# The Value of Home Charging Infrastructure to Electric Vehicle Adoption

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**ABSTRACT**

This study aims to estimate the relationship between home-based charging availability and electric vehicle (EV) ownership using revealed preference methodology. Additionally, we seek to quantify the willingness to pay (WTP) for home-based charging annually over the lifespan of a vehicle. We use a discrete choice linear probability model to estimate the marginal effect of home charging availability on EV ownership. Our model considers household characteristics, income levels, and location. We calculate willingness-to-pay (WTP) for home-based charging in both monetary terms and equivalent foregone convenience based on an assumed hourly wage. We find that median-to-high income households exhibit a higher WTP for home-based charging. Low-income households have significantly lower WTP, reflecting differences in consumer valuation. The estimated annualized WTP for home-based charging ranges from $302 to $1,033 among low-income households and $1,913 to $13,868 annually for median income households. While the difference in magnitude for WTP for home-based charging infrastructure (HBCI) may seem significant, we estimate foregone convenience using an assumption in respondents' hourly wage. We find the equivalent foregone time from not possessing home-charging infrastructure only results in a 1-10 hour weekly difference. Home-based charging infrastructure plays a crucial role in EV adoption. Policymakers, city planners, and private developers should all consider consumer WTP for HBCI when designing charging networks.

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# CHAPTER ONE

# INTRODUCTION

## Challenges to Electric Vehicle Adoption

Prior research establishes well-known obstacles to EV adoption in the United States and around the world. EVs tend to have a higher upfront cost compared to internal combustion engine vehicles (ICEVs). While EVs may provide lower operating costs throughout the life of a vehicle, the higher upfront price is a significant adoption barrier for consumers, particularly for low-income households (LaMonca et al., 2022, Bauer et al. 2021). This price disparity can make EVs unaffordable for many consumers, thereby limiting EV ownership. Further, fuel and maintenance savings from EVs are not fully understood by many US consumers. Gillingham et al. (2021) provide evidence of consumer undervaluation of vehicle lifetime fuel costs. Their experiment finds that consumers are indifferent between $1.00 in discounted fuel costs and $0.16-.0.39 in purchase price, showing that a much higher value is placed on upfront costs. Leard et al. (2023) provide evidence of the undervaluation of fuel cost savings and a high valuation of performance by US car consumers. These studies both provide evidence that consumers undervalue the potential long-term savings of EVs over ICEVs. Policies aimed at promoting EV adoption will need to address consumer undervaluation of fuel costs.

Consumers face “range anxiety” in reference to the mileage which an EV can travel using one full battery charge. Range anxiety is amplified by both the limited quantity of public charging infrastructure in the US and the charging speeds of the chargers available. Although more expensive to install and operate, Level III or fast-charging stations can provide a full charge in significantly less time compared to standard Level I and II charging stations. Level III charging stations can provide a full EV battery in as little as 30 minutes. Level I and II chargers, the most common type of charging found at home, can take 8 or more hours to fully charge an EV (LaMonca et al., 2022). Zhou et al. (2020) found that public fast charging infrastructure has been a more relevant factor in promoting EV demand than slow-charging infrastructure. Inconsistent charging station density has been found to increase range anxiety, particularly for households living in rural areas (Borlaug, 2023). The compatibility and standardization of charging infrastructure are also significant barriers to EV adoption. EV owners may experience range anxiety if they are unsure whether a charging station is compatible with their vehicle (Lamontagne et al., 2023).

The literature on EV demand has identified a “Chicken and Egg” problem between EV consumers and charging infrastructure (Shi et al., 2021, Green et al., 2020). Consumers may not buy EVs because of the lack of charging stations, and businesses hesitate to invest in charging infrastructure because there are not enough EVs on the road. Due to the limited demand of EVs, investors of EV charging infrastructure often experience a “cold business period” where low demand for charging does not allow companies to recoup their upfront infrastructure investment (Shi et al., 2021). Further, Springel (2021) discusses how low use and high upfront investment costs among EV charging infrastructure suppliers make profitability challenging.

Prior literature establishes a relationship between charging station density and EV ownership (Springel 2021, Hall et al., 2017, Javid et al., 2017). A household's income, education level, charging stations per capita, and gasoline prices were found to significantly influence EV adoption (Javid et al., 2017).

For over a decade, there has been uncertainty on where to efficiently build charging infrastructure (Jochem et al., 2022, Funke et al., 2019, Pagani et al., 2019, Micari et al., 2017). However, the development of both fast (DCFC Level III) and slow (Level II) charging stations will be required for significant EV adoption (LaMonaca et al., 2022, Hall et al. 2017). Prior literature reveals that most charging is done at home. Hardman et al. (2018) show that 50–80% of all charging occurs at home. While home charging infrastructure is understood to be a significant factor for EV adoption, little is known about how much EV owners are willing to pay for it.

**Objectives**

1. To estimate the relationship between home-based charging availability and EV ownership using revealed preference methodology.
2. To estimate the willingness to pay for home-based charging annually over the lifespan of a vehicle.
3. To reflect the willingness to pay for home-based charging in units of both USD and foregone convenience, based on an assumption of hourly wage.

# CHAPTER TWO

# LITERATURE REVIEW

## Public Charging Infrastructure

Forecasts suggest significant future US EV market growth. However, the growth will need to be supported by a robust EV charging infrastructure network. Funke et al. (2019) found that a lack of public charging infrastructure discourages EV adoption. LaMonaca and Ryan (2022) discuss the link between EV adoption and public charging infrastructure. Their review of the literature concludes that access to both public and home charging is important for EV ownership. Consumers want to feel confident in adopting an EV without fear that their driving behavior will need to be constrained due to refueling limitations. Empirical studies such as Sierzchula et al. (2014), show that  the number of public charging stations per capita is positively correlated with national EV market share. They conclude that investments in public charging infrastructure have a larger effect on EV ownership compared to financial incentives such as tax credits. The researchers find that installing an additional charging station per 100,000 people would increase EV market share by more than the effect of  an additional $1,000 subsidy of $1,000. Hall et al. (2017) find that increasing the number of charging stations per capita is associated with increased EV ownership.

## Residential Charging Infrastructure

As EV ownership increases, home-based charging is expected to decrease (Bauer et al., 2021). This prediction comes from the expectation that EVs will be increasingly adopted by people who do not live in single-family homes. Hall et al. (2017) concludes that lack of public charging infrastructure impacts households' ability to take long trips, reducing the utility of an EV for some consumers.

Based on the sample of data discussed in the data section, most current EV owners in the United States live in detached houses and have access to home-based charging. The ratio of DC charging points per gasoline stations is relatively low in the US (Funke, 2019). One reason might be that EV ownership is concentrated in certain regions in the US. Nicholas et al. (2019) finds that charging station density is highly concentrated and uneven across the country.

# CHAPTER THREE

## CONCEPTUAL FRAMEWORK

This study is an analysis of preferences of people who lack home-based charging capabilities, or garage orphans. We seek to quantify consumer willingness to pay (WTP) for home-based EV charging. We report our findings in both units of money and equivalent foregone convivence, assuming the value of time. WTP for home-based charging infrastructure (HBCI) is an important calculation for policymakers, city planners, housing developers, charging-infrastructure manufacturers, and alternative fuel stations developers. WTP for HBCI reflects the maximum amount of money a consumer would spend to obtain access to HBCI. The WTP for HBCI for EV owners can be inferred through the increased consumption of EVs when consumers are suddenly given access to HBCI. This is reflected visually in Figure 1 as a rightward shift in the demand curve for EVs. There are two demand curves, D0, representing the demand for EVs for households without access to HBCI, and D1 representing the demand for EVs for households with access to HBCI. For simplicity and tractability, we assume a constant supply of EVs. We assign a slope to the demand curves in Figure 1 by assuming a constant elasticity of demand for the price of EVs. The price elasticity of demand for EVs measures how quantity demanded for EVs changes in response to a one-percent increase in the price of EVs. While this assumption oversimplifies consumer behavior, it allows us to estimate WTP for home-based EV charging. We will not use time-series data, so it is safe to assume both the price elasticity of demand and the supply of EVs are constant during our experiment. Our evaluation lies not on the demand curves for EVs themselves, instead we focus on the difference in the quantity demanded for EVs for households with and without HBCI. In Figure 1 this is represented by the horizontal distance (Q1 - Q0). The vertical distance between the demand curves D0 and D1 represents the WTP for the attribute HBCI. The value of HBCI to EV adoption is interpreted as the additional amount that consumers with access to HBCI would be WTP for an EV compared to garage orphans. Further, we assume the value of a respondent's time and convert the additional dollars spent to obtain HBCI for EV owners to an equivalent number of hours a year.

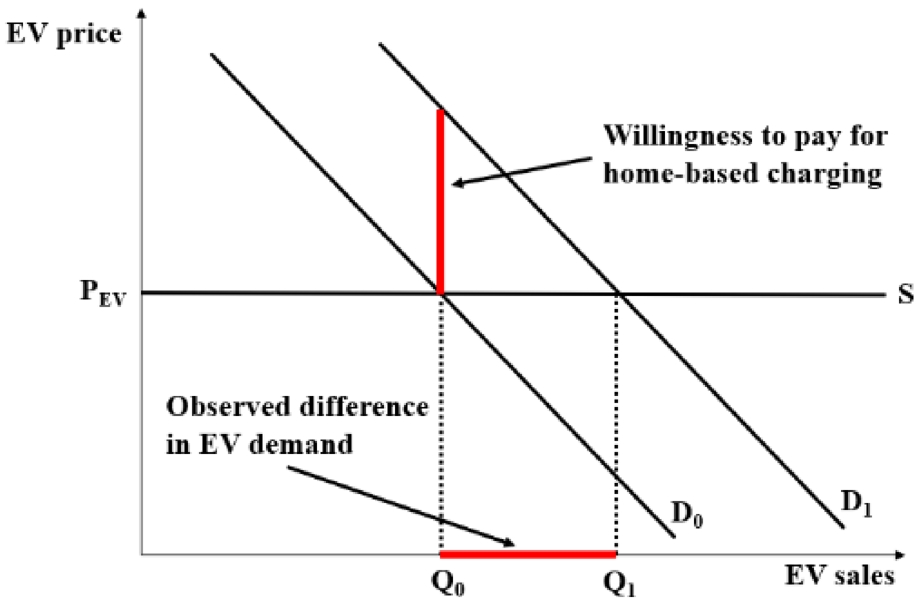


**Figure 1. Converting estimates to willingness to pay for home-based charging.**

# CHAPTER FOUR

# METHODS AND PROCEDURES

## Data Description

The U.S. Energy Information Administration (EIA) collects data from the Residential Energy Consumption Survey (RECS) once every five years. The 2020 wave of the survey sampled 18,496 households across all 50 states and Washington D.C. It contains information about housing unit characteristics, household demographics, and energy use patterns. This survey is valuable to our research as it provides data on both EV ownership and a proxy for home-based charging capabilities from a nationally representative sample. For our model, we approximate consumer behavior. Home-based charging availability is measured as a binary variable equal to one if the respondent has an outlet within 20 feet of their vehicle parking, and zero otherwise. RECS reports EV ownership as a binary variable equal to one if the household owns or leases at least one EV or PHEV and zero otherwise. RECS also includes sociodemographic characteristics such as income and race that we utilize to explore equity dimensions of EV adoption. Table 1 summarizes the relevant variables for our study.

The RECS is conducted in two phases by the EIA. The first phase is through a cross-sectional household survey which collects energy-related characteristics and energy usage data. The second phase corresponds with energy suppliers for the housing units surveyed, which is to estimate energy consumption and expenditure.

**Table 1. Variables from RECS**

| Variable | Type | Description |
|---|---|---|
| Own or lease an electric vehicle | Vehicle ownership | The household owns or leases at least one PHEV or electric vehicle. |
| Gross household income | Socio-demographic | Annual total household income |
| Low Income | Socio-demographic | If reported household income is $60,000 or less. |
| Type of housing unit | Socio-demographic | Type of house the respondent lives in (e.g., detached house) |
| Sex | Socio-demographic | Gender of respondent |
| Ethnicity | Socio-demographic | Ethnicity of respondent |
| Race | Socio-demographic | Race of respondent |
| Employment | Socio-demographic | Employment status of respondent |
| Education | Socio-demographic | Education level of respondent |
| State of residence | Socio-demographic | Which state the respondent lives in |
| Charging outlet | Home charging availability | Has an outlet within 20 feet of vehicle parking |
| EV charged at home | Home charging availability | The respondent charges its EV at home |

Table 2 displays RECs respondents home charging availability and EV ownership. Important for our study, 62% of households surveyed reported having an outlet within 20 feet of parking their car. This is a lower-bound estimate for HBCI access. Only 38% of households surveyed did not have access to HBCI. Notably, EV ownership is roughly 700% higher for respondents with access to HBCI than those without.

**Methods**

Our objective is to estimate the value of home-based charging infrastructure (HBCI) to EV ownership, annualized over the lifespan of the vehicle, or 12 years. We evaluate the number of households in RECs who report owning EVs and if they have an outlet within 20 feet of parking their vehicle, which is our proxy for HBCI availability. We estimate two demand lines for EVs assuming a constant price elasticity of demand. The demand equation for EVs for households without access to HBCI is represented by Equation 1. Equation 2 represents the demand line for EVs for households with access to HBCI.

Equation 1: $$ln(Q0) = \alpha 0 + \varepsilon * ln(P)$$

Equation 2: $$\ln(Q1) = \alpha 1 + \varepsilon * \ln(P)$$

In both equations, P is equivalent to the average price of an EV in 2020 in the US, and ε represents the constant price elasticity of demand for EVs. For our baseline estimation we assume that the median price of new and used EVs in 2020 was $27,058, and that the lifespan of the vehicle for a consumer is 12 years. The intercepts to our demand lines are represented by α0 and α1. The difference between α0 and α1, the vertical distance between the two demand lines, captures the impact of HBCI on EV demand. Q0 is given

**Table 2. Home Charging Capability and EV Ownership**

| Electric Vehicle Ownership | Home Charging Capability | | |
|---|---|---|---|
| | No | Yes | Total |
| No | 6,985 | 11,225 | 18,210 |
| Yes | 36 | 250 | 286 |
| Total | 7,021 | 11,475 | 18,496 |

by RECs, 36 households own EVs but report no access to HBCI. Q1 is estimated by multiplying the marginal effect of HBCI onto the sample of the population which does not report having HBCI. Theoretically, this is equivalent to giving all households access to home-based charging. In 2020 RECs the sample of households without HBCI was 6,985. Q1 is estimated through an assumption of β, the marginal effect of home-based charging.

Equation 3: $$Q1 = Q0 + \beta(6{,}985)$$

The dependent variable is binary; therefore, we use a logit model to estimate the marginal effect of HBCI. The model is structural in nature, where we assume respondents make decisions based on random utility theory. Our model uses a reduced-form econometric approach to define the decision of EV ownership as a function of household characteristics. The econometric estimation takes the form of a probability function:

Equation 4: $$Prob(EV_i = 1) = f(homecharge_i, X_i)$$

The term $EV_i$ is a binary variable indicating whether household $i$ owns an electric vehicle. The variable $homecharge_i$ is a binary variable indicating whether household $i$ has home charging capability, and the vector $X_i$ includes socio-demographic controls, such as income level, state of residence, etc. We use an approximation of our discrete choice model to estimate the marginal effect of home charging. For tractability we assume that there is a constant price elasticity of demand for EVs. Our price elasticity estimates come from Leard et al. (2021) and Muehlegger et. al (2020), which we use to assign a slope for our demand lines in Figure 1. For median income households EV price elasticities range between -1 and -2. We assume that lower income households, defined as households that reported earning $60,000 a year or less have more elastic demand for EVs, as EVs are considered a luxury good. We assume that price elasticity of demand for EVs for these households is between -2 and -3. The price elasticity is represented by $\varepsilon$ in Equations 1 and 2 and reflects the slope of the demand lines in Figure 1.

To estimate the marginal willingness to pay for HBCI annualized over the lifespan of a vehicle, we first estimate the horizontal difference between demand lines, or the increased quantity demanded for EVs after 100% of respondents are given access to HBCI. We compare 9 scenarios using different combinations of elasticity and EV Price ($P_{EV}$) assumptions. To find the vertical distance between demand lines we must estimate the parameter of EV ownership for D1, represented by $\alpha 1$

Equation 5: $$\alpha 1 = \ln Q1 - \varepsilon * \ln P$$

To solve D1 at Q0 we divide both sides of Equation 5 by $\varepsilon$.

Equation 6: $$\frac{\ln Q0 - \alpha 1}{\varepsilon} = \ln P$$

To find P*, the price of EVs demanded from household with home-based charging (D1) at Q0, we solve for P in equation 6.

Equation 7: $$P^* = e^{\frac{\ln Q0 - \alpha 1}{\varepsilon}}$$

To find the vertical distance between demand curves at Q0, representing the WTP for the attribute HBCI, we subtract P* from $P_{EV}$, our initial assumption of the price of an EV. In Tables 4 and 5, located in the Appendix, we present results which calculate the implied willingness-to-pay for home-based charging infrastructure. We report our calculation in units of both money and equivalent time foregone by assuming a respondent's average hourly wage. This can be interpreted as value of time foregone weekly by not having HBCI. We use a range of elasticities to develop a robust estimate of WTP for home-based charging and to reflect differences in consumer valuation of EVs.

# CHAPTER FIVE

# RESULTS

## Analysis

The coefficients in Table 3 come from a reduced form logit model, they represent the total effect of one variable on another. The increase in the fraction of households that own an EV is associated with home-based charging availability. Our results are reported in Table 3.

In model (1) the estimated constant is 0.005, which represents the fraction of households that own an EV and that do not have home-based charging. We know from Table 2 this fraction is 36 out of 7,021 households. The proportion of households that own an EV among households that possess home-based charging capability is 0.022. The coefficient in model (1) is 0.017, which reflects the difference between the ratios of EV owners with and without home-based charging. The interaction term "Home Charging * Low-Income" captures how the effect of home charging availability differs for low-income households, the coefficient is -0.019 with a standard error of 0.004. A negative coefficient suggests that the impact of home charging availability on EV ownership is weaker for low-income households. This validates our hypothesis that lower income households are much less likely to purchase an EV than median income households. We use the different estimations of marginal effect of HBCI found in Table 3 to calculate the marginal WTP for HBCI in Tables 4 and 5 over the lifespan of a vehicle, or twelve years.

In Table 3, income represents the midpoint estimate of annual gross household income based on income range categories from RECs; it is scaled to the nearest $100,000. College Degree is a binary variable indicating if respondents have completed an associate degree or beyond. Race was only found to be statistically significant to EV ownership for white and Asian households. White is a binary variable aggregating the category of race. It reflects if the respondent identifies as a person of color or white. Urban is a binary variable representing if a respondent lives in an Urban Census Tract. We cluster standard errors at the state level and report them in parentheses. Variables such as Male, White, Urban, College Degree, Home Charging, State of residence, and the interaction between Home Charging and Low-Income were all found to be statistically significant. Notably, the R-squared value for all four models is low. R-squared is the fraction of the variance in which the dependent variable can be explained by the independent variable. One reason the R-squared is low could be because we are using microdata.

Table 4 summarizes the predicted marginal WTP estimates for home-based charging by median to high income households. These are households which reported more than $60,000 annual income. The scenarios reflect varying price elasticity estimates and the different EV price assumptions. The benchmark EV price, $27,058 represents the average sticker price of a used EV in 2020. The high EV price, $37,100 represents the average sticker price of a new EV in 2020. Our low price estimate for an EV was $17,100. Our assumed price elasticity of demand for EVs at this income level is between -1 and -2. The marginal WTP across all 9 scenarios is between $1,913 and $13,868 annually. The average WTP for HBCI amongst median-to-high income households across the 9 scenarios was $5,973. This estimate represents a significant value to households, supporting that home-based charging is an especially important attribute to EV consumers.

Table 5 summarizes the predicted marginal WTP estimates for home-based charging by low-income households. We know from previous literature that the demand for EVs is more elastic for low-income households. In Table 5, our initial EV price assumptions stay the same, but the elasticity estimates range from -2 to -3. Our β values come from the regression coefficients in Table 3. The estimated marginal effect for HBCI (β) in Table 4 is 0.023, but only 0.004 in Table 5. This indicates that there is a significant difference in the marginal effect for HBCI between low and median-to-high income. Expectedly, the marginal WTP for HBCI is much lower across all 9 scenarios for low-income households. The marginal WTP for HBCI annualized 12 years ranges between $302 and $1,033 annually. The average WTP for HBCI amongst low-income households is $606. Our results indicate the valuation for HBCI differs significantly between income groups.

Column two of Table 6 compares the difference in WTP for HBCI between low income and median income households across all nine scenarios. The difference in valuation of HBCI between household income types of ranges between $1,611 and $12,835 annually. This is interpreted as the average additional money spent by a median-to-high income household to access HBCI. We estimate the average difference in WTP for HBCI between income groups to be $5,366 annually. This difference in valuation amongst income types is large. We can compare it to the WTP of other vehicle attributes. Using consumer valuation estimations from Greene et. al (2018), we find the value of home-based charging is similar in magnitude to significant increases in both acceleration and range. Daziano et. al (2017) uses microdata to estimate the WTP for autonomous vehicles. They find significant heterogeneity in consumer valuation for automated driving. The average respondent was found to be willing to pay $4,900 for automation technology. Notably, a substantial portion of their sample was willing to pay more than $10,000 while many reported being unwilling to pay any positive amount for the same feature. Greene et. al (2018) and Daziano et. al (2017) document variability in consumer WTP for vehicle attributes and emerging technologies.

The third column of Table 6 converts differences in consumer valuation of HBCI into an equivalent value of time, which we consider the foregone convenience of not possessing HBCI. We measure the value of time savings from having HBCI using an estimation from Goldszmidt et al. (2020) which determined that the Value of Time (VOT) to be equivalent to 75% of the mean wage rate. The U.S. Bureau of Labor and Statistics (BLS) reported the mean hourly wage in 2020 to be $29.81, which is close to the median hourly wage of our sample. We assume that respondents work an average of 40 hours a week and 50 weeks per year. The median income of 2020 RECs respondents were $67,500, therefore the median hourly wage for a RECs respondent is $33.75. The VOT in 2020 is between $22.36 and $25.31 hourly. For all nine scenarios we divide the difference in marginal WTP between low and median-to-high income households by the VOT ($23.84). This provides the marginal WTP for HBCI in an equivalent number of hours a year a household would need to work to make up this difference. To determine the weekly equivalent time foregone from not having HBCI, we divide the hours for each of the nine scenarios by 52 weeks. We find the time savings of possessing HBCI is equivalent to 1.3-10.4 hours per week. The median time savings of someone with HBCI is 4.3 hours per week. While paying an additional $12,835 a year for HBCI might seem steep, it is the equivalent of only 10.4 hours of a household's week. To understand if our findings are robust, we look at work-based and public charging data. Asensio et al. (2021) used data from EV owners charging at their workplace. They found that the average duration spent charging at the workplace for habitual users was only 2.85 hours and the mean repeat frequency from the users was 72.53 visits a year, or 1.38 visits to a workplace charger per week. We know that Level II and DC chargers are the most common for public charging and workplace charging locations. We know the average length of time to charge a full EV battery in from empty using a Level II charger is between 4-10 hours depending on kwh output. Our estimate of weekly time savings for people who possess HBCI over those who do not is 4.3 hours a week, which is approximately equal to the time it takes to charge an EV battery from empty on a Level II charger.

**Discussion**

Since public charging station infrastructure is expected to increase over the current decade, we would expect that households will value home-based charging less over time. Figure 2 depicts the cumulative growth of EV charging stations from 2009 to 2023 from the Alternatives Fuel Data Center. Our estimations for the time savings of possessing home-based charging and the WTP for the attribute will decrease as both workplace and DC/Level III public charging stations become more ubiquitous.

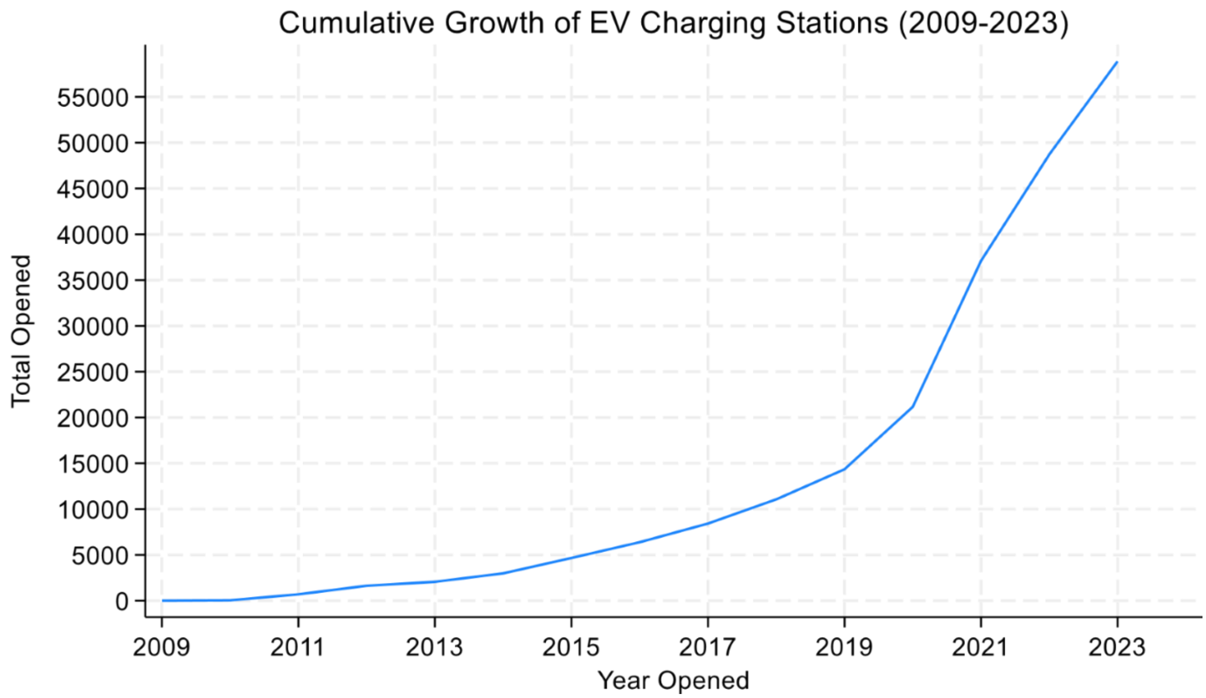


**Figure 2. Cumulative Growth of EV Charging Stations**

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## APPENDIX

### Table 3. Regression Results with Low Income Interaction

| Dependent Variable: Household owns an EV | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Home Charging | 0.017 | 0.023 | 0.023 | 0.024 |
| | (0.002) | (0.003) | (0.003) | (0.003) |
| Home Charging * Low-Income | | -0.019 | -0.019 | -0.019 |
| | | (0.004) | (0.004) | (0.004) |
| Low-Income Household | | -0.002 | 0.003 | 0.003 |
| | | (0.003) | (0.003) | (0.003) |
| Employed | | | 0.001 | 0.001 |
| | | | (0.002) | (0.002) |
| Age | | | -0.000 | -0.000 |
| | | | (0.000) | (0.000) |
| Male | | | 0.004 | 0.004 |
| | | | (0.002) | (0.002) |
| White | | | -0.010 | -0.010 |
| | | | (0.003) | (0.003) |
| Is Hispanic | | | 0.003 | 0.002 |
| | | | (0.003) | (0.003) |
| Urban | | | -0.006 | -0.006 |
| | | | (0.002) | (0.002) |
| College Degree | | | 0.010 | 0.010 |
| | | | (0.002) | (0.002) |
| Garage Size (# of Cars) | | | 0.002 | 0.002 |
| | | | (0.001) | (0.001) |
| Constant | 0.005 | 0.006 | 0.006 | 0.013 |
| | (0.001) | (0.002) | (0.006) | (0.006) |
| Observations | 18,496 | 18,496 | 18,496 | 18,496 |
| R-squared | 0.004 | 0.009 | 0.013 | 0.014 |

**Table 4. Median Income Household WTP (β = 0.023)**

| Scenarios | Price Elasticity | EV Price | Marginal WTP for Home-based Charging |
|---|---|---|---|
| Low PEV, Low Elasticity | -1 | $ 17,100 | $ 6,392 |
| Low PEV, Benchmark Elasticity | -1.5 | $ 17,100 | $ 3,007 |
| Low PEV, High Elasticity | -2 | $ 17,100 | $ 1,913 |
| Benchmark PEV, Low Elasticity | -1 | $ 27,058 | $ 10,114 |
| Benchmark PEV, Benchmark Elasticity | -1.5 | $ 27,058 | $ 4,759 |
| Benchmark PEV, High Elasticity | -2 | $ 27,058 | $ 3,026 |
| High PEV, Low Elasticity | -1 | $ 37,100 | $ 13,868 |
| High PEV, Benchmark Elasticity | -1.5 | $ 37,100 | $ 6,525 |
| High PEV, High Elasticity | -2 | $ 37,100 | $ 4,149 |

**Table 5. Low-Income WTP (β = 0.004)**

| Scenarios | Price Elasticity | EV Price | Marginal WTP for Home-based Charging |
|---|---|---|---|
| Low PEV, Low Elasticity | -2 | $ 17,100 | $ 476 |
| Low PEV, Benchmark Elasticity | -2.5 | $ 17,100 | $ 370 |
| Low PEV, High Elasticity | -3 | $ 17,100 | $ 302 |
| Benchmark PEV, Low Elasticity | -2 | $ 27,058 | $ 754 |
| Benchmark PEV, Benchmark Elasticity | -2.5 | $ 27,058 | $ 585 |
| Benchmark PEV, High Elasticity | -3 | $ 27,058 | $ 478 |
| High PEV, Low Elasticity | -2 | $ 37,100 | $ 1,033 |
| High PEV, Benchmark Elasticity | -2.5 | $ 37,100 | $ 802 |
| High PEV, High Elasticity | -3 | $ 37,100 | $ 655 |

**Table 6. Difference in willingness to pay for home charging in equivalent hours.**

| Scenario | Difference in WTP for home-based charging between income type | Equivalent number of hours per week based on Value of Time |
|---|---|---|
| Low PEV, Low Elasticity | $ 5,916 | 4.8 |
| Low PEV, Benchmark Elasticity | $ 2,637 | 2.1 |
| Low PEV, High Elasticity | $ 1,611 | 1.3 |
| Benchmark PEV, Low Elasticity | $ 9,360 | 7.6 |
| Benchmark PEV and Elasticity | $ 4,174 | 3.4 |
| Benchmark PEV, High Elasticity | $ 2,548 | 2.1 |
| High PEV, Low Elasticity | $ 12,835 | 10.4 |
| High PEV, Benchmark Elasticity | $ 5,723 | 4.6 |

**Table 6 Continued**

| | | |
|---|---|---|
| High PEV, High Elasticity | $ 3,494 | 2.8 |
| | | |

## VITA

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