CHARGING STATION LOCATION AND ELECTRIC VEHICLE DEMAND: EVIDENCE FROM NEW YORK STATE

A Thesis

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Master of Science

by

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ABSTRACT

Exploring the impact of charging station location on electric vehicle (EV) demand is crucial for understanding electric vehicle demand and developing additional policies. This paper examines how the number of charging stations near the town/city center, the distance between charging stations and the nearest highway, and the number of stations with facilities (car dealers, parking lots, office buildings, and hotels) affect electric vehicle demand. Based on quarterly data of EV sales and charging station locations in all counties of New York State from 2014 to 2021, this study concludes that more stations installed near the town/city center and highways, as well as more stations equipped with facilities like office buildings, could boost EV demand. These findings imply that future subsidies for charging infrastructure may be location-based.

BIOGRAPHICAL SKETCH

Zijian Zeng was born in Kunming, the capital city of Yunnan province in China. Prior to coming to Cornell, she earned a double degree in English language and literature and Economics from Beijing Normal University and Peking University.

ACKNOWLEDGMENTS

I would like to express my gratitude to my family for their unwavering support throughout my master's studies. Additionally, I would like to express my heartfelt appreciation to my advisors, Professor Shanjun Li and Professor Ariel Ortiz Bobea, for their guidance and wisdom as I completed this paper.

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CHAPTER 1

INTRODUCTION

In the past few decades, car emissions act as an important source of air pollution and pose a great environmental concern in urban areas. Vehicle emissions contribute significantly to the concentration of air pollutants (CO, VOC, NOx, SO_2, PM10) in the atmosphere (U.S. EPA, 2000). Cardiopulmonary diseases, respiratory infections, and lung cancer are all directly related to airborne pollutants (EPA, 2004). Air pollution has a significant effect on infant mortality, according to Chay and Greenstone (2003) and Currie and Neidell (2005). The WHO (2005) has warned that ozone levels greater than 100 micrograms per cubic meter over an eight-hour period endanger human health.

In 2006, the United States' transportation system accounted for 31% of global transportation energy consumption and greenhouse gas emissions (Jenn et al., 2018). In 2007, highway vehicles in the U.S. emitted 78 percent of total transportation CO_2 emissions and consumed 80 percent of the energy used in the U.S. transportation sector (EIA, 2009b). Transportation has experienced the fastest growth in energy consumption and greenhouse gas emissions of any end-use sector in the United States (Jenn et al., 2018). In comparison to conventional gasoline-powered vehicles, electric vehicles (EVs), including battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs), would emit significantly fewer pollutants than internal combustion engines vehicles (ICEVs). Arslan and Karasan (2013) find that PHEVs reduce costs by an average of 29.5 percent and CO_2 and NOx emissions by 79 and 83 percent, respectively, in California. Wu et al. (2018) estimate that relative to ICEVs, the potential total life cycle greenhouse gas emission reduction rate by BEVs could reach 13.4% in 2020. As a result, EV adoption is a promising strategy for mitigating greenhouse gas emissions in the transportation sector.

While the government is attempting to promote the adoption of electric vehicles, numerous barriers remain. Individuals may be concerned about the vehicle's limited driving range, high purchase price, and lack of charging infrastructure. Investors would be reluctant to build charging infrastructure if the market for EVs is too small. Throughout the United States, various entities such as federal governments, state governments, and electric utilities have offered incentives to reduce greenhouse gas emissions and promote the adoption of EVs. The government has announced a slew of subsidies, including those for the purchase of electric vehicles and the establishment of charging infrastructure. People could receive tax credits or rebates if purchasing electric vehicles. Individuals who purchase electric vehicles may qualify for tax credits or rebates. The credit amount varies by state and may be related to the vehicle's technology, battery size, model, and driving range. Additionally, large entities such as businesses, governments, and universities may qualify for fleet credits when they purchase electric vehicles. Subsidies may be available for the installation of electric vehicle charging infrastructure in public areas, depending on the charger type. In April 2021, the Biden administration announced a $15 billion investment in advancing electric vehicle charging infrastructure and establishing a nationwide network of 500,000 charging stations. New York State, too, has acted. The New York Power Authority's (NYPA) EVolve NY program has announced up to $250 million in funding to support plug-in electric vehicles (PEVs) and close gaps in the state's charging infrastructure. The New York State Energy Research and Development Authority (NYSERDA) offers tax credits of up to $2,000 toward the purchase or lease of a new eligible PEV. The NYSERDA Charge Ready NY program offers a $4,000 per port rebate for purchasing and installing level 2 electric vehicle supply equipment in public parking facilities, workplaces, and multi-unit dwellings.

This study aims to explore the impact of charging station locations on the electric vehicle demand in New York State and to examine the policy implications. The study analyzes quarterly data on new electric vehicle registrations and geographic information of newly built public charging stations in each county in New York State from 2014 to the second quarter of 2021. The study quantifies the effect on EV demand of the number of charging stations within three miles of the town/city center, the average distance between charging stations and the nearest highway, and the number of charging stations built in car dealerships, parking lots, hotels, and office buildings. The study finds that the charging station location is of great importance to the EV demand. According to the estimates, each additional ten charging stations within 3 miles of town/city center that a county added increases EV demand by 0.21%. While the estimate is not robust, every ten miles increase in the average distance between EV charging stations and the nearest highway result in a 1.4% decline in EV demand. A ten percent increase in the number of charging stations installed in car dealers, parking lots, and office buildings could raise EV sales by 6.5%, 1.2%, and 8.5% EV sales, respectively. We find that installing electric vehicle charging infrastructure in office buildings would be more effective at increasing EV demand. The more EV charging infrastructure with facilities there are, the higher the electric demand will be. But the estimates of the number of charging stations installed in car dealers and parking lots are not robust. The impact of the number of charging stations built in hotels on EV demand is insignificant.

This study adds the following to the body of knowledge. To begin, the study contributes to the growing body of knowledge regarding the location of charging stations. Numerous scholars have conducted research on the optimal location of electric vehicle charging stations with the goal of minimizing construction costs and travel costs to the charging station (Chen et al., 2013, Huang et al., 2016, Shahraki et al., 2015, Wang and Wang, 2010), minimizing investment costs (Yao et al., 2014), and effectively satisfying charging demand (Capar et al., 2013, Frade et al., 2011, He et al., 2019). According to Huang and Kockelman's (2020) findings, charging stations should be concentrated along major highways. However, none of them examines how to optimize charging locations in order to boost electric vehicle demand.

Secondly, the study contributes to the rich literature on electric vehicle demand. Langbroek et al. (2016) find that people who have a high sense of self-efficacy and response efficacy are more likely to adopt EVs. Li et al. (2017) investigate the indirect network effects of EV adoption and investment in charging stations. They estimate that a 10% increase in charging infrastructure could result in an 8% increase in EV sales. Carley and Nicholson (2019) discover that customers' awareness of EVs can influence EV demand, which is influenced by their perceptions of relative advantages, previous ownership, social influence, and charging infrastructure. Different from the previous research, this study examines the effect of charging station locations on EV demand.

Thirdly, this study contributes to the nascent literature regarding policies and incentives for EV adoption. Sierzchula et al. (2014) demonstrate that a country's market share for electric vehicles is significantly influenced by and positively correlated with financial incentives, charging infrastructure, and the presence of manufacturing facilities on the ground. Jin et al. (2014) find that state electric vehicle incentives are critical in the early stages of lowering the effective cost of ownership and increasing electric vehicle sales. Li et al. (2017) show that a subsidy in charging infrastructure was much more cost-effective than consumer subsidies. With the same amount of spending, a policy subsidizing charging infrastructure could have subsidized EV adoption more than twice as effectively. Jenn et al. (2018) estimate that each $1,000 rebate or tax credit could increase average electric vehicle sales by 2.6%, and increasing consumer awareness is critical for the success of EV incentive programs. Additionally, they demonstrate that high-occupancy vehicle lane access can help increase EV adoption, which is an indirect incentive. Zhou and Li (2018) demonstrate that more than half of the Metropolitan Statistical Areas in the US face critical mass constraints, implying that a subsidy policy aimed at this issue could be more effective than the current uniform policy at promoting EV adoption. Li et al. (2020) show that the green license plate policy, an indirect incentive for customers in China, has a strong influence on EV adoption. This study approaches the subject from a different angle and may have implications for how to offer incentives based on charging station locations.

The remainder of the paper is structured in the following manner. Chapter 2 describes the charging station data, the electric vehicle registration data, and the demographics data in New York State. Chapter 3 presents the empirical framework on how to examine the impact of charging station location and facility types on electric vehicle demand. Chapter 4 presents the empirical findings and discusses the policy implications. Chapter 5 concludes.

CHAPTER 2

DATA

From 2014 to 2021, we collect data on electric vehicle charging stations, electric vehicle registration, and census data by county in New York State. Collectively, we construct a county-level panel dataset consisting of quarterly electric vehicle sales and the number of charging stations around the town/city's center, the average distance between EV charging stations and the nearest highway, and the number of charging stations installed in car dealers, hotels, office buildings, and parking lots in each county in New York State from 2014 to 2021. Table 1 summarizes the variables we used in regression analysis.

2.1 Data of Electric Vehicle Registration

We obtain the registration data for electric vehicles from the New York State Department of Motor Vehicles. From 2014 to the second quarter of 2021, the EV sales data covers 62 counties in New York State and includes the time, place, vehicle model of each EV registration. The quarterly EV sales in each county are then calculated.

Figure 1 depicts the annual trend in total EV sales and the number of available EV charging stations in New York State from 2014 to 2021. The number of charging stations increases steadily at a constant rate from 2014 to 2021. The EV sales in New York State were quite low and remained stable before 2018, and it experienced a surge and reached near 20,000 until 2021. The expansion of charging infrastructure appears to be driving EV sales. The spatial pattern of total EV sales in each county in New York State from 2014 to the second quarter of 2021 is depicted in Figure 2.

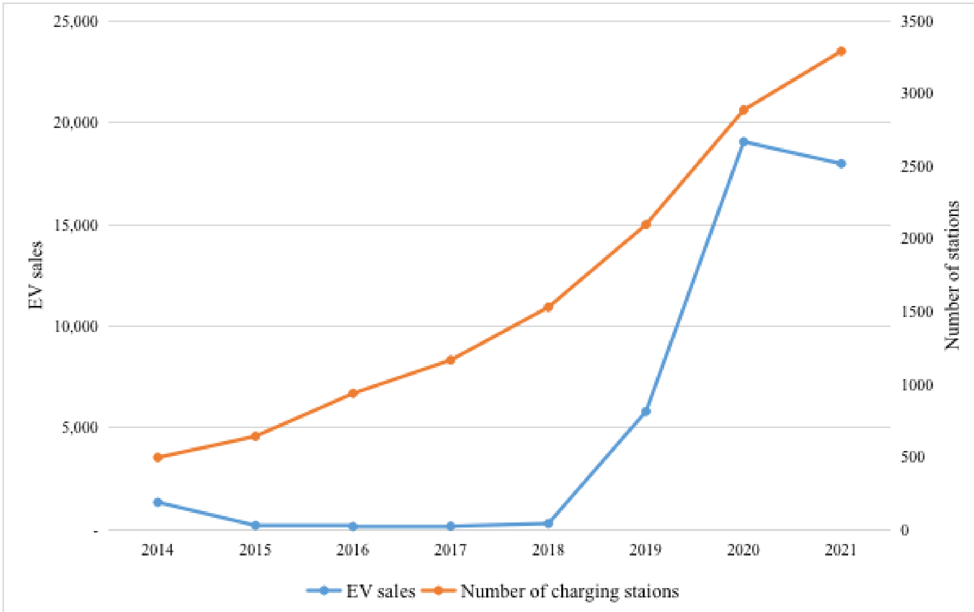

Figure 1. The Trend of EV Sales and the Number of Charging Stations in New York State from 2014 to 2021.

Notes: The figure illustrates the annual trend in EV sales trend and the number of charging stations in New York State from 2014 to the second quarter of 2021. The data is from NYS DMV and the Alternative Fuel Data Center (AFDC).

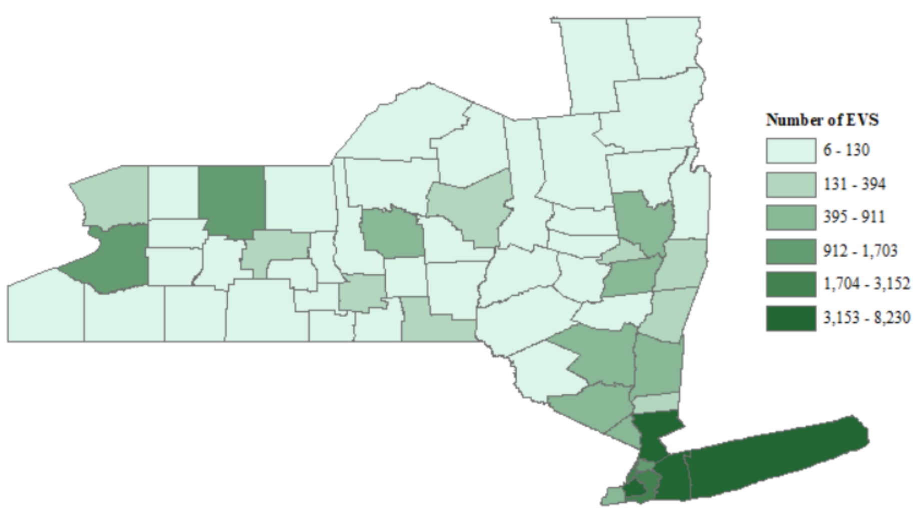

Figure 2 . Spatial Pattern of Total EV Sales in Each County in New York State from 2014 to the Second Quarter of 2021.

Notes: The figure illustrates the spatial pattern of total EV sales in each county in New York State from 2014 to the second quarter of 2021. Around 70% of electric vehicles are concentrated in and around New York City. The data is from NYS DMV.

It indicates that seventy percent of electric vehicle sales occurred in urban areas (New York City), while the remaining thirty percent occurred in other counties. Kings, Nassau, and Westchester counties have the most EV sales, with 8230, 5895, and 5202 EVs, respectively. All three counties are located near or within New York City. Figure 3 shows the manufacturers of EVs in New York State from 2014 to 2021. Tesla is the largest EV supplier, having supplied approximately 60% of EVs to New York State between 2014 and 2021. Chevrolet and Nissan are the second and third largest suppliers, having supplied 6.25 percent and 4.43 percent EVs from 2014 to 2021, separately.

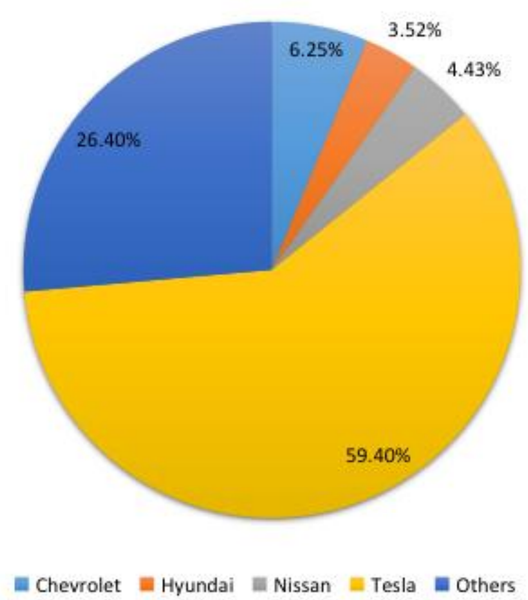

Figure 3. The EV Make in New York State from 2014 to 2021.

Notes: This figure shows the largest four EV manufacturers in New York State from 2014 to the second quarter of 2021. The data is from NYS DMV.

2.2 Data of Electric Vehicle Charging Stations

We obtain detailed information on the locations, opening dates, and facility types of all charging stations in New York State during 2014 and the second quarter of 2021 from the Alternative Fuel Data Center (AFDC) of the Department of Energy. The data covers 61 counties in New York State, but Chenango county is not included. We also collect information about highways and town/city centers in New York State from the ArcGIS database and the United States Census Bureau, respectively.

We calculate the distance from every EV charging station to the nearest town/city center and to the nearest highway. We discover that over half of all EV charging stations are located within three miles of a town/city center. Then, for each county, we calculate the total number of EV charging stations located within three miles of the town/city center, as well as the average distance between EV charging stations and the nearest highway. We observe that approximately 40% of EV charging stations are equipped with facilities, with the majority located in car dealerships, parking lots, office buildings, and hotels. As a result, we also calculate the number of EV charging stations installed in each county's car dealerships, parking lots, office buildings, and hotels.

Figure 4 depicts the average distance between EV charging stations and the nearest highway in each county in the second quarter of 2021. It demonstrates that nearly half of counties have an average distance of fewer than five miles, and nearly a third have a distance of fewer than two miles. The nearer to the urban areas (New York City), the shorter the average distance is. This pattern appears to be the inverse of the pattern of EV sales in each county, with a correlation coefficient of -0.11 between the two variables.

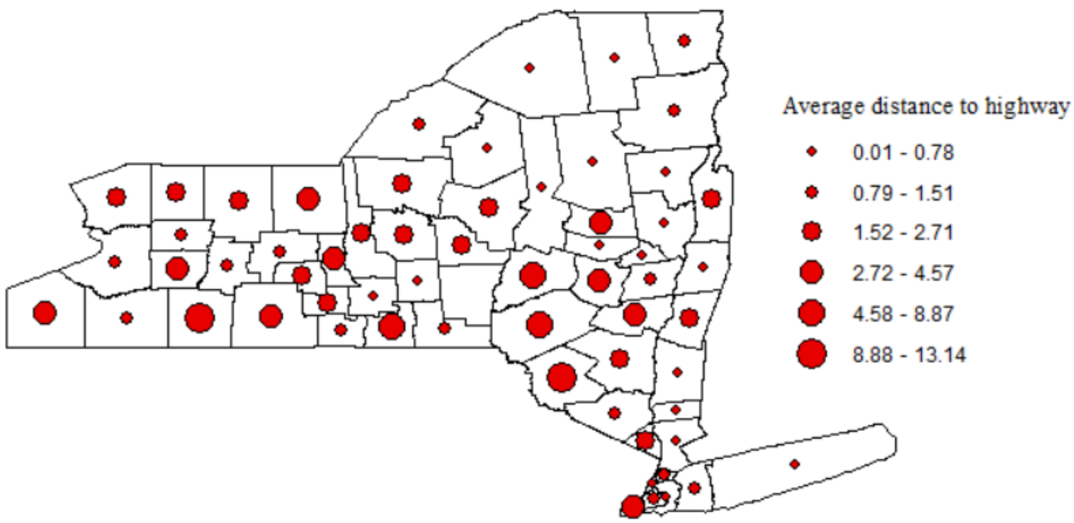

Figure 4. The Average Distance between EV Charging Stations and the Nearest Highway by County in New York State in the Second Quarter of 2021.

Notes: This figure shows the average distance between EV charging stations and the nearest highway at the county level in New York State in the second quarter of 2021. The unit of distance is the mile. The greater the diameter of the circle, the greater the distance. The charging stations data is from the Alternative Fuel Data Center (AFDC) and highway data is from the ArcGIS database.

Figure 5 demonstrates the number of charging stations within 3 miles of the town/city center in each county of New York State in the second quarter of 2021. The figure indicates that the majority of charging stations are located near the town/city center, with urban areas having more charging stations in close proximity to the town/city center. The pattern is strikingly similar to that of EV sales, with a correlation coefficient of 0.19 between the two variables.

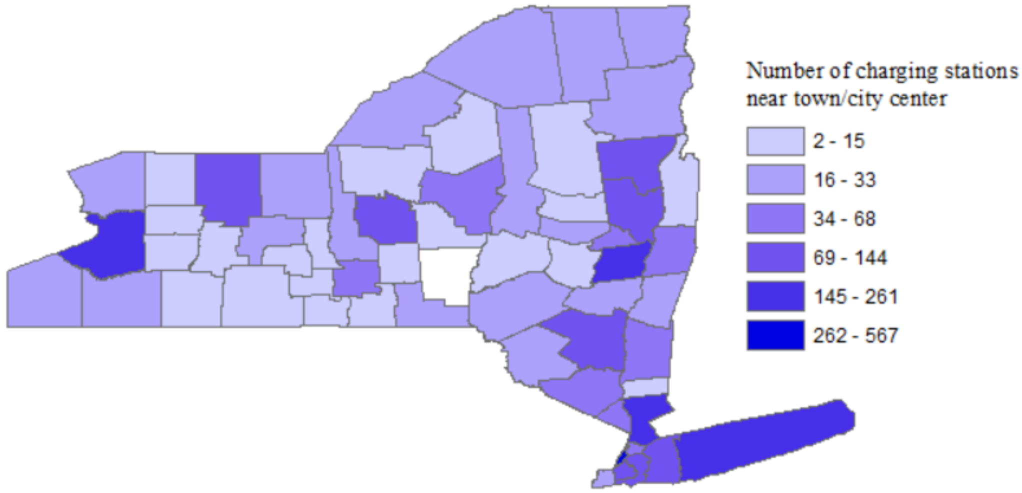

Figure 5. The Number of Charging Stations within 3 Miles of the Town/City Center by County in New York State in the Second Quarter of 2021.

Notes: This figure shows the total number of EV charging stations within 3 miles of the town/city center in each county of New York State by the end of the second quarter of 2021. The darker the county is, the more stations it has. The charging stations data is from the AFDC and town/city centers data is from the United States Census Bureau.

Figure 6 shows the number of charging stations built in car dealers, parking lots, office buildings, and hotels in each county of New York State in the second quarter of 2021. This graph demonstrates that urban areas typically have a greater number of charging stations equipped with the four kinds of facilities. All of the patterns are similar to the EV sales pattern (Figure 1), with correlation coefficients of 0.32, 0.13, 0.49, and 0.23 between EV sales and the four variables, respectively.

Figure 7 is a map showing locations of charging stations with facilities (car dealers, hotels, office buildings, and parking lots), as well as the locations of highways. We observe that the majority of charging stations with facilities are located near highways, regardless of which county they are in.

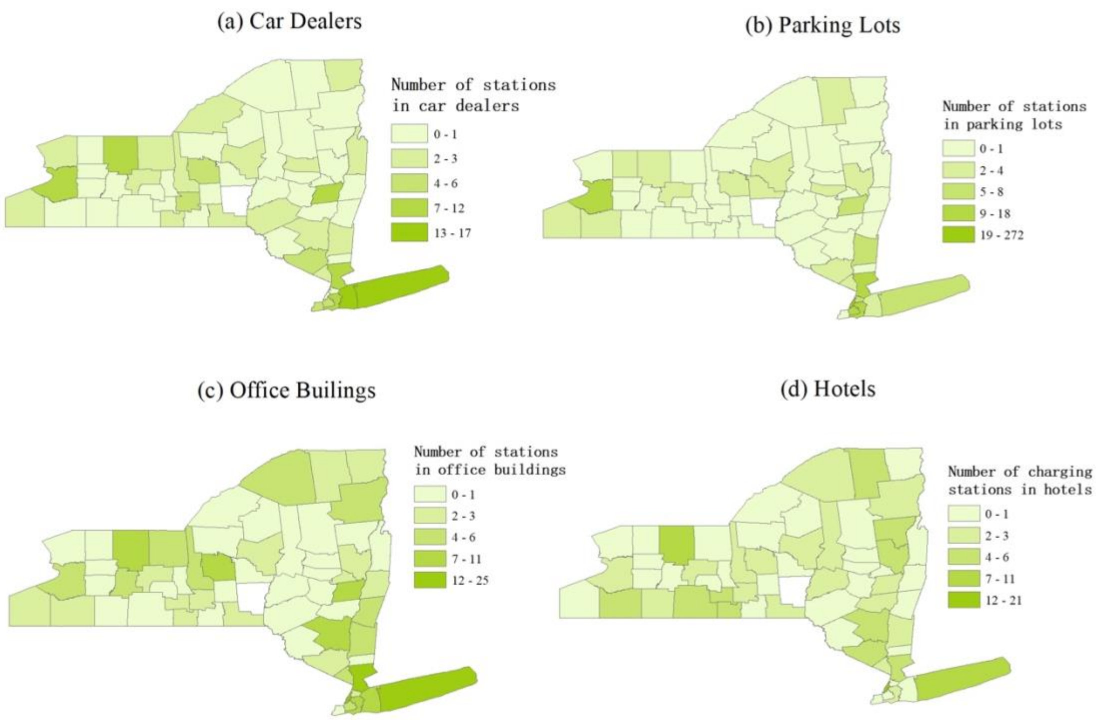

Figure 6. The Total Number of Charging Stations Built in Car Dealers, Parking Lots, Office Buildings, and Hotels in Each County of New York State in the Second Quarter of 2021.

Notes: This figure illustrates the number of charging stations built in car dealers, parking lots, office buildings, and hotels by county in New York State by the end of the second quarter of 2021. Panel (a) illustrates the number of charging stations installed in car dealers, panel (b) illustrates the number of charging stations installed in parking lots, panel (c) illustrates the number of charging stations installed in office buildings, and panel (d) illustrates the number of charging stations installed in hotels. The darker the county is, the more stations it has. The data is from the AFDC.

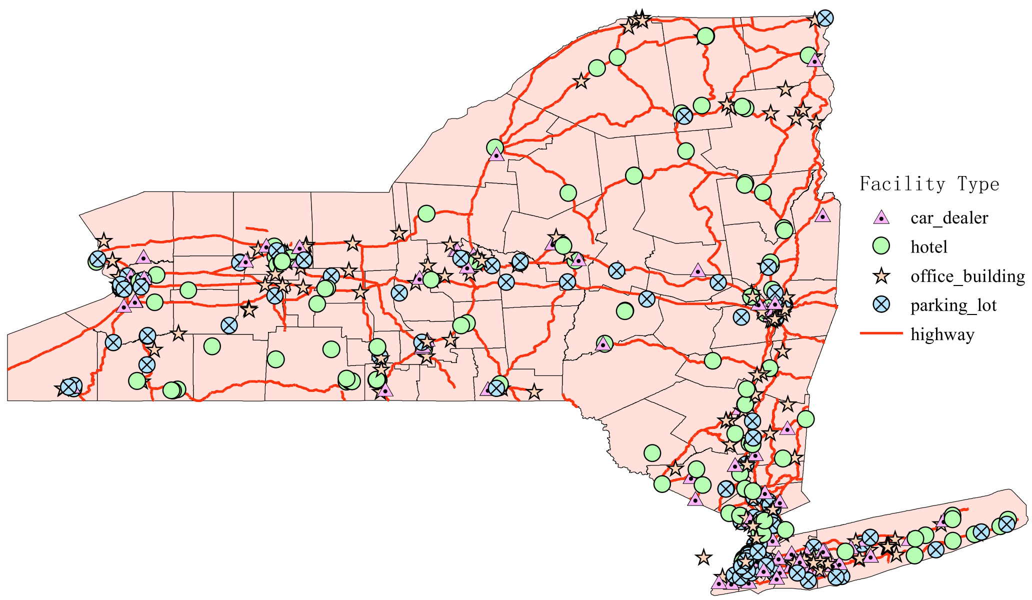

Figure 7. Map of New York State's Charging Stations with Facilities and the Highways.

Notes: This figure is a map showing locations of charging stations with facilities (car dealers, hotels, office buildings, and parking lots) and the highways in New York State. The county boundary is shown in this figure. The charging stations data is from the Alternative Fuel Data Center (AFDC) and highway data is from the ArcGIS database.

Figure 8 presents the locations of EV charging stations, the town/city centers, and the highways in Tompkins County. We observe that the majority of EV charging stations in Tompkins County are located near highways and in the central business district of Ithaca City, which is the county seat of Tompkins County.

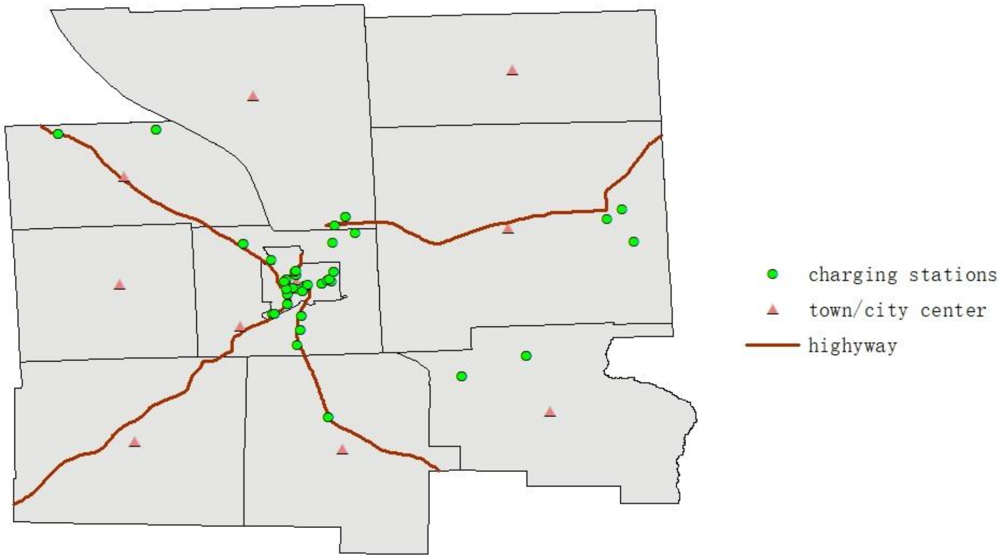

Figure 8. Map of EV Charging Stations, the Town/City Centers, and the Highways in Tompkins County.

Notes: This figure presents the locations of EV charging stations, the town/city centers, and the highways in Tompkins County. The town/city border is shown in the figure. The charging stations data is from the Alternative Fuel Data Center (AFDC), the highway data is from the ArcGIS database, and town/city centers data is from the United States Census Bureau.

2.3 Demographics Data

We collect the median household income, the number of people with a Bachelor's degree or above by county in New York State from the American Community Survey, which is available at United States Census Burau. Additionally, we collect population data from the New York State Department of Labor from 2014 to 2020.

From 2013 to 2018, annual data on median household income are available, but no quarterly data are available. For 2019 to 2021, we used the average growth rate of household income in each county from 2013 to 2018 to calculate the last three years' median household income. We calculate the percentage of people with higher education and the population density in each county in New York State using population data, the number of people with higher education, and the area of each county in New York State. The population density is available from 2014 to 2020.

The number of people with higher education (with a Bachelor's degree or above) is available from 2014 to 2019. We find that the percentage with higher education is stable in each county, so we construct the percentage of people with higher education in 2020 by taking the average of the percentage from 2014 to 2019. Figure 9 shows the percentage of people with higher education in Albany, Allegany, Cattaraugus, Cayuga, Chautauqua County. They remain stable from 2014 to 2019.

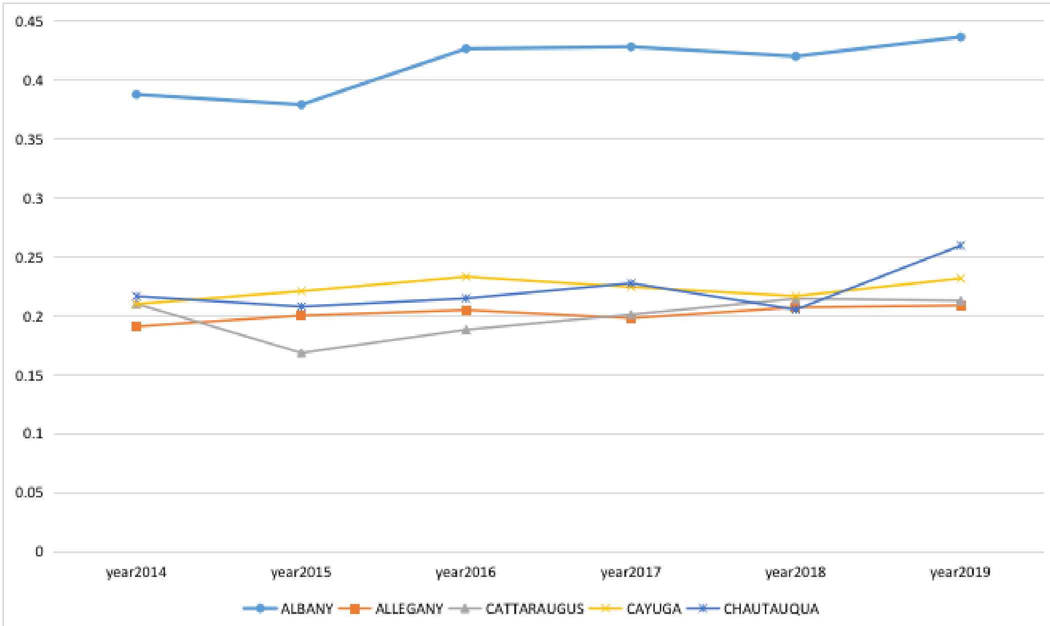

Figure 9. The Percentage with Higher Education in Albany, Allegany, Cattaraugus, Cayuga, Chautauqua County from 2014 to 2019.

Notes: This figure shows the percentage of people with higher education (with a Bachelor's degree or above) in five counties (Albany, Allegany, Cattaraugus, Cayuga, and Chautauqua) from 2014 to 2019. The data is from the American Community Survey and the New York State Department of Labor.

Table 1. Summary Statistics

	(1)	(2)	(3)	(4)	(5)
VARIABLES	N	Mean	SD	Min	Max
EV sales					
EV sales	665	67.56	236.5	1	4,207
Charging stations					
Average distance to highway	1,589	1.968	2.910	0.00560	24.85
No. of stations in hotel	1,830	1.225	2.397	0	18
No. of stations in office building	1,830	1.112	2.503	0	26
No. of stations in parking lots	1,830	3.577	23.59	0	260
No. of stations in car dealer	1,830	2.105	3.603	0	18
No. of stations within 3 miles of town/city center	1,830	16.32	39.52	0	414
Distance to town center	743	2.371	1.635	0.0528	10.06
Census data					
Household Income	1,830	60,691	15,655	33,712	127,007
Percentage of people with higher education	1,708	0.278	0.0937	0.142	0.620
Population density	1,708	3,141	11,115	2.530	71,718

Notes: Sources of the data are the New York State Department of Motor Vehicles (NYS DMV), Alternative Fuel Data Center (AFDC) of the Department of Energy, American Community Survey (ACS), and New York State Department of Labor. Units for variables of distance are miles. The unit for household income is the dollar. The EV sales data is from 2014 to the second quarter of 2021, covering 62 counties in New York State. The charging stations data is from 2014 to the second quarter of 2021, covering 61 counties in New York State (without Chenango county). The demographics data is from 2014 to 2021, covering 62 counties in New York State.

CHAPTER 3

EMPIRICAL FRAMEWORK

We assume that EV sales $q_t(tc_t)$ depend on the number of charging stations within 3 miles of the town/city's center.

Carley and Nicholson (2019) find that customer awareness also influences EV demand, so we use the percent of people with higher education (e_t) to indicate customers' awareness about EV technology and its potential benefits. EV demand is influenced by household income (i_t) and population density (p_t), as well as the electric vehicle price and the policy incentives for purchasing electric vehicles. We add i_t and p_t as control variables and will discuss the electric vehicle price and the policy incentives later.

To investigate the impact of charging station locations on the electric vehicle demand, we let k denote a county in New York State (such as Tompkins County and Albany) and t denote a year-quarter (such as 2014q1). We estimate the following equation:

$$\ln(q_{kt}) = \beta_0 + \beta_1 tc_{kt} + \beta_2 i_{kt} + \beta_3 e_{kt} + \beta_4 p_{kt} + \mathrm{T}_t + \delta_k + \epsilon_{kt} \tag{1}$$

In this equation, q_{kt} denotes the electric vehicle sales in county k and year-quarter t and tc_{kt} denotes the number of public charging stations within 3 miles of the town/city center in county k and year-quarter t. We use 3 miles as a benchmark because approximately half of the charging stations are located within 3 miles of the town/city center, allowing us to explore the impact of a dense network of public charging stations near the town/city center on the EV demand.

The remainder of equation (1) represents the control variables. i_{kt} denotes the median household income in county k and year-quarter t, e_{kt} denotes the percent of people with higher education, and p_{kt} is the population density in county k and year-quarter t. The log expression in this equation may capture the diminishing effect on the EV demand.

We also include a full set of year-quarter (from the first quarter of 2014 to the second quarter of 2021) fixed effects T_t and county (such as Tompkins County, Yates County) fixed effects δ_k in equation (1). The time fixed effects T_t account for the common demand shocks, such as a stational change in customers' perceptions about potential benefits, social influence, electric vehicle technology, and the policy incentives offered by the federal and state government. The county fixed effects δ_k could control for time-invariant local preferences for electric vehicles. The last term ϵ_{kt} captures the time-varying unobserved demand shocks, such as an unobserved county government incentive for purchasing an EV.

Other factors that could affect EV demand include the retail price of an EV, federal and state government tax rebates or credits for EV purchases, and the characteristics of EV models (like the driving range, battery capacity, and passenger capacity). Regarding the cost of an EV, we have already established that the top four EV manufacturers in New York State are Tesla, Chevrolet, Nissan, and Hyundai. The four EV manufacturers accounted for more than seventy percent of EV sales. At AFDC, we discover that manufacturer-suggested retail prices for popular models have remained constant from 2014 to 2020. Figure 10 illustrates the trend in EV prices for the Tesla Model S, Chevrolet Spark, Chevrolet Bolt, Nissan Leaf, and Hyundai Ioniq from 2014 to 2020. The five EV models represent each manufacturer's entry-level EV, and we notice that their prices remained relatively stable from 2014 to 2020. The average annual growth rate of the five EV models over the last seven years has been less than 0.5 percent. In comparison to the current inflation rate of around 5%, we could consider the EV price changes to be negligible.

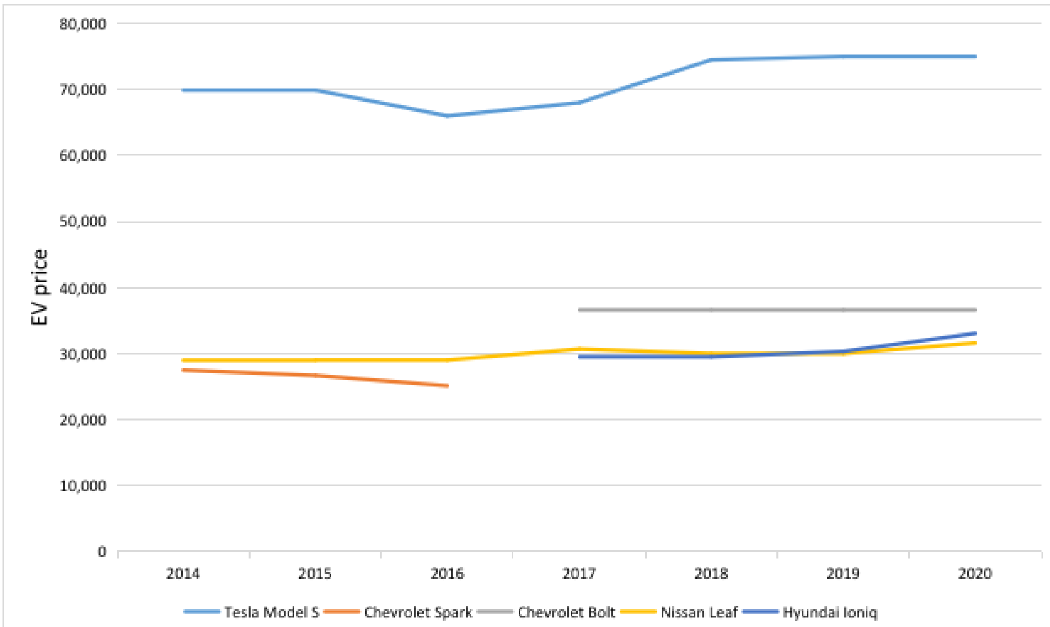

Figure 10. EV Price of Tesla Model S, Nissan Leaf, Chevrolet Spark, Chevrolet Bolt, and Hyundai Ioniq from 2014 to 2020. [1]

Notes: This graph illustrates the price trend of five popular entry-level EVs (Tesla Model S, Nissan Leaf, Chevrolet Spark, Chevrolet Bolt, and Hyundai Ioniq) from 2014 to 2020. The data is from AFDC. The unit of EV price is the dollar.

Thus, we argue that customers in New York State would pay the same price for an EV model in 2014 as they would in 2020. Additionally, we believe that there is no

[1] Tesla Model S Automatic (A1) EV shown in the figure has a 60 kW-hr battery pack from 2014 to 2017, is Tesla Model S 75D in 2018, and has the Standard Range in 2019 and 2020. Chevrolet Spark Automatic (A1) EV is available from 2014 to 2016, and it upgraded to Chevrolet Bolt Automatic (A1) EV from 2017 to 2020. The Nissan Leaf Automatic (A1) EV was introduced in 2016 with a 24 kW-hr battery pack and was upgraded to a 40 kW-hr battery pack in 2019-2020. The Hyundai Ioniq Electric Automatic (A1) EV debuted in 2018. All of the EV models depicted in the figure are the entry-level models offered by each year's EV manufacturers.

difference in EV prices between counties because it is simple to travel throughout New York State, and customers can always get the best deal.

The primary incentives for individuals to purchase an EV are the tax rebates/credits or other indirect incentives offered by the federal or state government. Although a few private incentives are offered by small entities (such as local governments), the quantity of local financial incentives available is limited, and their influence is negligible. Thus, we assume that at some point, there is merely a difference in policies and incentives related to purchasing an EV across counties in New York State. Therefore, we believe that the effective EV prices (the manufacturer's suggested retail prices less the tax rebates/credits) could be controlled by the time fixed effects and the county fixed effects in New York State.

Although there may be common unobservable factors affecting both EV sales and household income, our model has accounted for time and county fixed effects. These should account for time-dependent and county-specific unobservable variables.

Due to the limitation of data, we won't take changes in characteristics of EV models into account.

We further examine the impact of charging stations' locations and facility types on EV demand. The EV sales $q_t(ad_t, nc_t, np_t, nh_t, nb_t)$ could also be influenced by ad_t, the average distance between charging stations the nearest highway, and nc_t, np_t, nh_t, nb_t, the number of charging stations installed in car dealers, parking lots, hotels, and office buildings in each county.

Let k index a county in New York State, and t index a year-quarter. We estimate the following equation:

$$\ln(q_{kt}) = \beta_0 + \beta_1 ad_{kt} + \beta_2 nc_{kt} + \beta_3 np_{kt} + \beta_4 nb_{kt} + \beta_5 nh_{kt} + \beta_6 i_{kt} + \beta_7 e_{kt} + \beta_8 p_{kt} + \mathrm{T}_t + \delta_k + \epsilon_{kt} \quad (2)$$

ad_{kt} denotes the average distance between all available public charging stations and their nearest highway in county k and year-quarter t. nc_{kt}, np_{kt}, nb_{kt}, nh_{kt} denote the total number of available charging stations installed in car dealers, parking lots, office buildings, and hotels in county k by the end of year-quarter t. Our interests are in the four types of facilities because they account for approximately 80% of public charging stations with facilities. The log expression in this equation may capture the diminishing effect on the EV demand.

In equation (2), the control variables i_{kt}, e_{kt}, and p_{kt} are identical to those in equation (1). We also include a full set of year-quarter (from the first quarter of 2014 to the second quarter of 2021) fixed effects T_t and county (such as Tompkins County, Yates County) fixed effects δ_k in equation (2) to account for the common demand shocks and time-invariant local preference for electric vehicles. The final term, ϵ_{kt}, is used to account for time-varying unobserved demand shocks.

CHAPTER 4

EMPIRICAL RESULTS

We first present parameter estimates. Following that, we discuss the policy implications of the parameter estimates.

3.1 Regression Results for Charging Station Locations

The OLS (ordinary least squares) results for equation (1) are presented in Table 2. Column (1) contains only the key variable in question. In column (2), we add the year-quarter fixed effects to control for time-varying common unobservables across counties. Column (3) incorporates county fixed effects to control for time-invariant unobserved local preference for electric vehicles and county-specific demand shocks. From column (4) to column (6), we incrementally increase the number of control variables. Column (4) includes the median household income to control for the effect of income growth on EV. Column (5) adds in the percentage of people with higher education to reflect shifts in customers' attitudes toward EV technology, potential financial benefits, and potential environmental benefits of EVs. The final column contains population density data for each county, ensuring that the parameter estimates we are interested in are not skewed by population density.

The coefficient of the key variable is statistically significant. The coefficients in column (6) are consistent with our intuition. EV demand increases with more charging stations installed near the town/city center. Intuitively, more charging infrastructure installed near the town/city center would make it more convenient for EV users to charge EVs, thereby encouraging more customers to purchase an EV.

Table 2. Regression Results for Equation (1)

VARIABLES	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS
No. of stations within 3 miles of town center	0.0427***	0.0221***	0.0233***	0.0195***	0.0212***	0.0213***
	(0.00974)	(0.00542)	(0.00587)	(0.00572)	(0.00785)	(0.00797)
Household income				1.294***	1.118***	1.048***
				(0.293)	(0.278)	(0.295)
Percentage of people with higher education					1.000***	1.000***
					(0.323)	(0.319)
Population density						-7.285
						(4.878)
Observations	1,830	1,830	1,830	1,830	1,708	1,708
R-squared			0.766	0.786	0.753	0.755
Year-quarter fixed effects	NO	YES	YES	YES	YES	YES
County fixed effects	NO	NO	YES	YES	YES	YES

Notes: The regressions are constructed using the full sample of 61 counties. The dependent variable is ln(EV sales) by county by quarter. In estimation, we add one to EV sales to deal with zero values for some of the observations. Standard errors in parentheses are clustered at county level. Significance levels are indicated by *** p<0.01, ** p<0.05, * p<0.1.

Additionally, a higher median household income and a greater proportion of people with higher education could help boost EV demand. More affluent households would be less price sensitive, allowing them to purchase more EVs. The greater proportion of people with a higher education reflects more people possessing the knowledge necessary to comprehend EV technology and appreciating the enormous potential environmental benefits and financial incentives associated with purchasing an EV. Increased population density has an insignificant effect on EV adoption.

As shown in columns (1) and (2), when year-quarter fixed effects are included, the coefficient for the number of charging stations built near the town/city center changes significantly. Due to the prevalence of demand shocks affecting EV adoption, parameter estimates may be skewed. Increasing the number of control variables in columns (4) to (6) may help further address the endogeneity problem caused by omitted variables.

The results in column (6) imply that, holding all other factors constant, each ten additional charging stations within 3 miles of the town/city center that a county added would increase EV demand by 0.21%.

For the purpose of a robustness check, we construct three additional variables related to the charging stations located near the town/city center. We use a benchmark of 5 miles, 7 miles, and 10 miles to further investigate the effect of a dense public charging network near the town/city center on EV demand. As a baseline, we also include the total number of available charging stations in each county each year-quarter in column (1). We included year-quarter fixed effects and county fixed effects as well. Regression results are reported in Table 3. Results from column (1) show that increasing the base of charging stations will aid in EV adoption, but the effect will be less than the effect of increasing the number of charging stations in close proximity to the town/city center. From column (2) to column (5), the regression results for the four different miles are very similar in both magnitude and direction. The similarity of the results may imply that the 3 miles we use have little effect on estimating the parameters of the key variable.

The number of charging stations and the error terms could be correlated over counties. Following Conley (1999) and Hsiang (2010), we use Conley standard errors to account for both serial and spatial correlation. Different HAC standard errors are reported in Table 4. We employ the same regressions as in Table 3, adjusting only the standard errors. Column (2) contains the coefficient estimators for the total number of charging stations in the county and the number of charging stations within 3/5/7/10 miles of the town/city center, with the significance level denoted by stars based on the most conservative standard errors. Column (3) clusters the standard errors by county, allowing for any covariance structure within a county over time. Column (4) to column (7) present the Conley standard errors that account for spatial correlation for counties within 50, 100, 150, and 200 kilometers, respectively. For spatial correlation, we employ the uniform kernel. Within the chosen distances, all observations are given equal weight, and the spatial correlation is assumed to vanish beyond the chosen distances. The standard errors also enable serial correlation across all time periods. Although the Conley standard errors in columns (4) to (7) are slightly smaller than the

Table 3. Impact of Charging Stations Density Near the Town/City Center on EV Demand

VARIABLES	(1) within county	(2) 3 miles	(3) 5 miles	(4) 7 miles	(5) 10 miles
No. of stations within X miles of town center	0.00978	0.0213***	0.0200**	0.0203**	0.0200***
	(0.00722)	(0.00797)	(0.00783)	(0.00766)	(0.00720)
Household income	0.999***	1.048***	0.880***	0.800***	0.778***
	(0.300)	(0.295)	(0.260)	(0.262)	(0.265)
Percentage of people with higher education	0.975**	1.000***	1.054***	1.095***	1.096***
	(0.420)	(0.319)	(0.349)	(0.361)	(0.363)
Population density	0.477	-7.285	-1.684	-0.393	-0.713
	(5.060)	(4.878)	(3.119)	(3.878)	(3.699)
Observations	1,708	1,708	1,708	1,708	1,708
Adjusted R-squared	0.736	0.750	0.756	0.760	0.760
Year-quarter fixed effects	YES	YES	YES	YES	YES
County fixed effects	YES	YES	YES	YES	YES

Notes: The regressions are constructed using the full sample of 61 counties. The dependent variable is ln(EV sales) by county by quarter. In estimation, we add one to EV sales to deal with zero values for some of the observations. The first column uses the total number of available charging stations in each county each year quarter as the key variable. The other four variables are the number of charging stations within 3/5/7/10 miles of the town/city center, which are used to do robustness checks. Standard errors in parentheses are clustered at county level. Significance levels are indicated by *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4. Models with Different Standard Errors

(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Conley S.E. (Uniform)			
No. of stations within X miles of town center	Coef.	Robust S.E.	50km	100km	150km	200km
within county	0.00978	0.00722	0.00489	0.00493	0.00493	0.00498
3 miles	0.0213***	0.00797	0.00627	0.00642	0.00644	0.00656
5 miles	0.0200**	0.00783	0.00535	0.00546	0.00554	0.00561
7 miles	0.0203**	0.00766	0.0049	0.00504	0.00512	0.00518
10 miles	0.0200***	0.0072	0.0046	0.00476	0.00484	0.0049

Notes: All regressions have 1,708 observations. The dependent variable of regressions is ln(EV sales) by county by quarter. In estimation, we add one to EV sales to deal with zero values for some of the observations. The first row uses the total number of available charging stations in each county each year quarter as the key variable, while the other four rows use the number of charging stations within 3/5/7/10 miles of the town/city center. All regressions include control variables such as household income, the percentage of people with higher education, and population density. The second column contains the estimators of the key variables' coefficients. The third column contains robust standard errors clustered at the county level. Columns (4) to (7) contain Conley standard errors that account for both serial and spatial correlation for counties within 50/100/150/200 km. A uniform kernel is used for spatial correlation. Significance levels are indicated by *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

cluster-robust standard errors reported in column (3), they make no difference to our qualitative findings. Estimates continue to be significant.

Additionally, we construct four subsamples to do robustness checks. To begin, we rank counties according to their population density and calculate the median population density. We refer to the half of counties in New York State with a population density less than the median as relatively rural counties. The other half of counties in New York State are relatively urban. We begin by creating the two subsamples. Then, we create two subsamples from the full sample, each with a random half of the observations. Regression results for the four subsamples are reported in Table 5.

Column (1) summarizes the findings for relatively urban counties, while column (2) summarizes the findings for relatively rural counties. We discover that the number of charging stations located near town/city centers has a greater effect in relatively rural counties and a smaller effect in relatively urban areas. One possible reason could be that urban areas already have a sufficient density of charging stations near the town/city center, and thus potential customers in those areas would pay less attention to charging stations near the town/city center. Rural areas may be deficient in charging stations located near town/city centers, and potential customers in these areas would prioritize charging stations located near town/city centers.

Results from random sampling are shown in column (3) and column (4). The signs of the key variable are consistent with the full sample results, and the magnitudes are also very close to the full sample parameter estimates. The similarity between subsample and full sample results may imply that the dataset's limitations

Table 5. Impact of Charging Station Locations on EV Demand in Subsamples

VARIABLES	(1) urban	(2) rural	(3) 50% sample	(4) 50% sample
No. of stations within 3 miles of town center	0.0137*	0.0504***	0.0203*	0.0227***
	(0.00738)	(0.00851)	(0.0103)	(0.00518)
Household income	1.073***	0.821*	1.068***	1.081***
	(0.346)	(0.469)	(0.332)	(0.281)
Percentage of people with higher education	0.632*	1.118*	0.774**	0.859*
	(0.366)	(0.640)	(0.318)	(0.443)
Population density	1.741	-23.65***	-10.38**	-7.009
	(2.828)	(5.000)	(4.219)	(8.683)
Observations	868	840	847	866
Adjusted R-squared	0.768	0.781	0.733	0.759
Year-quarter fixed effects	YES	YES	YES	YES
County fixed effects	YES	YES	YES	YES

Notes: Robustness checks are performed on the regressions using the subsamples. The first two columns are the relatively urban counties and relatively rural counties in New York State. The term "relatively urban counties" refers to those with population densities greater than the state's median population density, while "relatively rural counties" refers to the remaining half of the counties. The final two columns summarize the results of the random 50% subsamples drawn from the full sample. The dependent variable is ln(EV sales) by county by quarter. In estimation, we add one to EV sales to deal with zero values for some of the observations. Standard errors in parentheses are clustered at county level. Significance levels are indicated by *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

have little effect on the key variable's parameters.

Figure 11 provides a falsification test by shuffling the number of charging stations within 3 miles of the town/city center for each year quarter while maintaining all other variables fixed. The figure depicts the histogram of 500 iterations' coefficient estimates for the number of charging stations within three miles of the town/city center. The true sample estimate (0.02) lies outside the distribution's 99th percentile. This allays concerns about the estimated impact being driven by unobservables.

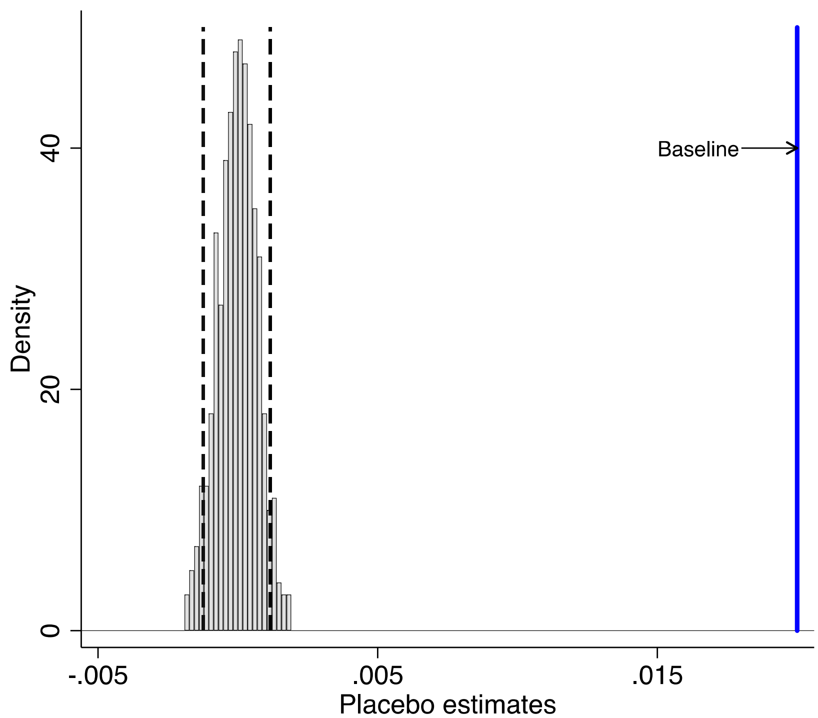

Figure 11. Falsification Test on the Number of Charging Stations Near 3 Miles of the Town/City Center.

Notes: The figure shows the distribution of coefficient estimates from placebo tests. Each year quarter, the number of charging stations within three miles of the town/city center is randomized. 90% of the coefficient estimates fall within the dashed vertical lines, while the solid vertical line indicates the true sample estimate (0.02).

3.2 Regression Results for Facility Types

The OLS results for equation (2) are presented in Table 6. Column (1) contains only the five variables that we are interested in (average distance between charging stations and highways, number of charging stations in car dealerships/parking lots/office buildings/hotels). In column (2) and column (3), we add the year-quarter fixed effects to control for time-varying common unobservables across counties, as well as county fixed effects to account for time-invariant unobserved local preference for electric vehicles and county-specific demand shocks. From column (4) to column (6), we incrementally add more control variables (median household income, percentage of people with higher education, and population density) to address the endogeneity problem introduced by omitted variables.

In Table 6, only the coefficients in front of the number of stations installed in parking lots and office buildings are significant. The sign of the coefficient for the number of stations installed in office buildings is consistent with our intuition, but that of the number of stations installed in parking lots is counterintuitive. The findings show that EV demand increases with more charging stations in office buildings but decreases with more charging stations in parking lots.

In order to do a robustness check, we report the regression results with the key variables in log form in Table 7. The estimated equation is as follows:

$$\begin{aligned}\ln(q_{kt}) = \beta_0 + \beta_1 \ln\,(ad_{kt}) + \beta_2 \ln(nc_{kt}) + \beta_3 \ln(np_{kt}) + \beta_4 \ln(nb_{kt}) \\ + \beta_5 \ln\,(nh_{kt}) + \beta_6 \ln(i_{kt}) + \beta_7 e_{kt} + \beta_8 \ln\,(p_{kt}) + \mathrm{T}_t + \delta_k \\ + \epsilon_{kt} \qquad (3)\end{aligned}$$

Table 6. Regression Results for Equation (2)

VARIABLES	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS
average distance to highway	0.0730**	-0.0172	-0.0517	-0.0301	-0.0321	-0.0302
	(0.0284)	(0.0231)	(0.0525)	(0.0476)	(0.0430)	(0.0430)
no. of stations in car dealers	-0.0439	0.0589***	0.135	0.103	0.0823	0.0878
	(0.0292)	(0.0224)	(0.0879)	(0.0738)	(0.0651)	(0.0675)
no. of stations in parking lots	-0.0169**	-0.00240	-0.00813*	-0.0115***	-0.0109***	-0.0118***
	(0.00833)	(0.00395)	(0.00416)	(0.00368)	(0.00344)	(0.00344)
no. of stations in office buildings	0.581***	0.301***	0.291***	0.264***	0.279***	0.277***
	(0.0479)	(0.0344)	(0.0401)	(0.0418)	(0.0403)	(0.0407)
no. of stations in hotels	0.0707	-0.0206	-0.00695	-0.0150	-0.0138	-0.0101
	(0.0778)	(0.0399)	(0.0428)	(0.0456)	(0.0436)	(0.0447)
household income				6.36e-05***	5.28e-05***	5.14e-05***
				(1.70e-05)	(1.59e-05)	(1.63e-05)
percentage of people with higher education					0.746*	0.739*
					(0.374)	(0.377)
population density						-0.000260
						(0.000202)
Observations	1,589	1,589	1,589	1,589	1,467	1,467
R-squared			0.820	0.829	0.807	0.807
Year-quarter fixed effects	NO	YES	YES	YES	YES	YES
County fixed effects	NO	NO	YES	YES	YES	YES

Notes: The regressions are constructed using the full sample of 61 counties. The dependent variable is ln(EV sales) by county by quarter. In estimation, we add one to EV to deal with zero values for some of the observations. Standard errors in parentheses are clustered at county level. Significance levels are indicated by *** p<0.01, ** p<0.05, * p<0.1.

As shown in Tables 6 and 7, the parameter estimates differ significantly between the two tables, with the exception of the coefficient in front of the number of charging stations in office buildings remaining significant and the sign remaining unchanged. Thus, only the number of charging stations installed in office buildings is a reliable estimate.

The majority of key variable coefficients are statistically significant in Table 7. In column (6), the coefficients for the average distance between charging stations and the highway, as well as the number of charging stations installed in car dealerships, parking lots, and office buildings, all agree with our intuition. EV demand decreases with more EV charging stations built far away from highways and increases as more EV charging stations are built in car dealers, parking lots, and office buildings. The number of charging stations in hotels has an insignificant effect.

Establishing EV charging stations near highways may alleviate customers' anxiety about running out of energy while driving an EV on the road, while also potentially lowering the cost of charging. When people realize that charging costs are decreasing and it is guaranteed that EVs can be charged immediately when the battery is about to run out, EV sales increase. Intuitively, increasing the number of EV charging stations in parking lots would make charging an EV more convenient and could reduce the time spent searching for charging stations. Charging stations at car dealerships would allow customers to experience EV technology firsthand, thereby increasing EV demand. Increased charging stations in office buildings would benefit customers who commute in electric vehicles. Additionally, a higher median household income, a greater proportion of people with higher education, and a higher

Table 7. Regression Results for Equation (2) Using Log-form

VARIABLES	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS
ln(average distance to highway)	0.153***	-0.0173	-0.168***	-0.158***	-0.151***	-0.135***
	(0.0329)	(0.0246)	(0.0387)	(0.0387)	(0.0402)	(0.0394)
ln(no. of stations in car dealers)	-0.229***	0.251***	0.628***	0.653***	0.538***	0.650***
	(0.0644)	(0.0511)	(0.149)	(0.148)	(0.151)	(0.148)
ln(no. of stations in parking lots)	0.375***	0.329***	0.218***	0.177***	0.130**	0.115**
	(0.0606)	(0.0435)	(0.0541)	(0.0549)	(0.0559)	(0.0547)
ln(no. of stations in office buildings)	1.703***	0.755***	0.860***	0.853***	0.881***	0.846***
	(0.0722)	(0.0562)	(0.0634)	(0.0632)	(0.0663)	(0.0649)
ln(no. of stations in hotels)	0.181***	-0.0405	-0.0297	-0.0459	-0.0471	-0.0699
	(0.0646)	(0.0503)	(0.0577)	(0.0576)	(0.0584)	(0.0571)
ln(household income)				2.142***	1.562***	0.924
				(0.564)	(0.582)	(0.575)
ln(percentage of people with higher education)					0.886**	0.951**
					(0.395)	(0.386)
ln(population density)						20.71***
						(2.560)
Observations	1,589	1,589	1,589	1,589	1,467	1,467
R-squared			0.791	0.793	0.768	0.779
Year-quarter fixed effects	NO	YES	YES	YES	YES	YES
County fixed effects	NO	NO	YES	YES	YES	YES

Notes: The regressions are constructed using the full sample of 61 counties. The dependent variable is ln(EV sales) by county by quarter. In estimation, we add one to EV sales and the number of charging stations built in car dealers/parking lots/office buildings/hotels to deal with zero values for some of the observations. Standard errors in parentheses are clustered at county level. Significance levels are indicated by *** p<0.01, ** p<0.05, * p<0.1.

population density may all contribute to increased EV demand.

As we can see, the coefficient in front of the number of EV charging stations in hotels is statistically insignificant and has a sign that contradicts our expectation. While hotels may install charging stations to advertise their brands, residents have very few opportunities to use hotel-installed charging stations. Thus, the impact of hotel-based charging stations is negligible.

The results in column (6) imply that, holding all other factors constant, each 10% increase in the number of charging stations installed in car dealers, parking lots, and office buildings could raise EV sales by 6.5%, 1.2%, and 8.5% EV sales, respectively. Holding all other factors constant, every 10% increase in the average distance between EV charging stations and the nearest highway result in a 1.4% decrease in EV demand.

The number of charging stations installed in car dealerships and office buildings has a much greater impact on EV sales than other key variables. There are two possible explanations for car dealers. To begin, there are numerous stations located within automobile dealerships. When this figure increases, the total number of EV charging stations in the market increases as well, which has an effect on EV sales. Secondly, charging stations in car dealerships could assist EV salespeople in promoting the positive perception of EV technology among customers. Customers would gain direct exposure to the convenience and potential benefits of EVs and EV charging stations, increasing their willingness to pay. For office buildings, it is understandable that potential customers would prefer to commute via EVs. Therefore, it is critical that office buildings have EV charging stations and that EVs can be charged while people are at work.

We observe that the average distance between EV charging stations and the nearest highway has a greater impact on EV demand than the number of charging stations located in town/city centers. This is because the current density of EV charging stations near the town/city center is sufficient. Over ninety percent of EV charging stations are located within 7 miles of the town/city center, which means that increasing the number of charging stations in close proximity to the town/city center has a limited effect on encouraging people to purchase an EV. Additional charging stations along highways may be more in demand by potential EV customers.

We construct four subsamples for the purpose of performing robustness checks. The first two subsamples are New York State's relatively urban and rural counties. The other two subsamples are two random samples of half of the observations from the full sample. Regression results for the four subsamples are reported in Table 8.

Column (1) shows the results for the relatively urban counties. The average distance to highways has a greater effect on EV adoption in the relatively urban counties, indicating that the urban areas rely more on the average distance to highways than the full sample. The parameters in front of the number of charging stations installed in automobile dealerships, parking lots, and hotels are trivial. The coefficient for the number of charging stations installed in office buildings is significant, indicating that EV demand in relatively urban areas continues to be dependent on the number of charging stations installed in office buildings. This is consistent with our intuition, given the high concentration of people employed in office buildings in

Table 8. Impact of Charging Stations Facility Types on EV Demand in Subsamples

VARIABLES	(1) urban	(2) rural	(3) 50% sample	(4) 50% sample
ln(average distance to highway)	-0.311***	-0.00723	-0.101*	-0.189***
	(0.0652)	(0.0484)	(0.0563)	(0.0563)
ln(no. of stations in car dealers)	0.106	1.287***	0.602***	0.823***
	(0.192)	(0.282)	(0.207)	(0.232)
ln(no. of stations in parking lots)	0.0357	0.303***	0.219***	0.0418
	(0.0695)	(0.0869)	(0.0738)	(0.0759)
ln(no. of stations in office buildings)	0.800***	0.882***	0.840***	0.904***
	(0.0862)	(0.0990)	(0.0886)	(0.0943)
ln(no. of stations in hotels)	-0.0270	-0.176**	0.0575	-0.137
	(0.0756)	(0.0847)	(0.0740)	(0.0861)
ln(household income)	-0.498	1.823**	0.0609	1.201
	(0.908)	(0.754)	(0.749)	(0.896)
ln(percentage of people with higher education)	0.996*	0.992*	0.854	1.049*
	(0.557)	(0.522)	(0.527)	(0.568)
ln(population density)	24.64***	11.11**	22.53***	17.78***
	(3.441)	(5.048)	(3.476)	(3.742)
Observations	802	665	735	727
Adjusted R-squared	0.797	0.745	0.786	0.743
Year-quarter fixed effects	YES	YES	YES	YES
County fixed effects	YES	YES	YES	YES

Notes: Robustness checks are performed on the regressions using the subsamples. The first two columns represent New York State's relatively urban and rural counties. The term "relatively urban counties" refers to those with population densities greater than the state's median population density, while "relatively rural counties" refers to the remaining half of the counties. The final two columns summarize the results of the random 50% subsamples drawn from the full sample. The dependent variable is ln(EV sales) by county by quarter. In estimation, we add one to EV sales and the number of charging stations built in car dealers/parking lots/office buildings/hotels to deal with zero values for some of the observations. Standard errors in parentheses are clustered at county level. Significance levels are indicated by *** p<0.01, ** p<0.05, * p<0.1.

relatively densely populated areas.

Column (2) reports the results for the relatively rural counties. The average distance to highways has a negligible effect on EV adoption in relatively rural areas, and the estimator is insignificant. The other four key variables all have statistically significant coefficients. The coefficient for the number of charging stations built in office buildings remains significant, demonstrating that the number of charging stations put in office buildings continues to be an important factor in determining EV demand in relatively rural counties. This demonstrates the robustness of the influence of the number of charging stations in office buildings. We observe that the number of charging stations installed in automobile dealerships and parking lots has a greater effect on EV demand than the full sample. However, the number of charging stations installed in hotels has a negative effect on EV demand in relatively rural counties, which may be explained by the fact that very few people in those areas require hotel accommodations.

Results from random sampling are shown in column (3) and column (4). For the two subsamples, the signs of all key variables are consistent with the full sample results, and the magnitude is also consistent with the full sample parameter estimates. The similarity between the results from subsamples and the full sample may imply that the dataset's limitations have little effect on the parameters of key variables associated with facility types.

3.2 Implications and Discussion

Numerous federal and state policies supporting EV adoption have been announced, the majority of which focus on financial incentives such as tax rebates or credits, indirect incentives such as providing EVs with access to HOV lanes, financial assistance for charging infrastructure development, and R&D support for battery and EV development. Li et al. (2017) find that a policy targeting expanding charging infrastructure could have been more effective than subsidizing EV adoption. Sierzchula et al. (2014) and Jenn et al. (2018) point out that increasing knowledge spillover and consumer awareness also contributes to the expansion of charging stations.

Our findings corroborate these findings. However, none of these examples demonstrate how policies could be designed to offer incentives based on the location of an EV charging station.

According to our findings, a sensible policy approach for increasing EV demand could include the construction of additional EV charging stations near town/city centers and highways, as well as charging stations connected to facilities such as car dealers, parking lots, and office buildings. Encouragement of investors to build additional charging stations at office buildings may have a stronger effect than others. The effect of the number of charging stations put near highways and in vehicle dealerships or parking lots is not robust. The number of charging stations installed in hotels has insignificant effects on EV demand.

In this study, we exclude EV price, EV model characteristics, and incentives. However, omitting these variables may introduce bias into parameter estimates. Also, we believe that the majority of incentives are provided by either the federal or state governments. But the local government would also provide incentives for residents to purchase an EV by reducing charging costs or by financing the construction of a home charging station. This may also introduce bias to the results. Besides, this study focuses exclusively on New York State from 2014 to 2021. The limited time span and the geographic area may limit the scope of application. Our analysis makes the assumption that EV demand is influenced solely by charging stations located within the same county. However, the charging station network in neighboring counties may be significant. Additionally, there might exist simultaneity between EV sales and the number of charging stations near the town/city center, but we do not account for this. Thus, further enhancements to these perspectives are possible.

CHAPTER 5

CONCLUSION

Automobile emissions have recently become a major source of environmental concern in urban areas. EVs are identified as a viable option for reducing greenhouse gas emissions and mitigating environmental concerns. Numerous policies and incentives aimed at encouraging EV adoption have been announced by the federal, state, and local governments. However, few have paid attention to the importance of charging station location on EV demand.

This study examines the impact of EV charging station locations on EV demand in New York State from 2014 to the second quarter of 2021. The data on EV registrations, EV charging stations, and demographics for all counties in New York State from 2014 to the second quarter of 2021 is used. We assume that the average distance between charging stations and the highway, the number of charging stations near town/city centers, and the number of charging stations with facilities (car dealers, parking lots, office buildings, and hotels) all influence EV demand. To address the model's endogeneity, we include additional control variables, year-quarter fixed effects, and county fixed effects to reduce parameter estimation bias.

We find that if more EV charging stations were built near city centers and nearby highways, and if more charging stations included facilities (car dealers, parking lots, and office buildings), EV demand would increase. The number of charging stations installed in office buildings has a relatively larger impact and has a robust coefficient. The estimates of the number of charging stations near the highway and installed in car dealers or parking lots are not robust, and the number of charging stations installed in hotels has an insignificant impact.

Our analysis indicates that future policies and incentives aimed at increasing EV adoption may place a greater emphasis on the location of charging infrastructure. With the same subsidy expenditure, an incentive focused on the location of charging infrastructure would be more effective than a blanket subsidy for all charging stations. More subsidies for charging stations positioned near town/city centers and outfitted with amenities such as office buildings will promote more EV purchases.

This study adds another dimension to the debate over the optimal location of charging stations. Additionally, it contributes to the study of electric vehicle demand and makes multiple proposals for future policies and incentives aimed at promoting EV adoption.

Given the availability of data and limited time, EV prices, EV model characteristics, and the incentives are not considered, which is left for future research.

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