on EV ownership rates at residential locations or origin-based commuting may be over or under-estimated charging demand at destinations. This study developed a regression-based model for estimating EV commuting at destinations with high resolution (census block group level) and more accuracy by eliminating the impact of commute trips by transit, walking, cycling, and working from home. Therefore, this study will contribute to the existing literature in that we estimate out-of-home charging demand based on destination-based EV commuting.

Our findings can be useful for planners and policymakers as they look into different scenarios of charging demand models and search for strategies to increase the penetration of EVs. The charging demand models in this study considered workplace charging costs, home charging accessibility, and the range of EVs. In particular, we observed a significant positive relationship between free workplace charging and charging demand at commute destinations, which implies that workplace charging may help to attract and retain potential EV owners. In addition, this study is based on the current EV fleet, but it can be easily converted to future scenarios with various EV penetration trends and charging behaviors. The results of this research not only provide policy guidance for charging infrastructure planning in California but can be applicable to other regions since the datasets used in our study are all publicly available.

The findings and limitations of this study point to the need for additional analyses and research. We rely on predicted EV commuting measured by predicted origin-destination car mode share and origin EV ownership rates, which does not explain actual proportions of EVs used in commuting. Since all EVs may not be used for commuting and EV commuting can be different from conventional commuting patterns, we suggest future research focusing on the EV owners' commuting behaviors. This can bring about specific opportunities for additional analyses and research on out-of-home charging infrastructure in the future.

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Presenter Biography

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Kihyun is currently a postdoctoral researcher in the Electric Vehicle (EV) Research Center at UC Davis Institute of Transporation Studies (ITS). His research extends to understanding EV users' travel behavior and charging needs, predicting charging locations, connecting with existing transportation systems, assessing spatial equity, and more.

Before coming to UC Davis, he holds a Ph.D. in City and Regional Planning from the Ohio State University, specializing in land use and transportation planning. He received his master's degree in Urban Planning and bachelor's degree in Economics from Chung-Ang University in South Korea.