How Do Electric Vehicle Drivers Substitute Between Stations?

Aspen Fryberger Underwood*†

November 12, 2021

Abstract

Growth in electric vehicle (EV) adoption over the last decade has increased the need for EV charging stations. However, existing research on optimal charging station placement assumes EV drivers substitute between stations similarly to drivers of gasoline vehicles, even though it take 4-12 hours to fully charge an EV. 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 gasoline stations, the number of stations in an area has little effect on station usage even when nearby stations have different prices. Instead, being located in places where 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 for gasoline and EV stations which should inform future station placement.

*afryber@clemson.edu, John E. Walker Department of Economics, Clemson University, NBER Pre-Doctoral Fellowship on Energy Economics

†A special thank you to Babur De los Santos, Matthew Lewis, and Chuck Thomas for their advice throughout the research process. I appreciate the comments I have received from Jorge Garcia, Jeremy Losak, Shilpi Mukherjee, Robert Underwood, and the members of the IO workshop at Clemson University.

1 Introduction

The expansion of electric vehicle (EV) charging stations is essential for the continued adoption of EVs. U.S. EV charging stations grew from only 541 stations in 2010 to more than 78,000 in 2019. This expansion of charging stations has increased EV driving ranges and made EVs a more realistic alternative to gasoline vehicles. Springel 2017 and J. Li 2017 found that increasing the availability of charging stations increases EV adoption. Unfortunately, existing research is unclear about how EV drivers substitute between charging stations, which has implications for where stations should be placed to best serve EV drivers.

While we know charging stations are essential for EV adoption, little is known about how EV drivers substitute between stations. Existing research on optimal EV station placement and models of station entry have largely assumed EV drivers substitute between stations similarly to drivers of gasoline vehicles. However, key differences between gasoline and EV charging stations, such as the time required to charge, may affect driver substitution between stations. How drivers substitute between stations has implications for station price competition, the optimal distance between stations, and station entry decisions. Understanding driver substitution is crucial for the efficient expansion of EV charging networks.

This paper uses unique transaction level charging data. 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. The data allows me to observe how drivers substitute across stations that become not free when the subsidy ended and stations that remain free by looking at changes in station and individual driver charging. I find driver specific preferences observed prior to the end of the subsidy had a greater impact on driver substitution than either station proximity to other stations or charging price.

The length of time required to charge an EV and the driver's ability to charge at home creates potential differences between gasoline and EV charging. It takes 4-12 hours to fully charge an EV on the most common type of charger. A 2020 Tesla will gain only 2-3 miles of additional driving range from 5 minutes of charging, whereas a gasoline vehicle will gain several hundred miles of range in the same time. Long charging times may make drivers more interested in charging at their destination and decrease the degree to which stations in the same area serve as substitutes. Second, EV drivers have the choice to charge at home, meaning stations on the network are not only competing with each other but also home charging.

In Section 3, I use a fixed effects approach to estimate how the number of stations located within 1 mile affects how much a particular station's usage decreases when the charging subsidy ended in 2018.[1] For stations that become not free, the number of stations within 1 mile had no effect on how much station charging decreased. For stations that remained free, the number of stations nearby had a small positive effect on usage in the downtown area. This is true 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 reveals limited spatial competition between stations.

In Section 4, I expand the analysis to explore individual driver substitution. Driver specific data allows me to observe how station and individual driver characteristics affect where drivers substitute. I use a hurdle model to estimate where drivers substitute. In the first stage I use a logistic regression to estimate how price, distance, and 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

[1]Density is used in Lewis 2008, Hastings 2004, and Syverson 2004

2017 charging behavior. A driver is much more likely to substitute towards a station where they charged in 2017 than to switch to a station that remains free but have not previously visited. The distance between stations and price has a greater effect when only including stations where the drivers have previously visited. I find similar results in the second stage when estimating the quantity of charging moving across stations. Because all charging is 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 indicates a greater emphasis on the convenience of the charging location than the price.

Previous research on optimal EV station placement and EV station entry have largely assumed EV drivers substitute between stations similarly to gasoline stations. Zhou and Li 2018 explore issues around having enough critical mass for full EV adoption by modeling how EV adoption fuels the expansion of EV charging stations, but they assume a perfectly competitive market where drivers substitute perfectly between stations in an area. If this not accurate, assuming drivers substitute perfectly between stations could affect when and where new stations are profitable and the charging accessibility they create for drivers. Additionally, He et al 2013 in the engineering literature 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 as is discussed with major gasoline chains. This paper contributes to the existing literature by testing assumptions about driver substitution which should inform future models of station entry and placement.

These results have implications for the existing research on optimal station placement and the expansion of charging networks. Research focusing on station placement needs to account for the differences in substitution between EV stations and gasoline. 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

The term EV commonly refers to hybrid electric vehicles(HEVs), plug-in hybrid electric vehicles(PHEVs), and battery electric vehicles(BEVs), but differ in their need for charging stations. Hybrid electric vehicles are often considered electric vehicles because they use an electric battery in addition to an internal combustion engine. However, they operate exclusively on gasoline so, for the purpose of this paper, they will not be considered electric vehicles. Plug-in hybrid electric vehicles also use a batteries with a gasoline engine, but can run exclusively off electricity and can plug in to charge. Plug-in hybrids typically have a limited fully electric driving range which can be extended by use of the gasoline engine. Battery electric vehicles operate exclusively off battery power and do not have a gasoline engine. These vehicles are fully reliant on electric charge, and typically have driving range of 150-350 miles.

The two types of public chargers that differ in the time required to charge a vehicle. Level 2 chargers are the most common form of public charger and typically deliver 3-12 KWs per hour. These chargers require 6-12 hours to fully charge a vehicle and cost 0.15-0.22$ per KW in the Kansas City area. Level 2 stations cost 2-5 thousand dollars to install. Alternatively, level 3 chargers deliver more than 50 KWs per hour, allowing most cars to charge in 30-60 minutes at a cost of around .33$ per KW. However, these chargers are less common due to the 20-50 thousand dollars cost to install. In Kansas City there are 268 level 2 charging stations, but only 16 level 3 stations.

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 different kinds of locations in urban and rural areas with varying levels of station and population density.

On January, 1 2018, Evergy ended the charging subsidy and 70% of 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 pattern of stations that remained free versus stations that became not free is apparent from the machine learning techniques used in Appendix A. Because Kansas City is split by the Kansas-Missouri boarder, charging stations exist on both sides of the state line with level 2 stations in Kansas charging .15$ per KW and stations in Missouri charging .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 and Hastings 2004 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 shows drivers visiting the stations closest to them in 2017 when all prices are zero and then substituting 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 inconvenience of charging time. Substituting to a station down the street from the driver's destination would requires the driver to walk the additional distance between the new stations and their final destination or spend minutes or hours at the new charging location.

Instead of substituting to a nearby station, it may be more convenient for drivers to

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

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.

When looking at how EV drivers substitute between stations, it important to note that these stations also differ in how drivers observe station 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 aboard navigations 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 for EV charging 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.

2.1 Data

This paper utilizes data from every station on the Evergy 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 spaces available at each station. Station location information can be used to determine spatial properties about each station such as the number of other charging stations nearby, the distance to downtown, the number of free charging station nearby and the distance to the nearest station. Additionally, google maps is used to determine the type of businesses that are located near the station such as a grocery store, shopping center, or school, which may influence a driver's charging decisions. Based on Google maps information stations have been classified into 11 business type 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, a station located at any medical facility, parking garage, a station at an entertainment location such as a park and community recreation facility, and other which includes a 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 median time spent at charging stations in grocery locations is 30 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 median grocery station is visited by 64 unique drivers in 2017 whereas the median work station is visited by only 12. Grocery stations are used by more drivers for shorter times, while work stations are used by a few drivers for longer. Differences in charging behavior and the services the business near the station offer for the driver may affect where and how much drivers substitute.

For the purpose of this paper, a charging station is defined as one or more ports at a single street address offering identical charging capability. Each station is one or more port in a single location that offer identical charging capability. If a single charger exists in a parking lot it is a station; if five chargers are in a parking lot, this is also a single station. However, if there are both level 2 and level 3 chargers in the same location they are treated as different stations because they offer different charging capabilities, but this only occurs in two locations, but level 3 stations are excluded from this analysis.

In addition to station information, the data includes driver specifics which allow me to track the usage of drivers across stations over time. Each driver is identified by a unique code. This allows me to observe changes in driver charging behavior at stations across the network and know what stations they frequent before and after the subsidy ends. The data also includes the home zip code for each driver, allowing for a general calculation of the distance between the driver's home and each station. Although the number of drivers increased over 2017 and 2018, to reliably observe how behavior changes before and after the subsidy ends, I only include drivers who began using the network before May 1, 2017.

In addition to information on stations and drivers, the data includes specifics about each charging transaction. Every time a driver plugs their vehicle into a charger, the data records the starting and ending date and time of the event, station specific identification, driver specific identification, and the KWHs charged in the session. This allows me to observe how much each driver charges on the network, the unique number of stations they visit, and frequency of visits for each driver. For stations it allows me to calculate the number of unique drivers, average length of charging time, and total usage in KWs over time.

Station and driver identifiers allow me to calculate how each driver's charging moves across stations by observing where drivers decrease and increase charging after the subsidy ends. The movement of charging across stations is calculated by observing the total amount of charging each driver charges at every station in 2017 and 2018. If a driver decreases charging at a station in 2018, then charging is leaving that station, but if the charging at a station increased, charging moving towards that station.

For each individual driver, charging that leaves each station moves proportionally to where they increases charging. In the example shown in Figure 3 the 200 KWH decrease in charging at the origin station flows to stations A and B where charging increased in 2018. Charging at station A increases by more than station B, so charging moves toward each station proportionally. So, 60% of the charging moves towards station A and 40% moves to station B. If a driver's total charging decreased from 2017 to 2018 the difference in charging moves outside the network.

Stations are found throughout the Kansas City area in urban and rural locations with varying numbers of stations located within 1 mile. As seen in Table 1, more than half (72.7%) 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 varies, with some stations having 0 or 1 stations nearby and others 30-40 stations. The distance between stations ranges from less and a tenth of a mile to almost 50 miles. Stations are located both at 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. Variation in station density can be used to better understand how the layout of stations affects where drivers substitute.

When the subsidy ended I observe how charging moved across the network, as seen in Table 2. Most of the decrease in charging at stations when the subsidy ended moved outside the network with only small amounts switching to other stations. This highlights the important role home charging plays in understanding EV charging. Additionally, for charging leaving a station that became not free, about half of the charging went to stations the 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, it is clear that driver substitution decisions are not only driven by price differences across stations. While the amount of charging that left stations that remained free is small, a significant amount of that charging that moved towards station that became not free. If drivers are substituting towards stations primarily because of price, I would expect to see more charging move to stations that remain free, and a lack of capacity constraint during this time would make that possible. However, the lack of movement towards stations the remained free indicates that more factors than just price play role in driver charging decisions.

Figure 4 shows the distance between stations drivers substitution between. Only

15.7% of charging moves to a station within a mile of the original charging location. While not every station exists near other stations, more than half of stations have a charging location within a mile, and 47% of stations 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.

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 toward 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 5 shows the percentage of charging moving towards each station type after normalizing the number of stations in the 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 by 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 easier to substitute towards.

3 Station-Level Analysis

This section uses station-level data to explore how the number of stations located nearby affect 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 for 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 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. γ_i are station fixed effects and ϕ_t are month fixed effects. ϵ_{it} is the error term.

Table 3 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 free stations within 1 mile. $NumStations_i$ in columns 3 and 4 includes the total number of stations and only stations that remain free within 0.5 a mile of station i respectively.[3] While stations that become not free see a decrease in usage across the network when the subsidy ends, the number of stations nearby does not have a significantly effect on station usage. The estimates show the number of stations located nearby has virtually no effect even when only looking at nearby stations that remain free. This indicates limited spatial competition between stations located near one another even when there is a significant price difference between

[3]Estimation uses Fixest package Berge, Krantz, and McDermot 2021 in R.

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.

While the number of stations nearby does not have 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 differences types of stations I interact NumStations $\times$ NotFree with the business classification. Figure 6 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.

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 station 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 4. 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.

Additionally, I look separately at stations in the quartile located nearest downtown Kansas City (<9 miles) and stations in the quartile furthest from downtown (>19 miles). Table 5 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 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, estimates indicate having other station around may increase usage when the price changed, but is not significant. The effect of nearby free stations does not appear to differ from stations near downtown.

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 station that remain free. To estimate how the end of the subsidy affects stations that remain free, I estimate

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

$Usage_{Fit}$ 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_t is the error term.

Table 6 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 station 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 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 station 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. This implies limited spatial competition between stations which is different from what is observed for gasoline stations. This has implications for where future stations should enter the EV charging market and the price charged. A lack of competition could increase the profitability of station entry in an area if drivers are not substituting to nearby stations. While this analysis looked at substitution in a local area, from these results, it is unclear how drivers are substituting outside the local area, which will be explored using driver level analysis in Section 4.

4 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.

Driver-level analysis observes driver's substitution across stations using the data formulation described in Section 2. The movement of charging from one station to another before and after the subsidy ends is calculated to observe where drivers substitute. 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, we 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 hurdle model because the decision to substitute towards a station is likely different than the choice of how much charging to move. In the first stage of the hurdel model I use a logistic regression to estimate what factors affect the probability a driver will switch any amount of charging towards a specific station. 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 the 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.

The second stage I estimate the number of KWHs a driver moves towards station j as provided 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 hurdle model is used to capture the extent to which drivers are substituting towards specific types of station's as well as the station where drivers substitute larger amounts of charging.

Table 7 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. 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 7 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 and a station being located within 1 mile of the original station increase the probability a driver's substitutes towards that station by 0.09. 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 0.47. In column 4, when only looking at station the driver visited at least once in 2017, a station remaining free increased the average probability a driver substitutes towards it to 0.19. 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 7 relative to grocery stations. 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 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.

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 the 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 affect 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 7 shows the interaction between busines type classification. Overall, it appears that grocery, hotel, medical facilities, shopping, and school locations had a significant effect on the driver's probability to substitute towards that station when they remained free. However, work and parking station do not have a significant effect on substitution even when they remained free.

Table 8 shows estimates for stations the driver chose to substiute towards as specified in equation 4. As in the case with Table 7, 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.

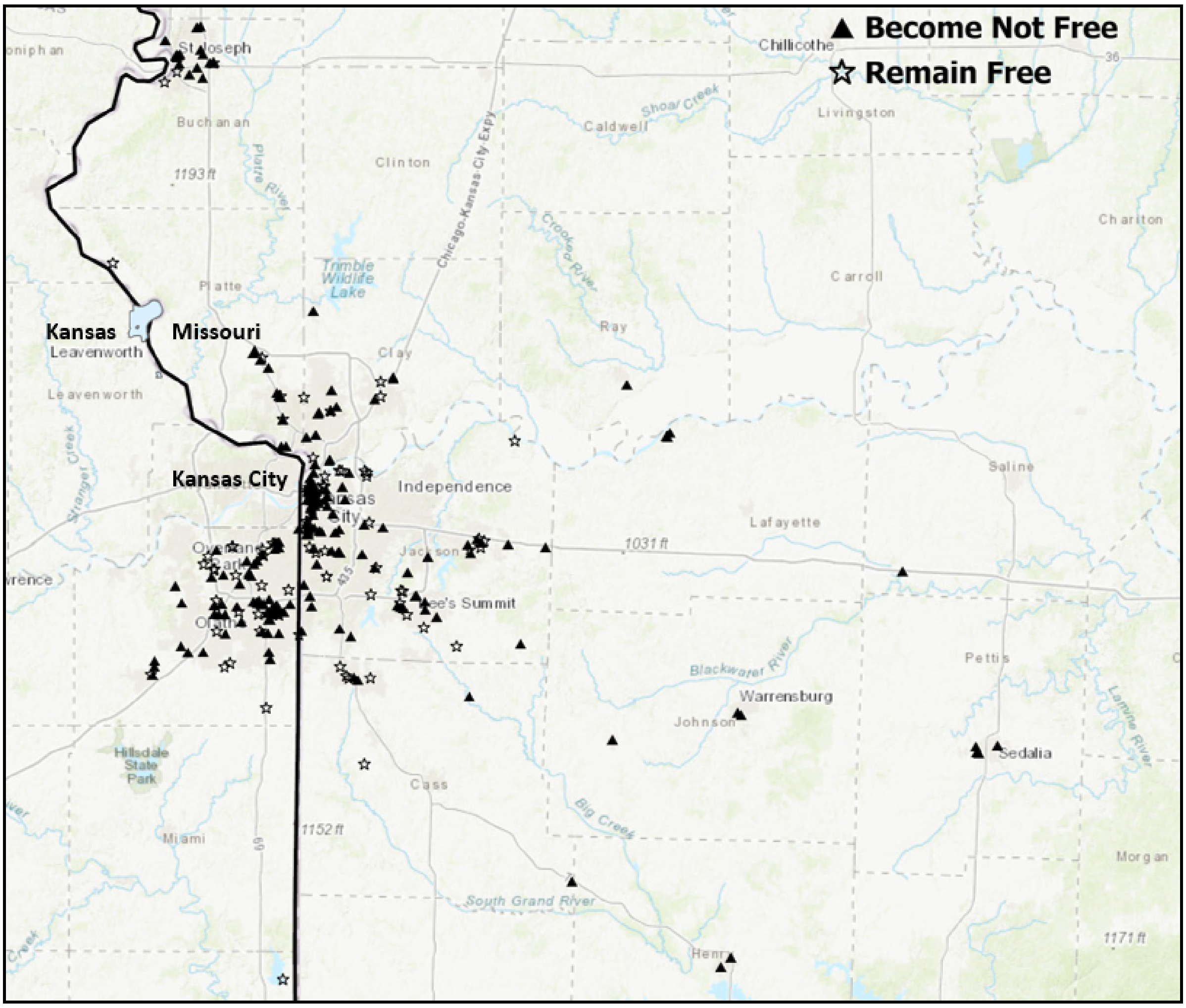
The KWHs a driver moves towards station j increases for stations drivers visited more in 2017. Remaining free after the subsidy ends has an effect on the share of charging moving towards those stations provided they visited the station less than 5 times in 2017. For stations that drivers visited more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

This section has three main implications. First, price differences between stations are often not a great enough incentive for a driver to substitute to a station they have not used before. Second, a station being located nearby has a small effect on substitution. Third, the type of business near a station affects how driver substitute towards stations that remain free. Remaining free has a greater affect on driver substitution for some types of businesses than others.

5 Conclusion

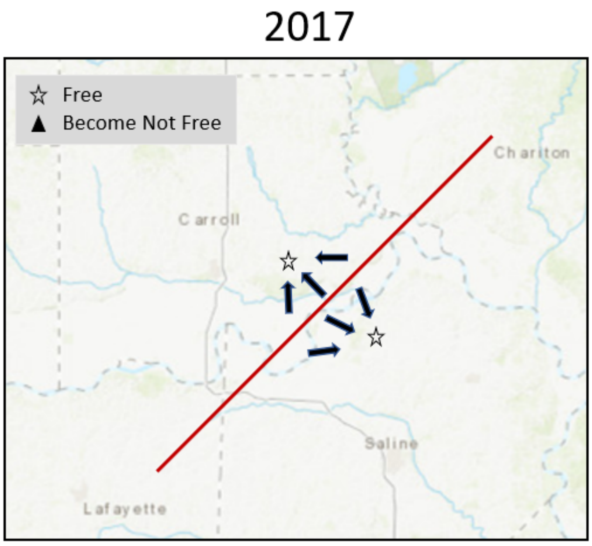
When analyzing substitution behavior of electric vehicles it is clear driver behavior is different from that of gasoline drivers. There is little substitution across stations located near each other even when there are significant price difference between them. Similarly, price differences between stations are often not a great enough incentive for a driver to charge their driving behavior and move to a station they have not used before. These results have several implications for future work on EV station networks. Instead of thinking about charging networks in terms of the possible range a station could provide to a driver, convenience of the station should be a priority. It is not clear that stations near each other are viewed as viable subsitutues by consumers. Instead, they may be competing on the convenience of charging with other stations where they also frequent.

Figure 1: Map of EV Charging Stations in Kansas City

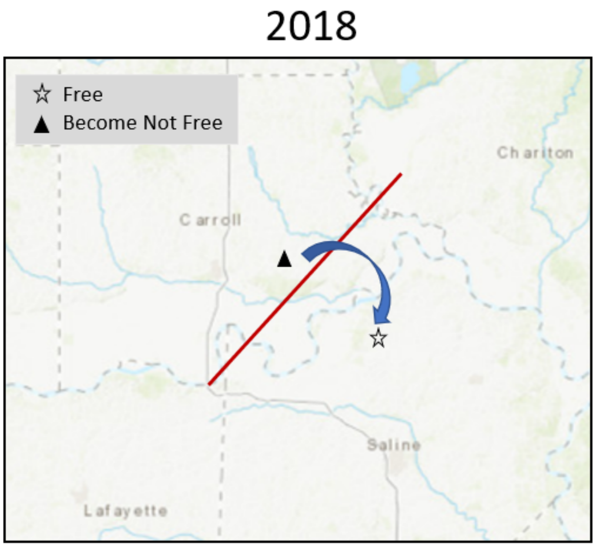


Note: This is a map of the Kansas City metro area with stations that remain free as stars and stations that became not free as black triangles. **Source:** Author's calculation

Figure 2: Common Expectation of Station Substitution



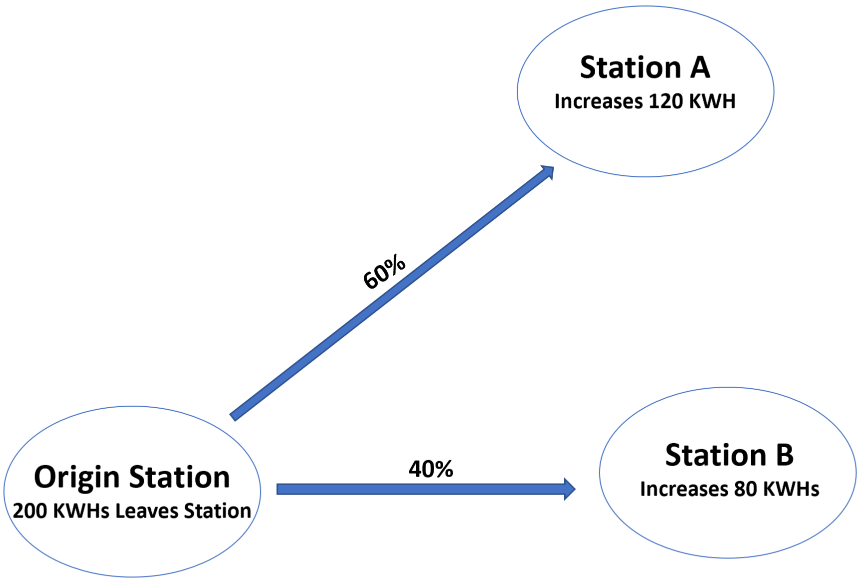
(a)



(b)

Note: Source: Author's calculation.

Figure 3: Example of Charging Movement Across Stations



Note: This is an example of how charging movement across stations on the network is calculated. **Source:** Author's calculation

Table 1: Station Spatial Description

	count	mean	min	25%	50%	75%	max
Station Density	268	6.6	0.0	0.0	2.0	6.2	41.0
Distance to Downtown	268	16.0	0.1	3.9	12.2	18.4	99.6
Distance to Nearest Station	268	1.5	0.0	0.2	0.4	1.0	48.1
Distance to Nearest Free Station	268	3.3	0.0	0.0	0.6	1.6	68.2

Table 2: Movement of Charging Across the Network Between 2017 and 2018

	Leave Network	**Switch to L2 Free**	**Switch to L2 Not Free**	**Switch to L3**
Stations Begin to Charge (KWH)	176,225	16,047.3	14,767.6	3,761.4
%	83.6%	7.0%	7.6%	1.8%
Stations that Remain Free (KWH)	22,359.9	4,051.6	2,697.1	593.9
%	75.3%	13.6%	7.6%	2.0%

Figure 4: Distances Charging Moves Across Stations

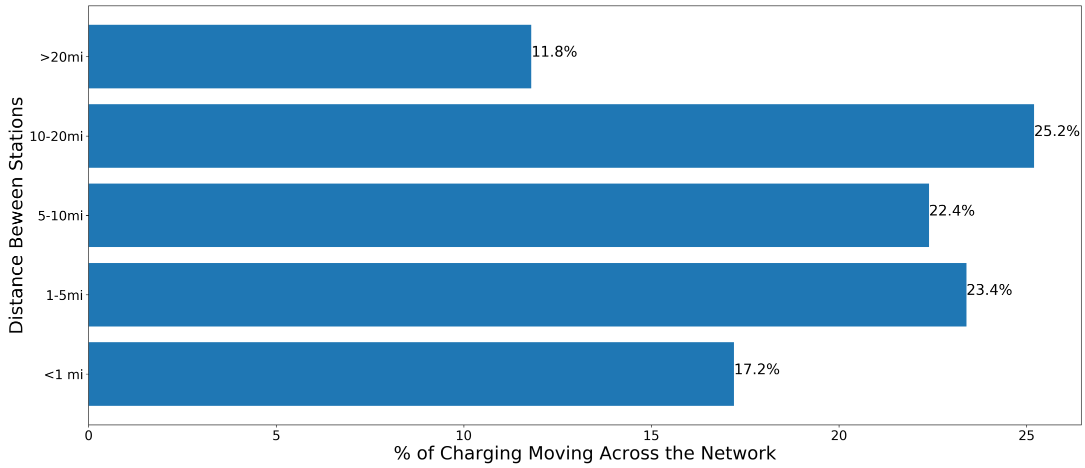
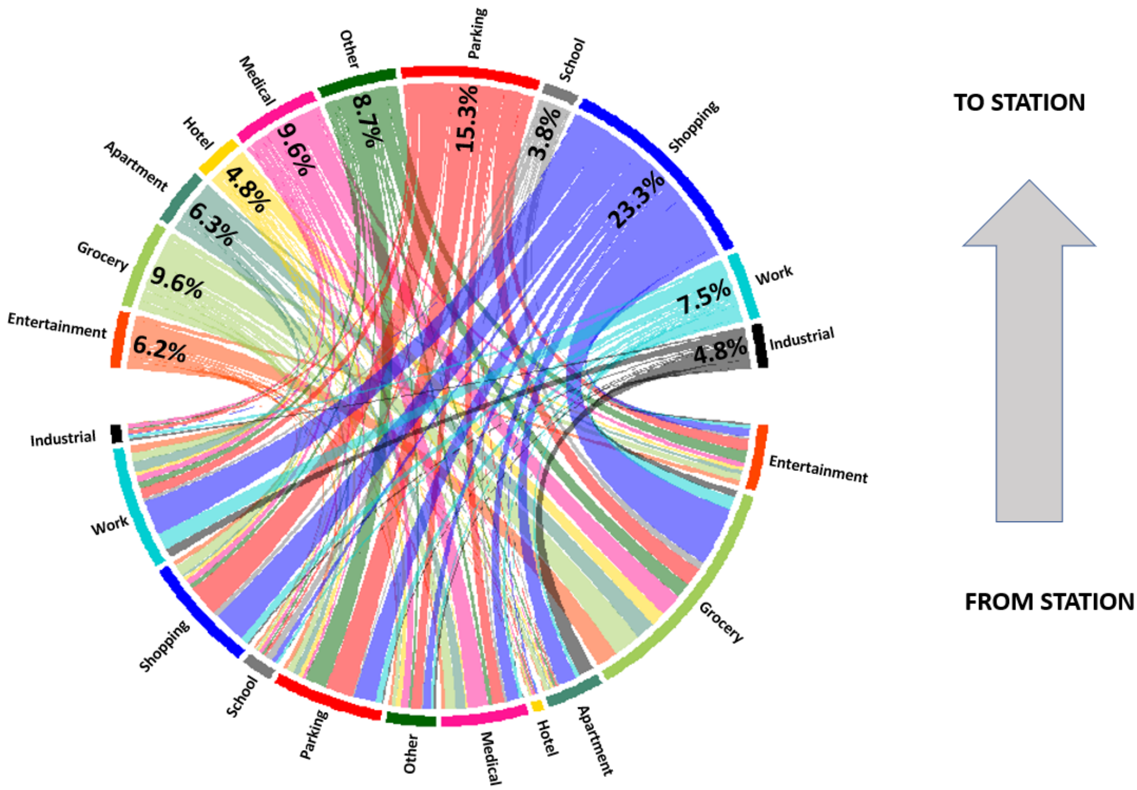


Figure 5: Chord Diagram of Average Movement to Each Station Type



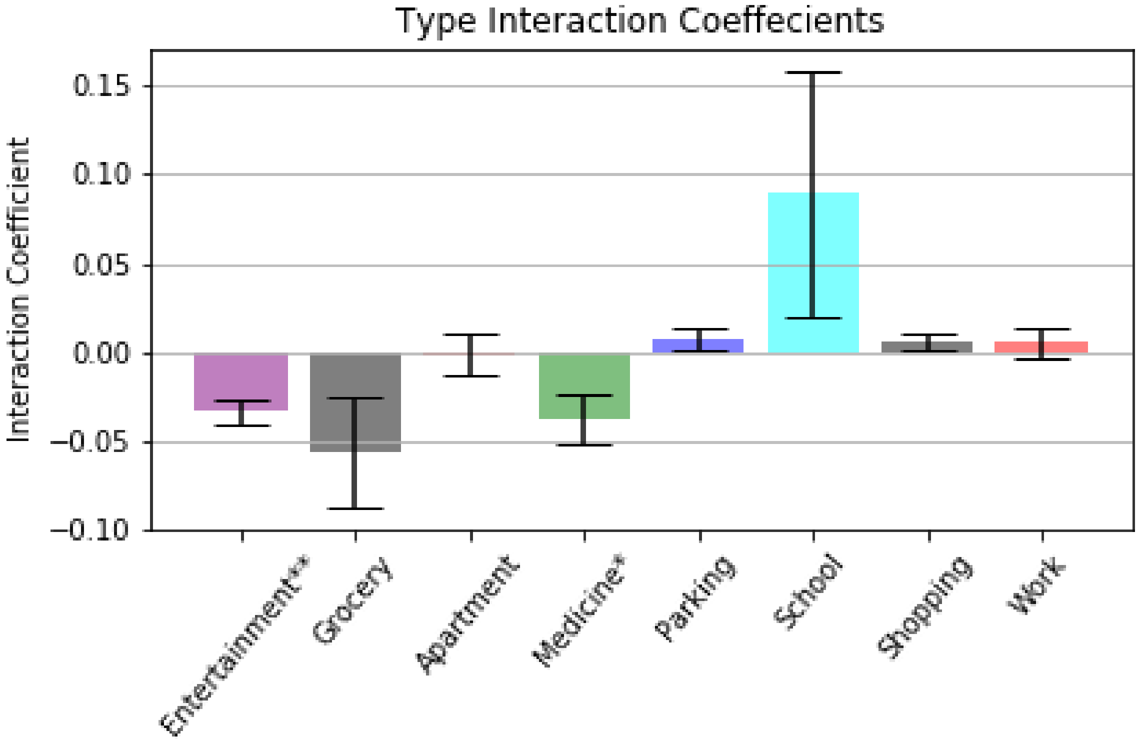
Note: KWHs moving to each type have been normalized by the number of stations in each type.
% indicates the movement of charging each type after accounting for differences in the number of stations.
Source: Author's calculation

Table 3: Estimates from Equation 1

Dependent Variable:	ln(KWH Usage)			
Model:	(1)	(2)	(3)	(4)
Variables				
NumStations 1mi	0.0020			
	(0.0045)			
NumStations 0.5mi		0.0077		
		(0.0100)		
Free NumStations 1mi			0.0050	
			(0.0153)	
Free NumStations 0.5mi				0.0023
				(0.0306)
NotFree	-0.7932***	-0.8011***	-0.7877***	-0.7810***
	(0.1261)	(0.1255)	(0.1247)	(0.1234)
Fixed-effects				
Station	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Fit statistics				
Observations	3,120	3,120	3,120	3,120
R^2	0.83770	0.83776	0.83768	0.83767

*Signif. Codes: ***: 0.01, **: 0.05*

Figure 6: Business Type and Density Interactions for All Density



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

Table 4: Estimates from Equation 1: Kansas and Missouri

Dependent Variable:	ln(KWH Usage)			
Model:	(1) Kansas	(2) Kansas	(3) Missouri	(4) Missouri
Variables				
NumStations 1mi	-0.0104		0.0003	
	(0.0387)		(0.0048)	
Free NumStations 1mi		-0.0906		-0.0009
		(0.1641)		(0.0161)
NotFree	-0.7590***	-0.7440***	-0.7888***	-0.7844***
	(0.2170)	(0.1789)	(0.1526)	(0.1513)
Fixed-effects				
Station	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Fit statistics				
Observations	900	900	2,220	2,220
R^2	0.85192	0.85215	0.82824	0.82824

*Signif. Codes: ***: 0.01, **: 0.05*

Table 5: Estimates from Equation 1: Near and Far from Downtown

Dependent Variable:	ln(KWH Usage)			
Model:	(1) <9mi from Downtown	(2) <9mi from Downtown	(3) >19mi from Downtown	(4) >19mi from Downtown
Variables				
NumStations 1mi	0.0026		0.1840	
	(0.0066)		(0.0875)	
NotFree	-0.9845***	-1.001***	-0.4436**	-0.1984
	(0.2428)	(0.2338)	(0.2005)	(0.1952)
Free NumStations 1mi		0.0129		-0.0048
		(0.0200)		(0.3057)
Fixed-effects				
Station	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Fit statistics				
Observations	816	816	768	768
R^2	0.85523	0.85537	0.79564	0.78623

*Signif. Codes: ***: 0.01, **: 0.05*

Table 6: Estimates from Equation 2

Dependent Variable:	ln(KWH Usage)				
Model:	(1) All Stations	(2) <9mi from Downtown	(3) <19mi from Downtown	(4) Kansas	(5) Missouri
Variables					
NumNotFree × 2018	0.0237	0.0328**	0.2100	0.0648	0.0198
	(0.0121)	(0.0146)	(0.1908)	(0.0386)	(0.0130)
Fixed-effects					
Station	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	888	240	192	288	600
R^2	0.83875	0.81985	0.79253	0.90238	0.81628

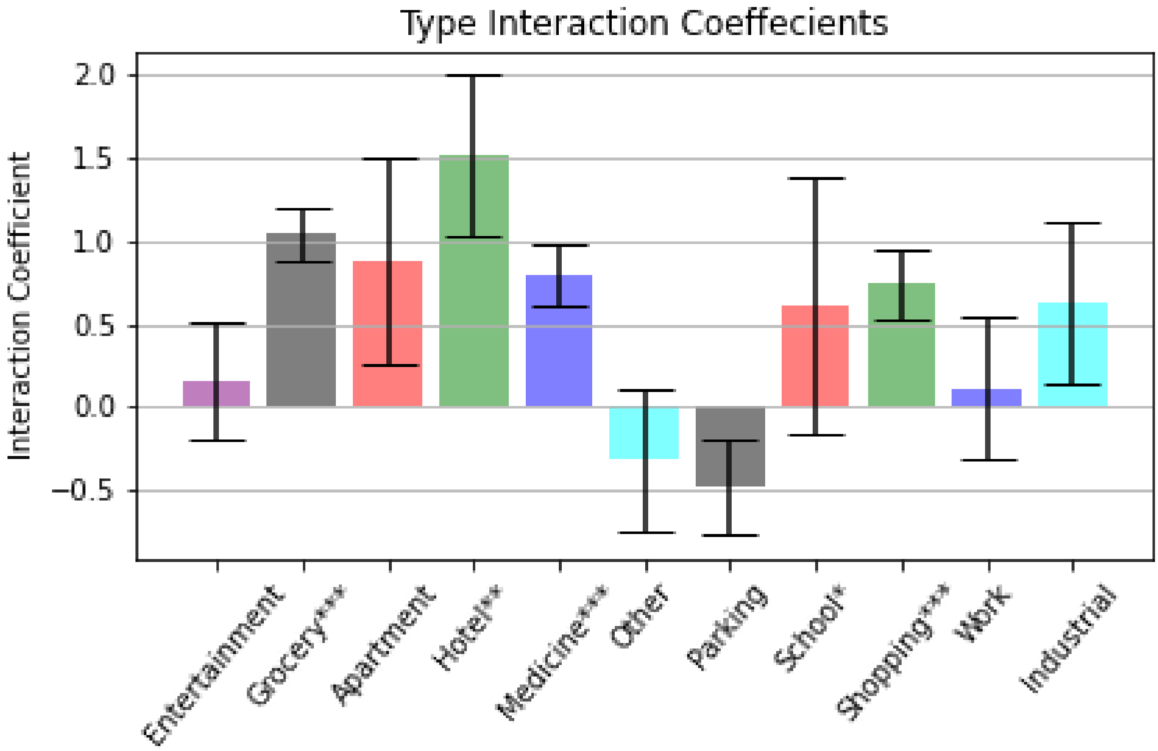
*Signif. Codes: ***: 0.01, **: 0.05*

Table 7: Estimates from Equation 3

Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Visites >1 in 2017	2.819***				
	(0.1340)				
Visites>5 in 2017		2.792***			
		(0.1409)			
Visites >10 in 2017			2.926***		
			(0.1636)		
Free	0.5004***	0.3991***	0.3937***	0.9528***	0.1778
	(0.1216)	(0.1434)	(0.1476)	(0.1387)	(0.1701)
Within 1mi	0.4504***	0.5714***	0.6199***	0.2310***	0.5234***
	(0.0578)	(0.0672)	(0.0756)	(0.0810)	(0.0790)
Station Density	0.0090	0.0118	0.0124	0.0032	0.0163
	(0.0081)	(0.0098)	(0.0102)	(0.0062)	(0.0115)
Distance to Downtown	-0.0263***	-0.0325***	-0.0336***	-0.0031	-0.0367***
	(0.0055)	(0.0064)	(0.0065)	(0.0059)	(0.0081)
No. Ports	0.0509***	0.0668***	0.0687***	0.0218**	0.0734***
	(0.0071)	(0.0076)	(0.0076)	(0.0085)	(0.0080)
Entertainment	-0.1716	-0.3427	-0.4243	-0.3063	-0.0735
	(0.2284)	(0.2665)	(0.2749)	(0.2077)	(0.3146)
Work	-0.7524***	-1.140***	-1.251***	0.0920	-1.211***
	(0.2059)	(0.2464)	(0.2543)	(0.2053)	(0.2644)
Apartment	-1.440***	-1.955***	-2.079***	-0.0362	-2.104***
	(0.3467)	(0.3904)	(0.3985)	(0.3308)	(0.4728)
Hotel	-0.9665***	-1.262***	-1.366***	-0.7094**	-1.316***
	(0.3259)	(0.4030)	(0.4200)	(0.3286)	(0.4018)
Medicine	-0.6601***	-0.9997***	-1.093***	-0.0068	-1.047***
	(0.1675)	(0.1880)	(0.1919)	(0.1973)	(0.2490)
Other	-0.5670**	-0.8789***	-0.9657***	0.1174	-0.7501**
	(0.2424)	(0.2727)	(0.2748)	(0.2838)	(0.3047)
Parking Garage	-0.7117**	-1.134***	-1.266***	-0.0704	-1.082**
	(0.3178)	(0.3836)	(0.3945)	(0.2615)	(0.4321)
School	-0.8967**	-1.292***	-1.396***	-0.0630	-1.268**
	(0.4336)	(0.4679)	(0.4713)	(0.3301)	(0.5701)
Shopping	-0.0022	0.0322	0.0337	-0.0190	0.2246
	(0.1655)	(0.1831)	(0.1952)	(0.1434)	(0.2231)
Industrial	-1.985***	-2.478***	-2.584***	0.1185	-2.735***
	(0.2783)	(0.3059)	(0.3063)	(0.4963)	(0.3695)
Fixed-effects					
User	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	1,258,144	1,258,144	1,258,144	62,113	1,031,337
Pseudo R^2	0.20364	0.14610	0.13292	0.23579	0.11019

*Signif. Codes: ***: 0.01, **: 0.05*

Figure 7: Business Type and Free Interactions



Note: Source: Author's calculation

Table 8: Estimates from Equation 4

Dependent Variable:			KWH		
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Visites >1 in 2017	0.2302***				
	(0.0447)				
Visites >5 in 2017		0.5678***			
		(0.0667)			
Visites >10 in 2017			0.7352***		
			(0.0903)		
Free	0.0859**	0.0556	0.0373	0.1584**	0.0101
	(0.0411)	(0.0389)	(0.0387)	(0.0777)	(0.0534)
Within 1 mi	0.1811***	0.1676***	0.1748***	0.1631	0.1423**
	(0.0588)	(0.0576)	(0.0585)	(0.0956)	(0.0627)
Station Density	-0.0008	-0.0018	-0.0014	-0.0023	0.0007
	(0.0026)	(0.0023)	(0.0025)	(0.0050)	(0.0028)
Dist to Downtown	-0.0040	-0.0035	-0.0033	0.0013	-0.0032
	(0.0024)	(0.0023)	(0.0023)	(0.0045)	(0.0029)
No. Ports	0.0087***	0.0096***	0.0094***	0.0076	0.0087**
	(0.0026)	(0.0026)	(0.0026)	(0.0052)	(0.0042)
Entertainment	0.1886***	0.2192***	0.1920***	0.1288	0.2075***
	(0.0608)	(0.0580)	(0.0556)	(0.1249)	(0.0728)
Work	0.2452***	0.2468***	0.2137***	0.2078	0.2941***
	(0.0768)	(0.0717)	(0.0690)	(0.1559)	(0.0749)
Apartment	-0.0050	0.0502	0.0384	-0.1789	0.1094
	(0.0896)	(0.0900)	(0.0925)	(0.1837)	(0.0895)
Hotel	-0.0118	0.0261	0.0294	-0.0322	0.2744**
	(0.1154)	(0.1148)	(0.1057)	(0.1156)	(0.1332)
Medicine	0.1722**	0.1570	0.1463	0.1349	0.2519**
	(0.0814)	(0.0814)	(0.0796)	(0.1406)	(0.1106)
Other_again	0.2372**	0.2487**	0.2111**	0.2606	0.2953**
	(0.0984)	(0.0981)	(0.0992)	(0.2174)	(0.1335)
PG	0.2147**	0.2737***	0.2234**	0.3858	0.2201
	(0.1011)	(0.0969)	(0.0967)	(0.1968)	(0.1185)
School	0.2949***	0.2674***	0.2281**	0.4094	0.2390***
	(0.0976)	(0.0897)	(0.0888)	(0.2208)	(0.0879)
Shopping	0.0862	0.1267**	0.1263**	0.0097	0.1777**
	(0.0647)	(0.0596)	(0.0589)	(0.0958)	(0.0759)
Industrial	0.5252***	0.4369***	0.4493***	0.7323**	0.2624***
	(0.1860)	(0.1666)	(0.1525)	(0.2848)	(0.0964)
Fixed-effects					
User.ID	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	9,034	9,034	9,034	4,023	5,011
Pseudo R^2	0.21418	0.21895	0.21964	0.25289	0.22480

Clustered (User.ID & Radio.Group.Name3) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05*