Oh the Places You'll Charge: Exploring EV Driver Charging Substitution Behavior

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Abstract

Growth in electric vehicle (EV) adoption over the last decade has increased the need for EV charging stations. However, affordable Level 2 (slow) EV chargers take hours to charge a vehicle, which makes EV charging a significantly different experience from faster forms of fueling like gasoline stations or fast chargers. These differences have implications for where stations may be most utilized and for charging station policy. This paper uses transaction-level charging data from the Evergy charging network in Kansas City to analyze how drivers substitute across charging stations. I find that, unlike faster forms of fueling, the number of stations in an area has little effect on station usage even when nearby stations have a lower price. Instead, being located in places drivers already frequent has a much larger effect on driver substitution than the distance between stations or the charging price. These results indicate differences in station substitution between gasoline and EV stations which should inform future station placement policy.

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1 Introduction

Charging stations are essential for electric vehicle adoption which has made them an important policy issue in recent years. Charging stations in the U.S. have expanded rapidly from just 541 charging locations in 2010 to more than 55,000 in 2023. While "fast chargers" and "extreme fast chargers" have made EV charging times more closely resemble gasoline stations times, "slow chargers" (Level 2) continue to be much more affordable than fast chargers and today represent the majority of public chargers. As the demand for EV charging continues to increase, it is likely a combination of fast and slow chargers will be required to affordably meet charging needs. However, slow chargers require several hours to charge which creates a significantly different charging experience than fast chargers or gasoline stations. For policies to facilitate the expansion of a reliable, convenient charging network, we need to understand how these differences affect driver charging behavior in order to determine the best locations for charging stations.

This paper explores how Level 2 stations compete and how drivers substitute between them. Because Level 2 stations require hours, not minutes, to charge they are likely to affect where drivers choose to charge and how they substitute between stations. First, I directly explore how Level 2 stations located near one another compete when there are price differences across stations. Second, I explore individual driver substitution behavior across stations. I find that, unlike faster forms of fueling, slow EV chargers experience limited spatial competition with stations located nearby. Instead, I find driver-specific location preferences had a greater impact on driver substitution than either station proximity to a nearby station or the charging price. This does not mean that drivers are not price sensitive (Underwood (2021) discusses driver price sensitivity to public charging). Instead, the results show how drivers substitute between public charging stations. These results have important policy implications for EV station placement. The lack of spatial competition across stations, when there are significant differences in the price, indicates that having consistent station coverage across an area may not be important to drivers. Instead of directly substituting to the nearest stations, drivers move to stations that are convenient for them. This result emphasizes the need for stations to be at locations that are convenient for drivers, and future station placement should prioritize these locations.

This paper uses unique transaction-level charging data to analyze individual driver substitution patterns. My data, which is described in Section 2, allows me to observe every charging transaction for 1048 drivers across the 284 charging stations on the Evergy (a regional utility) charging network in Kansas City for 2017 and 2018. Prior to 2018, Evergy subsidized charging, making it free at all stations, but in 2018 the subsidy ended for 70% of stations. By looking at changes in station and individual driver charging the data allows me to observe how drivers substitute across stations that become not free and stations that remain free when the subsidy ended.

In Section 3, I estimate how the number of nearby stations located within 1 mile of a station affects how much a particular station's usage decreases when the charging subsidy ended in 2018.[1] For stations that became not free, the number of stations within 1 mile had no effect on how much station's charging decreased. For stations that remained free, the number of stations nearby had a small, positive effect on usage for stations located in the downtown area. This is consistent across state lines, even though there are differences in charging prices between Kansas and Missouri. Unlike the intense spatial competition observed in gasoline markets, EV charging substitution reveals limited spatial competition between stations.

In Section 4, I expand the analysis to explore how individual drivers substitute between stations. Driver-specific data allows me to observe how station and individual driver characteristics affect where drivers substitute. I use a two-stage model to estimate what factors affect where drivers substitute. In the first stage, I use a logistic regression to estimate how price, distance, and individual driver charging behavior affect the probability that a driver will substitute towards a particular station. In the second stage, I estimate how station and driver characteristics affect how much charging moves towards a particular station, provided they chose to switch to that station. I find the most important factor in determining where a driver will substitute is the driver's 2017 charging preferences. A driver is much more likely to substitute towards a station where they charged in 2017 then to switch some charging to a station that remains free but which they have not previously visited. The distance between stations and charging price has a greater effect when only including stations the drivers have previously visited. Because all charging was free in 2017, it is reasonable to assume drivers charged at stations that were most convenient for them. The persistence of driver charging patterns and the lack of substitution between stations indicates a greater emphasis on the convenience of the charging location than the charging price.

[1] Density and the spatial placement of businesses are used in Lewis (2008), Barron, Taylor and Umbeck (2004) and Syverson (2004).

There has been quite a lot of recent research on optimal EV station placement, but much of this work has been focused on the spatial coverage of stations with the underlying assumption that EV charging is similar to filling up at a gasoline station. Zhou and Li (2018) explore issues around having enough critical mass for full EV adoption by modeling how EV adoption affects the expansion of EV charging stations, but they assume there is a market where drivers substitute easily between stations in an area based on their geography. If this is not accurate, assuming drivers substitute perfectly between stations could affect when and where new stations are profitable and convenient. Additionally, He, Yin and Zhou (2015) explores how to optimally deploy public charging stations in an area, but this paper specifically assumes drivers and stations will interact similarly to the market for gasoline. Likewise, Luo, Huang and Gupta (2017) simulates station placement, assuming an oligopoly of station networks competing through station placement similar to gasoline chains. Much of the conversation around charging station placement has focused on important considerations such as costs, fairness, and geographical coverage. Banegas and Mamkhezri (2023), Lamontagne et al. (2023), and Liu, Sun and Qi (2023) discuss models that include criteria such as station coverage across an area and geographical features such as distance. While these factors are important, these approaches leave out other important factors that may affect where drivers choose to charge and optimal station locations. This paper contributes to the existing literature by testing assumptions about how stations compete and how drivers substitute between stations. These behaviors have implications for how we think about optimal station placement.

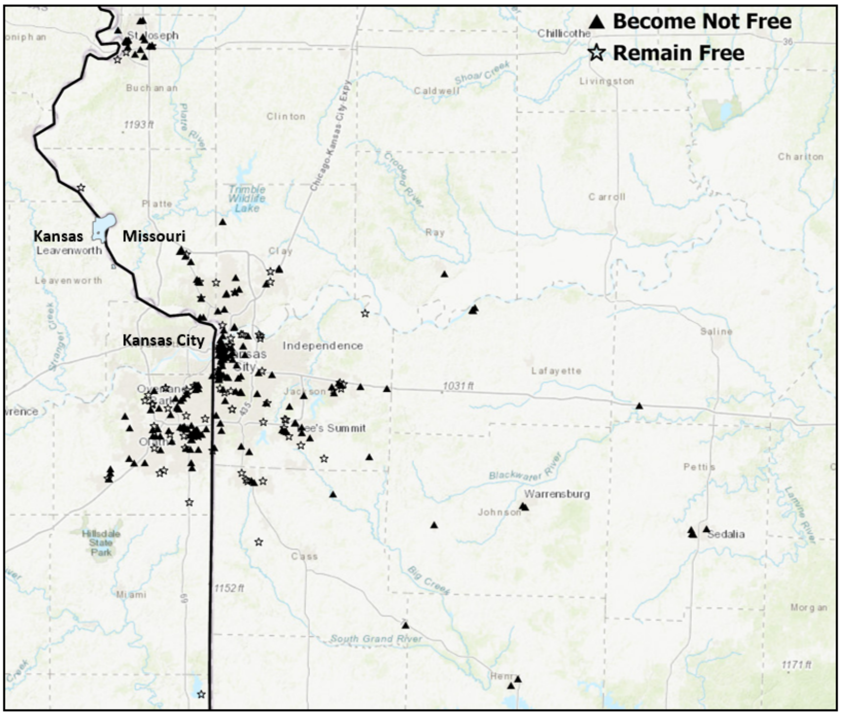
When analyzing policies that affect the growth of EV charging networks, it is crucial to consider driver preferences and substitution behavior. The lack of substitution across Level 2 stations, even when there are significant price differences, highlights important differences between slow EV charging stations and faster fueling options. Failure to account for these differences could lead to inefficient investments in future charging station networks by placing stations in locations where they will be underutilized.

2 Background

In 2015, the regional utility, Evergy, facilitated the development of 284 charging stations throughout the Kansas City area and made charging free at all stations until January 1, 2018. Stations are located at grocery stores, stores, parks, recreation facilities, offices, industrial plants, schools, apartments, hotels, and parking garages. While stations primarily exist around the Kansas City metro area, there are some stations almost 100 miles north and south of the city, as is seen in Figure 1. When Evergy developed the charging network, they used no specific criteria about where stations were located.[2] This allows me to observe stations at many kinds of locations in urban and rural areas with varying levels of station and population densities.

[2] Information about where stations were placed came from personal correspondence with Evergy

Figure 1: Map of EV Stations in Kansas City



Note: This is a map of the Kansas City metro area with stations that remain free as stars and stations that became not free as black triangles.
Source: Author's calculation

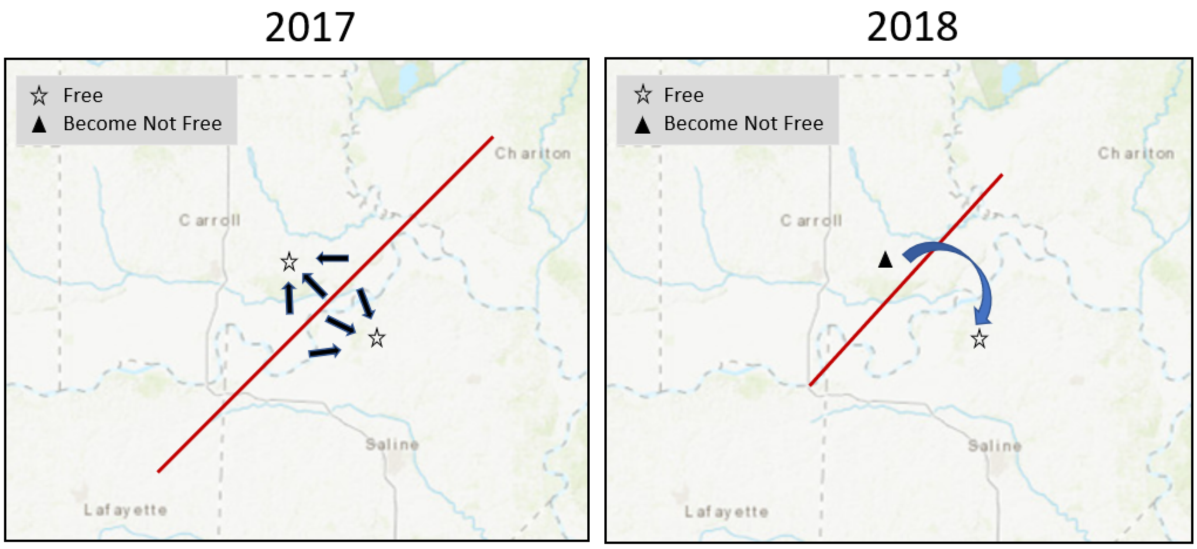
On January 1 2018, Evergy ended the charging subsidy and 70% of the stations became not free. When Evergy chose to end the charging subsidy they allowed the businesses hosting the stations to choose to continue the subsidy themselves and keep free charging at their station. This resulted in 30% of stations remaining free in 2018 after the subsidy ended. All 16 Level 3 stations became not free in 2018, but among Level 2 stations, no selection pattern of stations that remained free versus stations that became not free is apparent from the machine learning techniques used in the supplementary material[3]. Because Kansas City is split by the Kansas-Missouri border, charging stations exist on both sides of the state line with Level 2 stations in Kansas charging 0.15$ per KW and stations in Missouri charging 0.22$ per KW after January 1, 2018. Due to the limited number of Level 3 stations and their significant differences in charging time, this analysis only looks at Level 2 stations.

Conventional thinking on spatial competition and substitution would conclude that drivers substitute between stations located near one another. This substitution behavior can be clearly seen for gasoline stations in Lewis (2008) where increased station density leads to a decrease in price dispersion among gasoline stations. If EV drivers exhibited similar behavior to the drivers of gas-driven cars, we would see the substitution illustrated in Figure 2. This assumes drivers visit the stations closest to them in 2017 when all prices are zero and then substitute towards stations that remain free when the charging subsidy ends in 2018. However, the time required to charge an EV may decrease the substitutability of stations located near one another due to the inconvenience of charging time. Substituting to a station down the street from the driver's destination would require the driver to walk the additional distance between the new station and their final destination or spend minutes or hours at the new charging location which they may not frequent.

Instead of substituting to a nearby station, it may be more convenient for drivers to substitute towards a station at another location they also frequent. For example, instead of parking at a station near work and walking between the two stations, it may be more convenient to increase charging at a grocery store or park that they are already going to be visiting at a later time. The cost of time spent either waiting to charge or walking may outweigh the benefits of free charging and change how price and distance affect driver substitution.

[3]Available on my website at `https://aspenunderwood.github.io/static/paper2_suppA.pdf`

Figure 2: Common Expectation of Station Substitution



(a) (b)

Note: This figure shows a cartoon of possible movement between stations before and after the subsidy ends. **Source:** Author's calculation

When looking at how EV drivers substitute between stations, it is important to note that there is also a difference in how drivers observe EV station charging prices. While gasoline stations clearly post their prices so drivers can observe them when driving by, EV stations do not. Additionally, it may not be clear to a passerby that an EV station exists at a given location. Instead of relying on signs to notify drivers, EV drivers rely on applications that show where stations are located and the prices they charge. Even though these apps can also be used to find gasoline stations, they are often built into onboard navigation systems for EVs. There are differences between EV charging and gasoline in how prices are advertised. A driver looking to charge at a location has clear access to charging prices for every location they are considering through station websites and apps.

The substitution patterns of EV drivers have important implications for expanding EV charging networks. If drivers substitute between stations in a similar way to what is seen in Figure 2, spreading out stations along popular driving routes would be ideal. If instead, drivers substitute towards stations at other locations they frequent, instead of stations between or near their original destination, focusing station placement where drivers frequently visit may be optimal.

3 Data

This paper utilizes transaction data from every station on the Evergy charging network. This includes the exact location of the station and street address, if the station is Level 2 or Level 3, and the number of charging ports available at each station. Station location information can be used to determine spatial properties of each station such as the number of other charging stations nearby, the distance to downtown, the number of free charging stations nearby, and the distance to the nearest station. Additionally, Google Maps was used to determine the type of businesses located near each station such as grocery stores, shopping centers, schools, or workplaces which may influence a driver's charging decisions. Based on Google Maps information stations have been classified into 11 business categories. These categories are: grocery, shopping for any station at a non-grocery shopping location, school, work location, industrial site (mostly Evergy operation facilities), apartment, hotel, medical facility, parking garage, entertainment location such as a park or community recreation facility, and other, which includes any station that did not fit into the above categories.

The type of businesses near a station may affect how it is utilized. For example, the average time spent at charging stations located near grocery stores is 50 minutes instead of the more-than-2-hour median charging time for stations located at places where people work. Similarly, grocery and work stations are used by different numbers of drivers. The average grocery station is visited by 58 unique drivers whereas the average work station is visited by only 21. Grocery stations are used by more drivers for shorter times, while work stations are used by fewer drivers for longer. Differences in charging behavior and the services the business near each station offers drivers may affect where and how much drivers substitute between stations.

Stations are found throughout the Kansas City area in urban and rural locations with varying numbers of stations located within 1 mile of each other. More than half of stations have another station located within 1 mile, and 46% of stations have a station that remains free within 1 mile. Similarly, the number of stations within 1 mile of a station varies, with some stations having 0 or 1 stations nearby, while others have more than 30. The distance between stations ranges from less than a tenth of a mile to almost 50 miles. Stations are located both in the heart of downtown Kansas City as well as in the rural areas surrounding the city. While station density is highest in downtown Kansas City, high levels of station density are not exclusive to the downtown area. High station density is also seen in Overland Park, Kansas and St. Joseph, Missouri, as seen in Figure 1.

When the subsidy ended I observe how charging moved across the network, as seen in Table 1. Most of the decrease in station charging when the subsidy ended moved outside the network with only a small amount switching between stations. This highlights the important role home charging plays in understanding EV charging. Additionally, when charging left a station that became not free, about half of the charging went to stations that remained free while the other half moved towards stations that also became not free. While there are more stations that became not free than stations that remained free, driver substitution decisions are not only driven by price differences across stations. If drivers are substituting towards stations primarily because of price, I would expect to see more charging move to stations that remain free. While charging capacity at stations that remain free could restrict substitution, there is limited evidence for this. The lack of movement towards stations that remained free indicates that additional factors other than price play role in driver charging decisions.

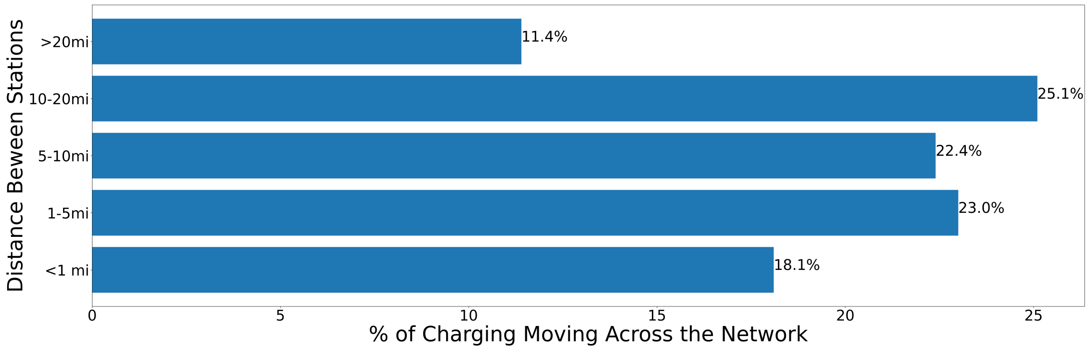
Table 1: Movement of Charging Across the Network Between 2017 and 2018

	Leave Network	**Switch to L2 Free**	**Switch to L2 Not Free**	**Switch to L3**
Begin to Charge (kWh)	211,425	23,345	20,031	6,877
%	80.8%	8.9%	7.7%	2.6%
Remain Free (kWh)	27,497	4,613	6,270	724.3
%	70.3%	11.8%	16%	1.9%

Note: This figure shows how charging moves between stations and outside the network on aggregate when the subsidy ends. **Source:** Author's calculation.

Figure 3 shows the percent of charging moving between stations by the distance between stations. Only 15.7% of charging moves to a station within a mile of the original charging station. While not every station exists near other stations, more than half of stations have a charging location within a mile, and more than half have a free station within 1 mile. The low percentage of charging moving to a station nearby indicates that proximity may not be the only factor when considering where to substitute. This may be the case because of long charging times which may make stopping at a nearby station inconvenient, while stopping at another location where a driver also spends time could be much more convenient, but it may not be located nearby.

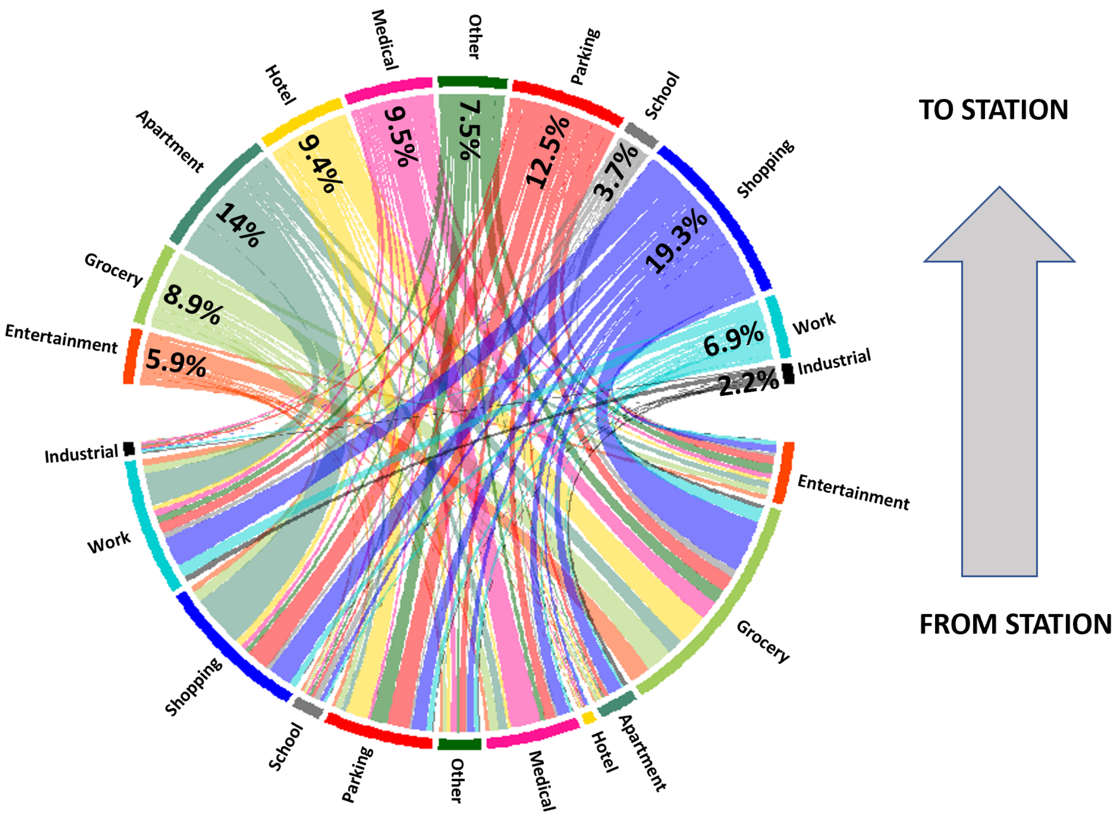
Figure 3: Distances Charging Moves Across Stations



Note: The figure shows the percent of charging moving between stations by the distance between stations. **Source:** Author's calculation

In addition to price and distance, the type of business near a station is likely to affect where drivers substitute. Some types of stations may be easier to substitute towards than others. For example, it is easier for a driver to change the store where they shop than to change their place of employment. Figure 4 shows the percentage of charging moving towards each station type after normalizing the number of stations in each group. Charging moves from the stations on the lower part of the circle towards the stations on the top of the circle and the width of the band between station groups indicates how much charging in kWhs moves between these types of stations. If drivers substitute across business types evenly then each group would receive just over 9% of charging moving across stations after accounting for the number of stations in each category. Instead, it shows shopping and parking garage stations being the most popular stations to substitute towards which may be because they may be easiest behavior to adjust.

Figure 4: Chord Diagram of Average Movement to each Station Type



Note: kWhs moving to each type have been normalized by the number of stations in each group.
% indicates the movement of charging for each type after accounting for differences in the number of stations. **Source:** Author's calculation

4 Station-Level Analysis

This section uses station-level data to explore how the number of stations located near a station affects that station's usage after the charging subsidy ends. How drivers substitute between stations has implications for station placement and entry. The effects of nearby competitors has previously been explored in the gasoline literature in Lewis (2008) and Barron, Taylor and Umbeck (2004), but there has been little analysis on EV charging stations. Lewis (2008) and Barron, Taylor and Umbeck (2004) look at gasoline stations by estimating how the number of stations in an area affect station price dispersion. Instead of using price dispersion, as is common for gasoline stations, I estimate how the number of stations in an area affects changes in station usage when the charging subsidy ends. Usage instead of price is used because station usage is easily observable in the data and, in this setting, prices are set by the network.

To estimate how nearby stations affect usage when the charging price subsidy ends, I estimate the fixed effects regression

$$ln(Usage_{it}) = \alpha NotFree_{it} + \beta NumStations_i X NotFree_{it} + \gamma_i + \phi_t + \epsilon_{it} \quad (1)$$

before and after the end of the subsidy. $Usage_{it}$ is the monthly kWhs used at station i in month t between July 2017 and June 2018. $NotFree_{it}$ indicates station i is not free in time t and controls for the effect of the price change. $NotFree_{it}$ is used instead of price because stations have similar prices after the subsidy ends. $NumStations_i$ is the number of stations near station i and is interacted with $NotFree_{it}$ to capture the effect of nearby stations on usage when the subsidy ends at a charging station. γ_i are station fixed effects and ϕ_t are month fixed effects. ϵ_{it} is the error term.

Table 2 shows the estimates from Equation 1 with standard errors clustered by station and month. In column 1, $NumStations_i$ includes all stations within 1 mile of station i. In column 2 $NumStations_i$ includes only the number of stations within 0.5 mile. $NumStations_i$ in columns 3 and 4 includes the total number of stations that remain free within 1 mile and 0.5 a mile of station i respectively.[4] While stations that become not free see a decrease in usage across the network when the subsidy ends, the number of stations within 1 mile does not have a significant effect on station usage, and the number of stations in half a mile has a small, positive effect on usage. The estimates show the number of free stations located nearby has virtually no effect. This indicates limited spatial competition between stations located near one another even when there is a significant price difference between stations. While these results differ from the literature on gasoline stations, it is consistent with the descriptive statistics in Section 2 and highlights differences in driver behavior between EVs and gasoline stations.

Table 2: Estimates of the # of Nearby Stations on Station Usage

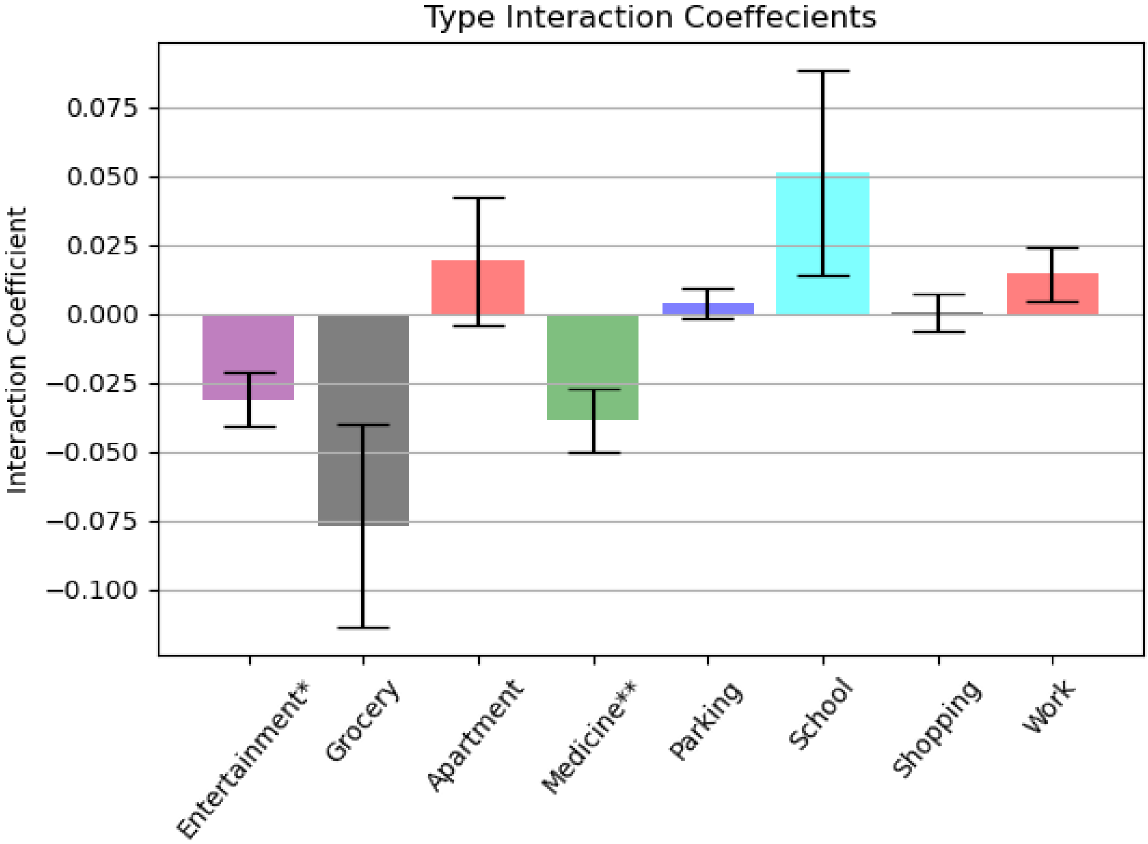
Model:	(1)	(2)	(3)	(4)
Variables				
NumStations 1mi X NOTFREE	0.0054			
	(0.0051)			
NumStations 0.5mi X NOTFREE		0.0222^{**}		
		(0.0097)		
NumFreeStations 1mi X NOTFREE			0.0136	
			(0.0144)	
NumFreeStations 0.5mi X NOTFREE				0.0419
				(0.0261)
Not Free	-0.7466^{***}	-0.7694^{***}	-0.7356^{***}	-0.7406^{***}
	(0.1273)	(0.1235)	(0.1240)	(0.1215)
Station Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	3,132	3,132	3,132	3,132
R^2	0.81528	0.81576	0.81523	0.81543

Note: Standard errors are in parentheses. The dependent variable is station i's kWh usage in month t. Column (1) includes the number of stations within 1 mile of station i interacted with NOTFREE. Columns (2), (3), and (4) include the number of stations within 0.5 mile, free stations within 1 mile, and free station within 0.5 mile of station i respectively. $^{**}p<0.05$; $^{***}p<0.01$

While the number of stations nearby does not have much of an effect on how much usage decreases when the subsidy ends, the type of business near a station may affect how stations nearby affect usage. Stations with different types of businesses may be utilized by drivers for different purposes and lengths of time. These differences could result in usage at some stations being more affected by nearby stations than others. For example, a parking garage may be more affected by nearby stations than a work location because drivers using parking garage stations may have a greater variety of driver destinations which could make them more likely to substitute to a nearby station. However, drivers at work stations are likely only interested in a single destination which may make them less likely to switch. To explore how nearby stations affect usage at different types of stations I interact NumStations $\times$ NotFree with the business classification. Figure 5 shows the interaction coefficients by business type. While the coefficients for most groups continues to be insignificant, entertainment stations are significantly affected by the number of stations nearby. Drivers visiting entertainment facilities may be in less of a hurry than when going to other locations such as work or grocery and may be willing to walk more than at other times. Additionally, it may be easier to substitute between entertainment locations, but the coefficient remains small.

[4] Estimation uses Fixest package Berge, Krantz and McDermot (2021) in R.

Figure 5: Business Type and Density Interactions for All Density



Note: This Figure shows coefficients for interactions between the DensityXNotFree and business types. The bars indicate standard errors and $*$ indicates the change is statistically significant. **Source:** Author's calculation

While many stations across the charging network became not free when the price subsidy changed, stations in Kansas increased to a price of \$0.15 per kWh and stations in Missouri increase to a price of \$0.22. If drivers were substituting between stations due to the increase in price, there may be more incentives to substitute towards a free station in Missouri than in Kansas. To explore the potential effects of differences in charging price, I estimate Equation 1 for Kansas and Missouri separately in Table 3. However, the results indicate very little difference in how the number of stations nearby affect usage in Kansas and Missouri. The effect of nearby stations continues to be close to zero and is not statistically significant in both states.

Table 3: Estimates of the # of Nearby Stations on Station Usage: Kansas, Missouri, Near Downtown, Away from Downtown

Model:	(1) Kansas Only	(2) Kansas Only	(3) Missouri Only	(4) Missouri Only	(5) <9mi from Downtown	(6) <9mi from Downtown	(7) >19mi from Downtown	(8) >19mi from Downtown
Variables								
NumStations 1mi X NOTFREE	0.0226		0.0034		0.0030		0.1932	
	(0.0340)		(0.0053)		(0.0064)		(0.1053)	
NumFreeStations 1mi X NOTFREE		0.0830		0.0077		0.0119		-0.1962
		(0.1429)		(0.0149)		(0.0154)		(0.3492)
NotFree	-0.8772***	-0.8481***	-0.7088***	-0.6994***	-0.7739***	-0.7820***	-0.4176**	-0.1425
	(0.2318)	(0.2092)	(0.1525)	(0.1489)	(0.2388)	(0.2206)	(0.1884)	(0.1879)
Station Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	900	900	2,232	2,232	804	804	780	780
R^2	0.80674	0.80664	0.80968	0.80964	0.83997	0.84008	0.77687	0.76907

Note: Standard errors are in parentheses. The dependent variable is station i's kWh usage in month t. **p<0.05; ***p<0.01

Additionally, I look at stations in the quartile located nearest downtown Kansas City (<9 miles) and stations in the quartile furthest from downtown (>19 miles) separately. Table 3 shows the estimates for stations near and far away from downtown. Drivers may substitute between stations differently when they are in the city than in rural areas, due to increases in the driving distance between towns. Estimates for stations near downtown continue to be close to zero and not significant. For stations outside the city, the results indicate having free stations around may decrease usage when the price changed but the effect is not significant.

To extend the analysis, I explore how the number of stations nearby affects usage at stations that remain free when the subsidy ends. If stations that remain free are located near stations that become not free, they could experience an increase in usage if there is substitution across stations. Because 70% of stations become not free, substitution towards stations that remain free may be concentrated on the small number of stations that remain free. To estimate how the end of the subsidy affects stations that remain free, I estimate

$$Usage_{Fit} = NumNotFree_{NFi} X2018_t + \gamma_i + \mu_{it}. \tag{2}$$

$Usage_{Fit}$ is the usage in kWhs charged at station i which is a subsample of stations conditional on station i remaining free. $NumNotFree_{NFi}$ is the number of stations near station i that become not free when the subsidy ends and is interacted with the dummy variable 2018 to capture the effect of nearby stations within 1 mile after the subsidy ended. γ_i are station fixed effects and μ_{it} is the error term.

Table 4: Estimates of the # of Nearby Stations on Free Station Usage

Model:	(1) All Stations	(2) <9mi from Downtown	(3) >19mi from Downtown	(4) Kansas	(5) Missouri
Variables					
NumNotFree x 2018	0.0249	0.0458^{**}	0.2174	0.0552	0.0247
	(0.0136)	(0.0173)	(0.1242)	(0.0462)	(0.0142)
Station Fixed Effects	Yes	Yes	Yes	Yes	
Year Fixed Effects	Yes	Yes	Yes	Yes	
Observations	936	264	204	288	648
R^2	0.82865	0.80864	0.79611	0.84993	0.82363

Note: Standard errors are in parentheses. The dependent variable is station i's kWh usage in month t at stations that remain free in 2018. Column (1) includes all stations. Column (2) only includes stations less than 9 miles from downtown and column (3) includes stations greater than 19 miles from downtown. Column (4) only includes stations in Kansas and column (5) only includes stations in Missouri. **p<0.05; ***p<0.01

Table 4 shows the estimates from Equation 2 with clustered standard errors by station and month. The first column shows the estimates for all stations that became not free. There is a small increase in usage at free stations located near stations that became not free, but the increase is not statistically significant. Columns 2 and 3 show estimates for stations near downtown (< 9 miles) and stations further from downtown (> 19 miles) respectively. The number of stations nearby has a positive and significant effect on station usage for a station near downtown, but it is relatively small. Columns 4 and 5 show estimates for stations in Kansas and Missouri separately. Stations that remain free in Kansas may have a slightly greater increase in usage relative to stations in Missouri, but this difference is not statistically significant. Overall, usage at stations that remain free is not significantly affected by the number of nearby stations that became not free.

Station level analysis indicates there is limited substitution between stations located near each other even when there is a difference in the charging price. Limited spatial substitution has important policy implications for new station construction. A station nearby may not be a good substitute if it is located at a place where a driver does not want to spend a lot of time. This has important implications when charging networks or governments are creating subsidies for new station construction. New stations and new station subsidies should be focused on placing stations where drivers frequent. While this analysis looked at substitution in a local area, from these results, it is unclear how drivers are substituting, which will be explored further using driver-level analysis in Section 5.

5 Driver-Level Analysis

This section expands the analyses in Section 3 by looking at individual driver substitution decisions. Unlike the station analysis, exploring driver-specific substitution allows me to better understand how station price, the type of businesses near a station, and a driver's previous charging behavior affect driver substitution decisions.

The movement of charging from one station to another before and after the subsidy ends is calculated to observe where drivers substitute.[5] Due to the length of time required to charge, drivers may be more likely to substitute towards a location they already frequent instead of a station that is nearby. It may be inconvenient to charge at a location half a mile away from your original destination and walk to the destination. Instead, it may be more convenient for drivers to charge at other locations they already frequent. While it is impossible to observe every place a driver frequents, I do observe locations where the driver choose to charge prior to the end of the subsidy. Descriptive analysis of the data indicates more than half of drivers moved at least 47% of their charging towards a station they visited in 2017.

To understand what factors affect driver substitution, I use a two-stage approach because the decision to substitute towards a station is likely different than the choice of how much charging to substitute. In the first stage, I estimate what factors affect the probability a driver will switch any amount of charging towards a specific station. In the second stage, I estimate the number of kWhs a driver substitutes towards a station using lognormal distribution, provided substitution is not zero. The first stage regression is estimated as

$$U_{ijk} = \alpha free_j + \beta X_{ijk} + \epsilon_{ijk}. \tag{3}$$

U_{ijk} is the utility of driver i moving from station k towards station j. The variable $free_j$ indicates station j remains free after the subsidy ends, and X_{ijk} are driver and station-specific characteristics such as the distance from station k to station j, station j's distance to downtown, the number of times the driver visited station j in 2017, the number of ports at station j, and the type of business nearby. ϵ_{ijk} is the error term.

In the second stage, I estimate the number of kWhs a driver moves towards station j if substitution is greater than zero as

$$kWhs_{ijk} = \alpha free_j + \beta X_{ijk} + \epsilon_{ij} \quad \forall \ j \ \ where \quad kWhs > 0, \tag{4}$$

provided substitution is greater than zero. $kWhs_{ijk}$ are the kWhs driver i moves from station k to j. The variable $free_j$ indicates j remains free after the subsidy ends and X_{ijk} are station characteristics, which are similar the characteristic from stage 1. ϵ_{ij} is the error term. The two-stage model is used to capture the extent to which drivers are substituting towards specific types of stations as well as the stations where drivers substitute the largest amounts of charging.

Table 5 shows the results from the logit estimates. The first three columns include a dummy variable that indicates if the drivers had previously visited the station in 2017 at least one, five, or ten times respectively. The number of times the driver visited that station in 2017 indicates the convenience the station offers to drivers, and more visits may indicate a higher level of convenience. Column 4 only includes stations the driver had visited at least once in 2017 and column 5 only includes stations the driver did not visit in 2017.

The results in Table 5 indicate that the previous charging behavior is the greatest predictor of driver substitution. Previous behavior has a much greater effect on where drivers substitute than either the station being located nearby or remaining free. A station remaining free increases the average probability a driver chooses that station by 10 percentage points and a station being located within 1 mile of the original station increases the probability a driver's substitutes towards that station by 9 percentage points. However, if a driver visited a station at least one time in 2017 it increases the average probability a driver substitutes towards that station by 47 percentage points. In column 4, when only looking at stations the driver visited at least once in 2017, a station remaining free increased the average probability a driver substitutes towards it to 19 percentage points. However, in column 5, when only looking at stations the driver did not visit in 2017, stations remaining free had no significant effect on substitution.

The type of business near a station is also seen in Table 5. Overall, drivers are less likely to substitute towards work and apartment stations than grocery stations unless they have visited that station before. This may be because

[5] Further description of the data formulation is available online at: `https://aspenunderwood.github.io/static/paper2_suppA.pdf`

it is easier to switch between grocery stations than work and apartment locations. However, stations located at shopping stations are not significantly different than grocery stations regardless of a driver's previous charging habits. While overall substitution across stations is low, drivers are more likely to substitute towards shopping and entertainment locations than work and apartment stations.

Table 5: Logit Estimate of Driver Subsitution

Model:	(1)	(2)	(3)	(4)	(5)
Visits >1 in 2017	2.959***				
	(0.1079)				
Visits >5 in 2017		2.796***			
		(0.1362)			
Visits >10 in 2017			2.971***		
			(0.1398)		
Free	0.5288***	0.4338***	0.4313***	1.059***	0.2270
	(0.1135)	(0.1370)	(0.1390)	(0.1180)	(0.1491)
Within 1 mi	0.4657***	0.6269***	0.6693***	0.1647**	0.6037***
	(0.0531)	(0.0654)	(0.0717)	(0.0706)	(0.0747)
Station Density	0.0076	0.0100	0.0098	0.0064	0.0129
	(0.0081)	(0.0101)	(0.0104)	(0.0061)	(0.0112)
Dist to Downtown	-0.0233***	-0.0293***	-0.0304***	-0.0037	-0.0319***
	(0.0048)	(0.0057)	(0.0058)	(0.0059)	(0.0068)
# of Ports	0.0486***	0.0638***	0.0658***	0.0260***	0.0671***
	(0.0067)	(0.0074)	(0.0074)	(0.0084)	(0.0075)
Entertainment	-0.1155	-0.3026	-0.3666	-0.1837	-0.0469
	(0.1975)	(0.2397)	(0.2470)	(0.1837)	(0.2643)
Work	-0.7221***	-1.102***	-1.203***	0.0744	-1.167***
	(0.2064)	(0.2544)	(0.2610)	(0.1910)	(0.2597)
Apartment	-1.342***	-1.850***	-1.950***	0.0024	-1.889***
	(0.3477)	(0.3969)	(0.4010)	(0.2679)	(0.3943)
Hotel	-0.6961**	-0.9955**	-1.084***	-0.5052	-0.9332**
	(0.3124)	(0.3909)	(0.4029)	(0.2944)	(0.3627)
Medicine	-0.5731***	-0.9287***	-1.013***	-0.1758	-0.8180***
	(0.1523)	(0.1807)	(0.1822)	(0.2036)	(0.2047)
Other	-0.5507**	-0.8715***	-0.9406***	0.0689	-0.7021**
	(0.2247)	(0.2581)	(0.2632)	(0.2551)	(0.2890)
Parking Garage	-0.6454**	-1.060***	-1.173***	-0.0955	-0.9511**
	(0.3003)	(0.3718)	(0.3787)	(0.2483)	(0.3903)
School	-0.7685**	-1.165***	-1.258***	0.1833	-1.138***
	(0.3328)	(0.3689)	(0.3715)	(0.3067)	(0.4021)
Shopping	0.0200	0.0568	0.0711	-0.0919	0.2878
	(0.1446)	(0.1698)	(0.1807)	(0.1234)	(0.1929)
Industrial	-2.200***	-2.717***	-2.820***	-0.2623	-2.846***
	(0.2341)	(0.2621)	(0.2641)	(0.3659)	(0.2774)
Driver Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	1,766,197	1,766,197	1,766,197	83,482	1,399,529
Pseudo R^2	0.20961	0.14296	0.13174	0.23676	0.10338

Note: Standard errors are in parentheses. The dependent variable has a value of 1 when the kWhs driver i switched from station k to j are greater than 0 and 0 otherwise. In column (1), visits >1 in 2017 indicates the driver visited station j at least one time in 2017. Columns (2) and (3) indicate 5 and 10 visits in 2017 respectively. Column (4) only includes stations the driver visited in 2017 and column (5) only includes stations the driver did not visit in 2017. All business type estimates are relative to grocery stations. $^{**}p<0.05$; $^{***}p<0.01$

Table 6: Lognormal Estimate of Driver Substitution When Substitution >0

Model:	(1)	(2)	(3)	(4)	(5)
Visits >1 in 2017	0.2565***				
	(0.0366)				
Visits >5 in 2017		0.6240***			
		(0.0583)			
Visits >10 in 2017			0.7648***		
			(0.0775)		
Free	0.0932***	0.0562	0.0548	0.1262*	-0.0012
	(0.0358)	(0.0344)	(0.0340)	(0.0747)	(0.0492)
Within 1 mi	0.1629***	0.1522***	0.1521***	0.1746**	0.1324**
	(0.0496)	(0.0486)	(0.0484)	(0.0817)	(0.0555)
Station Density	-0.0021	-0.0030	-0.0022	-0.0016	-0.0030
	(0.0023)	(0.0021)	(0.0022)	(0.0046)	(0.0028)
Dist to Downtown	-0.0041*	-0.0040*	-0.0031	0.0031	-0.0064**
	(0.0022)	(0.0021)	(0.0021)	(0.0040)	(0.0029)
# of Ports	0.0080***	0.0087***	0.0089***	0.0075	0.0097**
	(0.0027)	(0.0027)	(0.0027)	(0.0050)	(0.0040)
Entertainment	0.2551***	0.2752***	0.2277***	0.1977*	0.2566***
	(0.0530)	(0.0485)	(0.0497)	(0.1024)	(0.0577)
Work	0.3266***	0.3275***	0.2860***	0.3087**	0.3383***
	(0.0670)	(0.0633)	(0.0624)	(0.1292)	(0.0716)
Apartment	0.1689*	0.1830**	0.1853**	0.0357	0.2022*
	(0.0936)	(0.0867)	(0.0915)	(0.1562)	(0.1037)
Hotel	0.0988	0.1440*	0.1191	-0.0890	0.3281***
	(0.0776)	(0.0840)	(0.0749)	(0.1380)	(0.0865)
Medicine	0.2668***	0.2444***	0.2046***	0.1845	0.2934***
	(0.0693)	(0.0693)	(0.0682)	(0.1363)	(0.0841)
Other	0.3072***	0.3245***	0.2741***	0.1387	0.3220***
	(0.0977)	(0.0962)	(0.0987)	(0.1977)	(0.1148)
Parking Garage	0.3372***	0.3980***	0.3378***	0.5043***	0.3653***
	(0.0847)	(0.0831)	(0.0815)	(0.1849)	(0.1029)
School	0.3098***	0.2955***	0.2563***	0.4230***	0.2802***
	(0.0856)	(0.0759)	(0.0758)	(0.1456)	(0.0776)
Shopping	0.1187**	0.1462***	0.1414***	0.0981	0.1796***
	(0.0524)	(0.0514)	(0.0488)	(0.0886)	(0.0615)
Industrial	0.5113***	0.4465***	0.4582***	0.7630***	0.3072***
	(0.1656)	(0.1506)	(0.1386)	(0.2888)	(0.1116)
Driver Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	12,878	12,878	12,878	5,797	7,081
Pseudo R^2	0.21805	0.22354	0.22383	0.25202	0.23823

Note: Standard errors are in parentheses. The dependent variable is the kWhs driver i switched from station k to j when the kWhs >0. In column (1), visits >1 in 2017 indicates the driver visited station j at least one time in 2017. Columns (2) and (3) indicate 5 and 10 visits in 2017 respectively. Column (4) only includes stations the driver visited in 2017 and column (5) only includes stations the driver did not visit in 2017. All business type estimates are relative to grocery stations.$^{**}p<0.05$; $^{***}p<0.01$

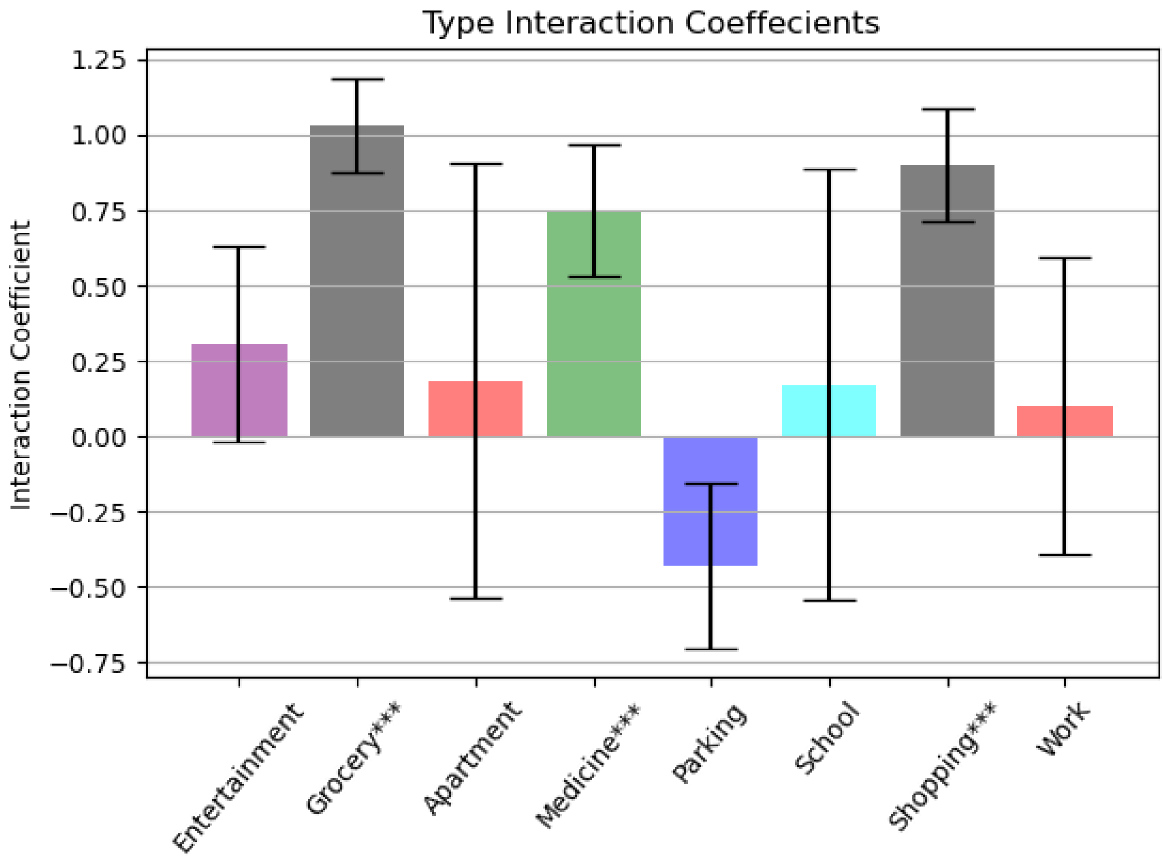
The effect of price and location in relation to previous driver charging behavior indicates drivers are much more likely to substitute towards a station they previously visited than a station that remains free. However, when comparing across stations the driver had previously visited, remaining free has a greater effect. Drivers may choose to substitute towards the stations that remain free when they have already visited that station, but free charging may not be enough of an incentive to begin charging at a new station. This is consistent with the hypothesis that the convenience of charging stations may have a larger effect on driver charging decisions than the charging price.

To look more into the effect of station type and a station remaining free on driver substitution, Figure 6 shows the interaction between business type classification. Overall, it appears that grocery, medical facilities, and shopping locations had a significant effect on the driver's probability to substitute towards that station when they remained free. However, work and parking stations do not have a significant effect on substitution even when they remained free.

Table 6 shows estimates for stations the driver chose to substitute towards as specified in Equation 4. As in the case with Table 6, the first three columns include dummy variables if the driver visited the station one, five, or ten times in 2017 respectively. Column 4 only includes stations the driver visited at least once in 2017 and column 5 only includes stations the driver never visited in 2017.

The kWhs a driver moves towards station j increases for stations drivers visited more in 2017. Remaining free after the subsidy ends influences the share of charging moving towards those stations provided they visited the station less than 5 times in 2017. For stations that drivers visited more than 5 times, the station remaining free has no significant effect. When looking at stations where the driver had not previously charged, the price does not affect the quantity of substitution.

Figure 6: Business Type and Free Interactions



Note: This Figure shows coefficients for interactions between the DensityXNotFree and business types. The bars indicate standard errors and $*$ indicates the change is statistically significant. **Source:** Author's calculation

This section has three main implications. First, price differences between stations are often not a great enough incentive for a driver to substitute towards a station they have not used before. Second, a station being located nearby has only a small effect on substitution near downtown. Third, the type of business near a station affects how drivers substitute towards stations that remain free. Remaining free has a greater effect on driver substitution for some types of businesses than others. These results again highlight the need for new station placement and station placement programs to prioritize locations where drivers already spend significant amounts of time.

6 Conclusion

When analyzing substitution behavior between slow electric charging stations, it is clear that driver behavior is different from that of faster forms of fueling. There is little substitution across stations located near each other even when there are significant price differences between them. Similarly, price differences between stations are often not a great enough incentive for a driver to change their driving behavior and move to a station they have not used before. These results have two important policy implications for charging station placement and charging station subsidy programs.

First, the number of available charging stations in a region should not be the sole indicator of charging availability or convenience. Public charging stations located near one another may not be substitutes for one another. A competitor for a station may be miles away from that station at another location drivers frequent. Given a basic amount of charging access, simply increasing the density of stations may not improve the charging experience of drivers.

Second, charging networks building new stations and government programs that provide subsidies for new Level 2 stations should focus not only on providing charging coverage to a region, but also on the types of businesses near potential station locations. It is essential that stations be located where drivers are spending time already. Simply building new stations in an area will not necessarily increase the number of charging substitutes a driver has. This is evident from the lack of substitution observed between stations even when free and not free stations are located near each other. Instead, drivers choose to substitute towards stations that are convenient for them. The business near a station may affect where a driver chooses to substitute.

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