Plugging Into Driver Preferences: How Charging Station Prices and Characteristics Affect Electric Vehicle Driver Charging Decisions

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Abstract

Vehicle manufacturers and governments across the U.S. employ various subsidies to promote the adoption of electric vehicles (EVs). These subsidies develop networks of EV charging stations and subsidize the price consumers pay for charging. However, doing so sensibly is hampered by a poor understanding of EV drivers' demand for stations and charging. Using charging-session level data from the Evergy charging network in Kansas City, at a time when there was a discrete end to a charging price subsidy, I empirically analyze drivers' charging behavior. I find driver charging decreased 55% when the price subsidy ended, and station characteristics, such as the type of business near a station, play an important role in driver demand for stations. Counterfactual analysis indicates the charging price subsidy provided $0.81 in value to drivers for every dollar spent on the subsidy and stations vary significantly in the value they provide to drivers. These findings suggest the need to account for the effects of station characteristics and charging price in future EV subsidy programs.

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1 Introduction

Recent technological advances make electric vehicles (EVs) a plausible alternative to gasoline vehicles and give them the potential to enable zero or low emission transportation. Improved batteries are cheaper and permit longer driving ranges making EVs more attractive to consumers than in the past. By 2019, there were more than 43,000 charging stations in the U.S. and EV sales had risen from just 17 thousand vehicles in 2011 to more than 300 thousand annually.[1] However, convenient EV charging continues to be a pain point for EV adoption, as is seen in Hardman (2020).

Governments, utilities, and vehicle manufacturers across the U.S. have promoted the adoption of EVs by subsidizing them in three ways. The first subsidizes the sale of EVs. The federal government's subsidizes EV sales up to $7,500 per vehicle and state and local agencies provide additional subsidies for EV purchases.[2] The second subsidizes building new EV charging stations. Local governments, utilities, and vehicle manufacturers such as Nissan, Tesla, and BMW have built many new EV charging station networks over the last decade.[3] The third subsidy makes charging free to drivers. Charging price subsidies which make charging free have been implemented by a variety of localities, utility providers, individual stores, and vehicle manufacturers such as Nissan, Tesla and BMW.[4]

Understanding the how EV charging stations are utilized is crucial as EV adoption grows. The effects of charging station characteristics and charging price subsidies on driver charging decisions may have implications on what subsidies are implemented and where new stations are located. Price and station characteristics such as the location within a city, density of stations in an area, the number of ports at a station, and

[1]More information on charging stations and vehicle sales is found at `https://afdc.energy.gov/stations/#/find/nearest` and `https://afdc.energy.gov/data/10567`.

[2]Specifics on federal tax rebates are found at `https://www.fueleconomy.gov/feg/taxevb.shtml`.

[3]Additional local subsidy information is found at `https://clippercreek.com/evse-rebates-and-tax-credits-by-state/`.

[4]Vehicle manufacturer partnerships with EV charging networks specifics are found at `https://www.evgo.com/nissanenergyperks/`, `https://www.businessinsider.com/tesla-supercharger-network-expansion-costs-8-billion-ubs-2017-3`, and `https://www.evgo.com/bmwcharging/`.

the type of business located near a station may significantly affect driver demand for a station and lead to variation in how much stations are used. Of the 284 stations in this analyses, 10 stations charged less than 70 KWHs in total over two years, with two stations charging less than 3 KWHs. Concurrently, the top 25% of stations charged more than 10,000 KWHs over same time frame. Station characteristics may affect how much stations are used and the benefit they provide to drivers. Additionally, how drivers respond to changing price subsidies may be key in reducing future congestion at charging stations.

This paper uses unique transaction level charging data to explore how stations are utilized by analyzing how station characteristics and charging price affect driver charging decisions. My data, which is described in Section 2, allows me to observe every charging transaction that occurs on the Evergy (a regional utility) charging network in Kansas City. The 284 Evergy charging stations are located throughout the region and provide a variety of charging characteristics to drivers. In the first year of the data, Evergy subsidized charging to make it free for all drivers. In the second year of the data, the subsidy ended at 70% of the stations, and I am able to observe how charging price and characteristics affect driver behavior. I find that station characteristics as well as price significantly affect driver charging decisions.

Like EVs, a robust network of gasoline stations was essential for the early adoption of the gasoline vehicle, but EV charging differs from gasoline vehicle fueling in two important ways.[5] First, it takes 5-11 hours to fully charge an EV.[6] A 2020 Tesla will only gain 2-3 miles of additional driving range for 5 minutes of charge, whereas a gasoline vehicle will gain several hundred miles of range in the same time.[7] Because of the time required for charging, the characteristics that make EV stations convenient for drivers will likely be different than gas stations. EV drivers may be more likely to charge at locations where

[5]Melaina (2007) discusses early gasoline stations in the U.S.

[6]More information on EV charging is found at `https://chargehub.com/en/electric-car-charging-guide.html`.

[7]Vehicle charging information can be found at `https://insideevs.com/reviews/428113/tesla-model-3-highway-range-test-70mph/` and `https://evcharging.enelx.com/resources/blog/577-how-long-does-it-take-to-charge-a-tesla`.

they are already spending time, such as work, grocery stores, and movie theaters and may be less interested in charging at places they are driving past. Second, EV drivers can charge at home. Provided a driver has the range to get home, they can choose to charge their vehicle at home where the time required to charge may be less burdensome.[8] The outside option of home charging further differentiates EVs from gasoline vehicles and may change how drivers utilize charging stations and respond to changes in price.

Convenience of the charging locations may have a significant impact on how stations are utilized and what locations provide the greatest value to drivers. EV drivers may consider stations at their final destination most convenient, while charging at stations along the driving route would require a significant increase in the commuting time. Drivers seeking to charge at their end locations may place a higher importance on the businesses around a station than drivers of gasoline vehicles.

In Section 3 I use differences-in-differences and synthetic control approaches to estimate how charging price and station characteristics affect station utilization using the discrete end to the charging price subsidy. I find average station usage decreased 55% when the charging subsidy ended. Additionally, the type of business near a station significantly affected how much it was used, and how much charging decreased when the subsidy ended. Stations located at work places, public parking garages, and when the charging subsidy ended grocery stores are used most, but grocery station charging decreased more than charging at stations located where people work.

In Section 4 I use a discrete choice approach to estimate the effects of station characteristics and charging price on driver charging decisions. The estimates from this section are used to perform counterfactual analysis in Section 5. The results show that station characteristics and price play an important role in driver charging decisions. Station price elasticity is affected by the type of business near a station with some stations being more elastic to price than others. However, other location factors such as a station's proximity

[8] EV vehicle range differs over time and is found at `https://newmotion.com/en/knowledge-center/news-and-updates/the-electric-range-of-an-ev`.

to downtown and a driver's home location have a limited effect on charging decisions.

Section 5 uses the estimates from Section 4 to perform 2 counterfactuals. The first counterfactual calculates the consumer surplus created by the charging price subsidy and finds that fully subsidizing EV charging increases driver surplus by $0.81 for every dollar spent on the subsidy. The second counterfactual calculates the value of each charging station to EV drivers over 6 months. I find station's value to drivers range from less than a dollar to more than $600, but stations located near work, grocery, and shopping locations are frequently valued more than stations near other types of locations.

These results have important policy implications and contribute to the existing literature on EV adoption. Previous economic literature on charging stations shows the important effect EV stations have on EV adoption, but does not address differences in station characteristics and charging price.[9] Using data from the U.S. and Norway Springel (2017) and Li et al. (2017) find that building stations is essential for EV adoption, but subsidies for new stations are more effective than subsidies on vehicle purchases. However, they do no differentiate stations by location, price, or characteristics. Understanding the importance of stations Zhou and Li (2018) address issues around having charging station critical mass for full EV adoption by looking at how increases in EV drivers affect new station development, but they also assume demand and prices are identical across stations.

This paper also complements the engineering literature on optimal station placement. For example, Lam, Leung and Chu (2014); and Liu, Wen and Ledwich (2013) use electrical grid data and population density to determine optimal locations for charging stations.[10] Greene et al. (2020) uses station-level data to assess the additional value a station provides a driver based on their driving range and station location. While these papers perform important technical analyses of the costs of building EV infrastructure,

[9]Sierzchula et al. (2014), Li (2017), Clinton and Steinberg (2019), Sheldon and DeShazo (2017), DeShazo, Sheldon and Carson (2017), and Holtsmark and Skonhoft (2014) also discuss charging stations and EV adoption.

[10]Cui, Weng and Tan (2019), He et al. (2013), Mehta et al. (2018), and He, Yin and Zhou (2015) also discuss optimal station placement.

they do not account for driver station preference. Straka et al. (2020) begins to address this problem by using transaction-level charging data and neighborhood geospatial data to predict station popularity based on neighborhood characteristics, but does not consider station specific characteristics. This paper contributes to these groups of literature by expanding our understanding of driver demand for charging accounting for station price and characteristics.

The effects of price and station characteristics on driver charging behavior has important policy implications for how future subsidy programs are implemented and where future charging stations are located. Understanding what station characteristics are valued by drivers is crucial as EV charging networks continue to expand. Not accounting for these important factors could lead to wasted resources on charging stations that are not convenient for drivers and become underutilized. Additionally, understanding how drivers responds to changes in price has implications for potential station capacity constraints and the efficiency of future charging price subsidies.

2 Kansas City Charging Network

2.1 Electric Vehicles and the Kansas City Charging Network

The term EV commonly refers to three classes of vehicles with different needs for charging stations. The first is the Hybrid Electric Vehicle (HEV), such as the Toyota Prius, which has an internal combustion engine but use batteries to store energy generated while driving.[11] HEVs operate exclusively on gasoline, so for this paper, they are not considered EVs because they do not plug in and charge. The second is the Plug-in Hybrid Electric Vehicle (PHEV). They differ from HEVs in that they can plug-in and run exclusively on electric power or use their internal combustion engine. PHEVs offer flexibility but have a

[11] More information on types of EVs can be found at https://afdc.energy.gov/vehicles/how-do-hybrid-electric-cars-work, https://afdc.energy.gov/vehicles/electric.html, https://www.evgo.com/why-evs/types-of-electric-vehicles/.

limited driving range of 20 - 50 miles in their fully electric mode. The third is the Battery Electric Vehicle (BEV). Like PHEVs, they plug in to charge, but they do not have an internal combustion engine. BEVs are fully dependent on electric charge. However, they have a longer driving range than the PHEV ranging between $80-350$ miles.[12]

There are two types of public chargers that differ in the time required to charge a vehicle. The more common Level 2 charger delivers 3-8 KWs per hour. Using a level 2 charger fully charging an EV takes 5-11 hours, depending on its battery size and vehicle type.[13] These chargers cost $400-$6,500 including installation and are available at 268 of the 284 locations in the data set. The less-common Level 3 charger ("Fast Charger") delivers 40-50 KWs per hour. Charging an EV to 80% takes 30-60 minutes, but charging slows after the battery reaches 80%. These chargers cost between $10,000-$40,000 including installation and are only available at 16 locations in this data set.[14] Additionally, Level 3 chargers are incompatible with PHEVs, small battery BEVs, and experience compatibility issues across vehicle makes.

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. For example, a group of five Level 2 chargers in a parking lot is one station, and so is a single Level 2 charger in a parking lot. However, Level 2 and Level 3 chargers located near each other are considered different stations because they offer substantially different charging speeds. This only occurs at 6 locations. Charging stations across the city offer drivers different charging speeds, number of charging ports, and convenience.

In 2015, the regional utility, Evergy, subsidized the development of an EV charging network around Kansas City, and made all charging free to drivers until January 1, 2018.

[12]Specifics on BEV range and qualities can be found at https://www.autoblog.com/2015/04/30/2015-ev-range-per-dollar-ranking/ and https://newmotion.com/en/knowledge-center/news-and-updates/the-electric-range-of-an-ev.

[13]More Level 2 charging information can be found at https://www.nrel.gov/docs/fy20osti/77508.pdf, https://chargehub.com/en/electric-car-charging-guide.html, and https://afdc.energy.gov/files/u/publication/evse_cost_report_2015.pdf.

[14]Level 3 charging information can be found at https://afdc.energy.gov/files/u/publication/evse_cost_report_2015.pdf, https://chargehub.com/en/electric-car-charging-guide.html, and https://chargehub.com/en/electric-car-charging-guide.html.

The city-wide network has 284 charging locations at work places, grocery stores, shopping malls, schools, and other public locations. When KCPL choose where to place the stations in 2015 did not have any specific criteria for where stations were placed in the area or the type of businesses near the stations. As a result, stations are located throughout the Kansas City metro area at a variety of different types of locations. Stations are located in both in both Kansas and Missouri, with a few stations extending north to the Iowa state line and 100 miles south to Nevada, Missouri. Stations exist in both urban and rural locations, but the majority of stations are located in the Kansas City metro area.

Evergy ended the charging subsidy on January 1, 2018, but the businesses located near each station could choose to continue the subsidy themselves and keep charging free at their station. Using the machine learning techniques discussed in Appendix A, level 2 stations did not appear to have a clear systematic difference between stations that remained free and those that became not free, but all level 3 stations became not free. The price at Level 2 stations were the subsidy ended increased to an average of \$0.15 per KWH in Kansas and \$0.22 per KWH in Missouri and level 3 stations cost between \$0.28-0.33 per KWH. Overall, 89 station or 30% of all stations remained free in 2018.

When the subsidy ended, drivers could continue charging at stations that became not free, switch to stations that remained free, or begin to charge outside the network such as at home. All charging stations utilize the ChargePoint App so there is no technical barrier for substitution between stations. Home charging can be done from a traditional wall plug, but this takes a few days or weeks to fully charge a vehicle, but this can be made more convenient by installing a Level 2 home charger which costs around \$200-\$2,000.[15] In Kansas City the per KW cost of home charging is \$.10-\$.12 per KW versus the \$.15-\$.22 per KW cost of level 2 charging on the Evergy network.[16] Cheaper home charging may have led more drivers to investing in home charging systems when the subsidy ended,

[15] More charging station cost specifics can be found at `https://www.fixr.com/costs/home-electric-vehicle-charging-station` and `https://www.edmunds.com/fuel-economy/the-true-cost-of-powering-an-electric-car.html`.

[16] Kansas and Missouri average residential electricity costs are found at `https://www.electricitylocal.com/states/kansas/` and `https://www.electricitylocal.com/states/missouri/` respectively.

which may made them less reliant on public charging as a whole. Unfortunately, I do not have data on home charging.

For drivers who had the option of using gasoline, the end of the charging subsidy could have caused them to substitute towards the use of a gasoline vehicle. However, it typically costs less per mile to pay for EV charging than to buy gas. For example, the 2019 Fiat 500 comes as both a fully electric or fully gasoline vehicle. The fully electric version requires 30 KWHs to travel 100 miles and the fully gasoline vehicle requires 3.7 gallons of gasoline.[17] At a typical cost for public EV charging of $.22 per KWH and $2 per gallon of gas, 100 miles costs $6.60 for the EV and $7.40 for the gasoline vehicle.[18] While the cost of charging increases when the subsidy ended, EV charging still costs less than buying gasoline and with the switching costs associated with vehicles, it is unlikely many drivers switched back to gasoline vehicles as a result of the end of the subsidy. Instead, it is more likely drivers began charging at home.

Due to the time required to charge, the businesses near charging stations likely play an important role in where drivers choose to charge. These factors may affect how much stations are utilized, frequency of utilization, and the length of time drivers charge at a station. A station located at a grocery store may provide a different service to drivers than a station at school or work. Drivers may charge for several hours at work but only a short time at a grocery store. It is crucial to account for the effect the business near a station may have on driver charging decisions.

To better understand the effect of the type of business near a station may have on usage, I categorized stations into eleven business categories using Google Maps location information. Stations are categorized based on the businesses directly next to each station as grocery, office work locations, industrial work location, parking garages, apartments, hotels, shopping centers, medical facilities, schools, entertainment, or other. While the stations in each group share common types of businesses, there are still regional and

[17] Specifics on the Fiat 500 can be found at `https://www.fueleconomy.gov/feg/Find.do?action=sbs&id=41143&id=41148`

[18] Two dollars is used as a lower bound for the cost of gasoline.

location-specific differences within groups.

The grocery station classification includes any station located near a Walmart, Sam's Club, or other grocery store. Some stations may have other shopping options nearby while others may be a single grocery store. Work stations are located at corporate offices or small firms for many different types of businesses. Industrial stations exist at any industrial factory or service center, but most of the industrial stations are Evergy locations. Parking garage stations are located at any public parking garage, and apartment stations are located in apartment parking areas. Similarly, hotel stations offer charging to their customers in hotel parking areas. Shopping locations are frequently located at shopping malls, locations with a group of stores, or large single store. Medicine stations are located at hospitals or doctors' offices. Schools stations are at either K-12 schools or college campuses. Entertainment stations are at outdoor entertainment areas such as parks or indoor entertainment centers such as movie theaters or community recreation centers. "Other" includes all stations that did not fit into any of the above categories, and mostly consists of gas stations, airports, and stations without a clearly identified classification.

2.2 Data

This paper utilizes data from every charging session that occurred on the Evergy network in 2017 and 2018. Each observation includes a unique station identifier, number of ports, the type of port (Level 2 or Level 3), station location coordinates, charging start and end date, driver id, price charged, and total KWHs charged. Using station coordinates I have expanded station specific data to include station density, the distance from downtown, distance to the nearest interstate, and the distance to the nearest station. When the subsidy ended station price information is used to determine which stations remained free and which stations became not free.

Unique driver ids and home zip codes are used to calculate the distance between the center of a driver's home zip code and each charging station. While the zip code does not give an exact location of the driver's home, it generally indicates where a driver lives relative to downtown and charging stations. Zip codes are also used to identify average demographic characteristics for each driver such as population density and the average income of their home zip code. The unique driver identifier lets me observe individual charging behavior changes over time.

EV charging in Kansas City increased during 2017 and 2018, so, for the purpose of observing driver charging behavior over time, only drivers who used the network before May 2017 are included in the analysis. Similarly, I only include drivers who live within 100 miles of the Kansas City network so that changes in cross-country travel patterns do not affect the analysis. As a result, this paper primarily applies to drivers living within or near the Kansas City metro area.

For each charging transaction the data records the KWHs charged, the station id, the driver id, the charging start and stop date, the charging duration, and the fee charged to the driver. The fee and KWHs of every charging session are used to calculate the price per KWH of charging. The station, individual, and record level data allows me to calculate the total number of charges each driver makes, total usage per driver, the unique stations each driver visited, and the frequency of driver visits at each station. This level of detail allows me to observe every change in driver's charging behavior including how charging changes in 2018, what stations each driver leaves, and total charging usage.

Table 1 reports descriptive statistics between July 1, 2017 and June 30, 2018, revealing differences in usage across drivers. On average, drivers charged 72 times over 12 months, but a quarter of drivers charged fewer than 10 times and the top quartile charged more than 101 times. Similarly, the lowest quartile of drivers visited 3 or fewer unique stations, while the highest quartile of drivers visited more than 10. 87% of charging occurred within 20 miles of the driver's home zip code, which suggests home charging may be a viable substitute to charging on the network, because 20 miles does not exceed the range of most EVs. Overall, charging is inexpensive, with more than half of charging sessions costing less than \$1.30 at stations that became not free in 2018.

Usage also varies across stations. While price may cause variation in usage, the data shows that differences in usage across stations occurred prior the end of the charging price subsidy in 2017. Stations in the lowest quartile of usage experienced less than 25 KWHs of usage per port than the median port usage of 129 KWHs. The median port usage is less than half of the 355 KWHs of usage at the 75th percentile, and the top quartile of stations are used between 355 and 7,348 KWHs per port in the same time. The variation in usage when all prices were equal supports the hypothesis that station and location factors, and not just price, play an important role in understanding charging station usage.

Table 2 shows station descriptive statistics for stations by business type classification. This table includes 278 of the 284 stations, because the other 6 stations were not used between July 2017 and June 2018. The total number of visits and KWHs vary some by station type, but the standard errors are very large. There are some differences in driver usage across business types such as the average length of each visit, the number of unique drivers, and how frequently drivers visit a station. Grocery and shopping stations have more unique drivers than other stations, but drivers visit them less frequently. In contrast, work stations have fewer unique drivers, but much higher visit frequency. Straka et al. (2020) use the number of unique drivers who visit a station as a measure of station popularity, but this may leave out the important role different stations play for drivers in the length of charge and frequency of visits. Stations used for long amounts of time may provide different benefits to EV drivers then stations used by many for less time. Simply looking at the number of unique users that visit a station may not capture the true popularity of a station.

2.3 Changes in Usage From the End of the Charging Subsidy

As seen in Figure 1, charging on the network decreased when stations became not free in 2018. The solid line shows usage for stations that become not free and the dotted line shows total usage for stations that remain free in 2018. The vertical line indicates when the charging subsidy ended.[19] It appears stations that remained free did not experience the decrease in usage seen by stations that became not free.

Table 3 shows the average change in charging for stations that became not free and stations that remained free. Stations that become not free experienced a statistically significant drop in usage, a decrease in the number of unique drivers, and a decrease in visit frequency. Concurrently, the end of the price subsidy did not have a significant effect on usage for stations that remained free. Stations that remained free experienced only a slight, not statistically significant increases in KWHs used when the subsidy ended. There was a statistically significant increase in the length of charging sessions for stations that remained free, but it is small. The limited increase in usage for stations that remain free when the subsidy ends indicates movement from stations that became not free to stations that remained free is probability limited.

Figure 2 shows the total change in usage by business type classifications and location. While there are differences within business classification, there is some indication that the business type may affect how much charging decreased after the subsidy ended. Work station usage decreased 38.2%, but grocery and shopping station wage decreased almost twice as much. The difference in the decrease for stations near downtown Kansas City versus those further away is less. While this does not give a complete picture of the effect of the type of business near a station and station location, it highlights some differences which will be explored with analysis.

3 Empirical Analysis of Station Usage

This section explores how charging price and station characteristics affect station usage using difference-in-difference and synthetic control approaches. Estimating how drivers respond to changes in charging price cab be used to reduce station congestion through pricing in the future. Similarly, better understanding of how station characteristics affect

[19]Driver frequency is calculated by the number of visits driver i makes at station j each year.

where drivers choose to charge should inform future station development and placement. Understanding the affects of station characteristics and price is crucial for future pricing and the expansion of EV charging networks.

3.1 Difference-in-Difference

As seen in Figure 2, station usage across the network decreased after the charging subsidy ended on January 1, 2018. In this section, I use a difference-in-difference approach to estimate how station characteristics and the end of the charging subsidy affect station usage using data from six months before and after the end of the subsidy. Stations that remained free after the subsidy ended are distributed throughout the city (seen as stars on the map in Figure 3) and serve as the control group. Stations that became not free in 2018 are the treatment group (seen as black triangles in Figure 3). Charging in both groups is observed in 2017 when charging was free at all stations and after the subsidy ended when 70% of station become not free.

Using a difference-in-difference approach I estimate

$$ln(Usage_{it}) = \beta_0 + \beta_1 NOTFREE_i + \beta_2(NOTFREE_i \times T_{it}) + \beta_3 X_i + \lambda_s + \lambda_m + \epsilon_{it}, \quad (1)$$

where $Usage_{it}$ is the average number of KWHs charged per port at station i in month t plus one to account for stations with zero usage in some months. NOTFREE is a dummy variable that indicates if the station is in the treatment group and becomes not free in 2018. $NOTFREE_i \times T_{it}$ indicates station i is not free in time t and can be interpreted as the difference-in-difference estimator. X_i are the station characteristics of station i. λ_s are station fixed effects and λ_m are month fixed effects. ϵ_{it} is the error term and is clustered by station.

Station characteristics include both the regional characteristics of the area where a station is located and the characteristics at the station site. Characteristics of the area around a charging station include, population density of the zip code, the number of EV drivers near the station, the distance from downtown, the distance to the nearest interstate, and the density of charging stations. These are similar to the variables used in Straka et al. (2020) and assume separate regions in a city have different levels of demand for EV charging. Regional characteristics such as the distance to downtown Kansas City and the distance to the nearest interstate could play an a role in how much stations are used. The distance to downtown gives a measure of the urban nature of the station. The distance to the nearest interstate is an indicator of how accessible a station is to drivers. Other location factors include the demographics of the zip code where the station is located including the population density, the number of registered EVs within 10 miles of a station, and station density within 1 mile. These factors may affect variation around the local area, but as EVs become prevalent, differences across demographic groups may fade. Characteristics of the site where stations are located include the speed of charge (Level 2 or Level 3) and the business type classification.

Table 4 presents the results from the difference-in-difference regression. Column 1 includes both month and station fixed effects along with the difference-in-difference estimator $NOTFREE_i \times T_{it}$. Estimates from column 1 indicate stations that became not free decreased usage by 55% when the charging subsidy ended. However, column 1 does not show the effect of station characteristics.[20] Column 2 only includes regional characteristics without accounting for station site characteristics, more similar to the variables in Straka et al. (2020), but column 2 estimates of the difference-in-difference estimator are similar to column 1.

Column 3 includes station site characteristics and driver density. Station business classification variables are estimated relative to grocery stations. Grocery stations are chosen as the reference due to their clear definition and high average use per station. Column 3 shows a similar estimate of the difference-in-difference estimator as is in columns 1 and 2. On average, Level 2 stations have less usage relative to Level 3 stations, which is

[20]The percent decrease is calculated using $(exp(\beta) - 1) \times 100$ as is specified in Halvorsen and Palmquist (1980).

likely due to the slower electricity transfer of Level 2 stations. Entertainment, apartment, and hotel stations have the the largest negative effect on station usage relative to grocery stations, which is significant. However, other stations such as work, shopping, medicine, and parking garage station's usage are not significantly different from grocery stations.

Figure 4 shows interactions of the difference-in-difference estimator $NOTFREE_i \times T_{it}$ with business classification. The bars show the 95% confidence interval and $*$ indicates statistical significance. Parking garage and work stations decrease on average 44% and 46% respectively and are statistically different from grocery and shopping stations which decrease 65% and 62% respectively.[21]Due to the time required to charge, stations that are less convenient may experience a larger decrease in usage than stations which are more convenient. Differences across station business classification may affect the level of convenience stations provide to drivers.

The difference-in-difference assumes the control group is a good proxy for the usage of the treated stations had the subsidy not ended. This requires that there is not a systematic difference in the trends of usage between stations that remained free and those that became not free, and the end of the subsidy does not affect station usage in the control group. While there does not appear to be a clear systematic difference between stations that become not free and stations that remained free, I use machine learning techniques to predict which stations will become not free using available station data. The machine learning techniques were not able to predict which stations remained free with a high degree of precision, but more discussion is found in Appendix A.

If drivers switched from stations that became not free to stations that remained free when the subsidy ended it could affect the control group and cause bias in the estimate. If this was the case, there should be an increase in charging at stations the remained free in 2018. However, as is seen in Table 3, stations the remained free only experienced a 2.4%, not statistically significant, increase in KWH usage. While there are some small

[21]Grocery stations are not significantly different from shopping, but are significantly different from work, parking, entertainment, and apartment stations.

changes in the frequency of use and the number of unique drivers, the change in actual usage for these stations is quite small. While 70% of the stations became not free, there is only small and not statistically significant increase in usage at the 30% of stations that remain free. This indicates there is not a significant amount of charging moving from stations that became not free to stations that remained free, and the potential bias is likely small. Appendix B has further discussion on the movement of charging between stations.

3.2 Synthetic Control

For robustness, a synthetic control approach is used to complement the difference-in-difference estimates. This approach is similar to a difference-in-difference in that it estimates the effect of the subsidy on station usage by comparing treated station with other stations in the area. However, the synthetic control does not require parallel trends of the treated and control stations before the end of the subsidy. This mitigates potential selection bias from underlying differences between treatment and control stations before the subsidy ended.

The synthetic control is made up of a group of J control stations weighted by a $J \times 1$ vector of weights $W = (w_1, ..., w_J)$. Stations in the synthetic control are weighted to closely mirror the treated station prior to treatment to create a control that matches the pretreatment usage of station i using

$$\hat{Y}_{it} = \sum_{j=1}^{J} w_j Y_{jt}. \tag{2}$$

$\hat{Y}_{it}$ is used to find the effect $\hat{\tau}_{it}$ of the end of the subsidy on station usage

$$\hat{\tau}_{it} = Y_{it} - \hat{Y}_{it}. \tag{3}$$

Weights for the synthetic control are calculated using station usage and other station characteristics such as the number of ports, station type, unique users, the distance to the interstate, and station density. If stations are weighted properly, the treated station and the synthetic control should have similar station usage before the subsidy ended, as is seen in Figure 5.[22]

The synthetic control approach estimates the end of the subsidy decreased average usage for stations that became not free by 55%. This is very similar to the difference-in-difference estimates and indicates there is probability limited bias in the difference-in-difference price estimation.

4 Driver Choice Analysis

This section continues to explore the affects of station characteristics and price on driver charging decisions using transaction-level charging data to estimate a mixed logit with random coefficients. This complements the estimates from Section 3 and expands our understanding of how stations characteristics and price affect driver charging decisions. Section 4.1 discusses the specifics of the estimation, required assumptions, and population level results. Section 4.2 calculates station and driver elasticities, and Section 4.3 explores the accuracy of the model and alternative specifications for robustness. These results are then used to construct counterfactual analysis in Section 5 which allow me to calculate the value of the charging price subsidy and individual stations to drivers.

4.1 Mixed Logit

This section uses a mixed logit discrete choice model with random coefficients. Drivers choose charging locations from a choice set of stations and the outside option, which are differentiated by station characteristics and price. The random coefficients are normally distributed across the driver population.

[22] Abadie (Forthcoming) and Bouttell et al. (2018) discuss synthetic control methods.

Home charging makes the outside option an important component of the choice set. Unfortunately, I am not able to directly observe out of network charging, but I can observe how much each driver charges and how this changes when the charging subsidy ended. While this does not demonstrate how much drivers are charging outside the network, it does indicate how much charging moved outside the network as a result of the change in subsidy. Because it is unlikely the price increase caused drivers to switch back to gasoline, the difference in charging between years is used to determine the increase in charging events each driver made outside the network. The number of charging events that moved outside the network are events where the outside option was chosen. Including these outside charging events, each driver is credited with the same number of charging events in 2017 and 2018 and if a driver's charging on the network decreased, charging outside increased. The outside option is normalized to zero utility so if a driver has positive utility from charging at any station on the network they would presumably choose a network station, but if no station provides positive utility they would choose to charge outside. While this approach does not account for all outside charging, it does capture movement on and off the network between 2017 and 2018.

In addition to the outside option, the choice set of stations must be defined. The naive approach would be to include all stations in the choice set. However, of the 284 charging stations on the Evergy network, most drivers visited only a few. While all the drivers were able to find the location and prices of stations through an online application, it is unlikely that all stations are truly in every driver's choice set. It is more reasonable to assume that drivers choose from a set of stations located at places they frequent.

Additionally, it is not possible with our computing resources, although they are quite robust, to estimate the model using all 284 stations in every choice set. While it is impossible to truly know all locations a driver is considering, the data does allow us to observe where drivers are charging and the locations that are likely in their choice set. The choice set is defined as all stations where each driver chose to charge more than one time over the course of two years. Each choice set is specific to each driver and while it is possible that a driver may choose from a broader set of stations, it is unlikely that stations where a driver never chose to charge more than once in two years time was a serious consideration.

The process described above creates a unique choice set of stations for each of the 1134 drivers. The smallest choice set has 2 stations with the driver charging at only one station on the network and the outside option. The largest choice set has 21 stations, and the average choice set has 5.2 stations. The station choice sets make this estimation different from the analysis in Section 3. Here the coefficients indicate the effect a characteristic has on the probability that a driver will choose a particular station, conditional on a station being in the driver's choice set. Because the estimation is conditional on the choice set, the effect of station characteristics are different from the results in Section 3.

If a driver choses to frequently visit a work location this will increase usage at the station, but does not account for the number of people who use that station. If a station is lightly used by a large number of people it may have high usage but may not have high visit frequency, as is seen in Figure 6. Work and grocery stations both have a positive effect on station usage, as is seen in Section 3, but grocery stations were used by a large number of drivers, while work locations were often used by a small number of drivers.[23] 68% of the driver choice sets contain a grocery station, but only 32% contain a work station. Given that estimates are conditional on the choice set, grocery stations could have less of a positive effect on an individual driver's charging choice, but still have relatively high usage overall.

The initial utility specification for the mixed logit is

$$u_{ijt} = \alpha_{it} p_{jt} + \beta_{it} X_{ij} + \epsilon_{ijt}, \tag{4}$$

where α is the price coefficient for driver i at time t, and p_{jt} indicates if station j is

[23]Grocery and shopping stations are statistically different from school, parking, and work stations using the Mann-Whitney test at a 95% confidence interval.

not free at time t. X are station characteristics for driver i and station j, and ϵ is the error term. X contains characteristics that do not change across drivers such as the type of charger and business classification as well as driver specific characteristics such as the distance between the station and the driver's home zip code.

Station characteristics that do not vary across drivers are similar to the variables used in Section 3. Characteristics that are driver specific include the distance between station j and driver i's home and the average time driver i spends charging at station j. The distance to the driver's home indicates whether stations closer to the home or farther away were preferred. The average length of time an individual charged at a station is included because the length of time a driver is looking to charge may affect the choice.

Tables 5 and 6 show the summary of results from equation 4. The first set of columns in Tables 5 and 6 include all 1134 drivers in the data set. The following columns of Table 5 show subsections of drivers based on zip code income. The second set of columns in Table 5 include drivers who's average zip code income is in the lowest income quartile for EV drivers ($76,000 or less). The third set of columns includes drivers with zip codes in the highest income quartile (greater than $118,000). The second set of columns in Table 6 includes subsections of drivers by the distance of the home location from downtown. Column 2 of Table 6 includes drivers living in the quartile living nearest downtown (less than 9 miles), and column 3 includes drivers who live in the quartile furthest from downtown (more than 19 miles).

Allowing the coefficients to vary across driver's choices allows us to better understand how characteristics affect drivers differently. The coefficients are estimated using 100 random draws from a normal distribution for each driver's decision with mean β and variance σ. Price, distance to the driver's home, grocery, and shopping all have statistically significant variance σ, which indicates these characteristics vary significantly across drivers in the population while other characteristics such as work, parking garage, grocery, medical stations, and station density, distance to downtown do not vary significantly over the population.

For all drivers, on average, price has a negative coefficient indicating a negative effect on the probability a driver will visit a station. The regional characteristics such as distance to downtown, station density, and distance to the interstate have a small effect on the choice with average elasticities of only 0.1, 0.04, and -0.08 respectively. The small effect of these variables is consistent with the results from Section 3. Work and medical stations have a positive average elasticity of 0.63 and 0.29. Parking garage and apartment stations have somewhat smaller positive effect with elasticities of 0.14 and 0.38 respectively, but the importance of apartment stations differs significantly across drivers.

Unlike the result in Section 3, grocery and shopping stations have a negative effect. Grocery stations do not have a significant effect and shopping stations has a significant, negative effect. This does differ from the results in Section 3 where both grocery and shopping stations had a significant, positive effect on usage. Grocery and shopping stations have many more unique drivers per station than work stations which have relatively few drivers per station, and 67% of the choice sets contain at least 1 grocery station. Grocery stations may have a limited effect on the probability a specific driver will choose to charge, but they serve many different drivers and are in many choice sets. Whereas, work stations have a significant effect on driver's probability of visiting a station. Work stations may be used intensely by a smaller number of drivers, but grocery stations less intensely by a larger number of drivers.

Columns 2 and 3 of Table 5, show that drivers in the lowest income quartile, on average, are less reactive to price than high income drivers.[24] This is opposite of what is expected, but drivers with higher incomes may be more likely to have level 2 home chargers or may drive vehicles with longer ranges, making them less dependent on public charging. Also, price varies significantly across the drivers in both groups. It also appears that high income drivers have more of a preference for work stations than other drivers. Grocery has more of a negative effect on low income drivers. As seen in columns 2 and 3 of Table 6, price has less of an effect on drivers who live near downtown and more of

[24]Estimation is done in R using the mlogit package from Croissant (2021).

an effect on drivers further away. This may be due to a lack of alternative charging for drivers living in a downtown environment whereas drivers living outside the city may be more likely to have home chargers. Similarly, drivers living further away from downtown are more negatively affected by grocery and shopping stations relative to drivers who live closer to the downtown area. However, drivers living further away have more of a negative effect from level 2 chargers and may be more interested in the faster level 3 charging options.

4.2 Station and Individual Elasticities

The coefficients in Tables 5 and 6 are used to calculate the probability

$$P_{ijt}(\beta_{it}) = \frac{e^{\beta_{it}' X_{ijt}}}{\sum_k e^{\beta_{it}' X_{ikt}}}. \tag{5}$$

a driver will visit a specific station. The probability P_{ijt} of station j being chosen by individual i in time t is found using coefficients β_{it} and characteristics X_{ijt} from Section 4.1. The price elasticities are calculated with the individual price coefficients α_{it}, price p_{jt}, and the probability of P_{ijt} of choice j for individual i. The elasticity of station j for driver i at time t is

$$\frac{\partial P_{ijt}}{\partial p_{jt}} \frac{p_{jt}}{P_{ijt}} = E_{ijtp_{jt}} = \alpha_{it} p_{jt}(1 - P_{ijt}). \tag{6}$$

Elasticities are used to find the average price elasticity for every station and individual driver. Figure 7 shows the average price elasticity of each driver and station. There is variation across drivers by driver zip code income and distance from downtown. Figure 7a shows average price elasticities of each driver who live near to downtown(within 9 miles) and drivers who live further away from downtown(greater than 19 miles), and there is a clear difference for drivers who live close to downtown and those who live farther away. Drivers who live near downtown may have less access to home charging, making them less responsive to charging price. Similarly, Figure 7b shows the average elasticity for drivers who live in the lowest and highest income zip codes. Contrary to expectations, high income individuals are more elastic than lower income drivers. These differences may be due to systematic differences in access to home charging and longer driving ranges for more expensive EVs.

The average elasticities of stations by business classification can be seen in Figure 7c. Overall the range of average station elasticities vary between 0 and -3 with an average near -2.5. However, this is not unexpected due to the nature of the outside option in EV charging. When elasticities are broken down by station type as seen in Figure 7c, there are differences in the distribution of elasticities across station types. Work and parking garage stations are less elastic, and using a Mann-Whitney test the distribution of work and parking garage stations are different from grocery stations at a significance level of 0.01, but other categories are not significant, which is consistent with the results in Section 3.

4.3 Estimation Accuracy and Robustness

This section looks at the accuracy of the model estimated in Section 4.1 and estimates alternative specifications for robustness. Accuracy of the mixed logit comes from the model's ability to predict movement of charging in and outside the network and accurately predict the station the driver chose. For robustness, alternative definitions of the choice set are estimated.

4.3.1 Accuracy

First, I look at the ability of the model to predict movement in and out of the network. When the coefficients in Tables 5 and 6 are applied to the data, the choice with the highest calculated utility is the choice the model predicts the driver will choose. The estimates from equation 4 correctly predict the driver's choice 58% of the time, but correctly predict if the driver will choose to charge at the outside option 85% of the time. The predicted movement of charging in and outside of the network can be seen in Figure 8a.

To further test the accuracy of the model, the data is split with a 75% to 25% train-test split with data stratified by user and year. Coefficients are estimated on the training portion of the data, and prediction accuracy is tested on the test portion of the data. Using this approach, the model predicts the correct station the driver will choose with an accuracy of 48%, and accurately predicts when the outside option will be chosen 72% of the time. The movement of charging in and out of the network predicted in the stratified estimates is seen in Figure 8b.

To see how accurately the model selects the correct station, I look at how closely the model predicts the total share of visits at each station by business classification. This can be seen in Table 7. In reality 9% of visits occurred at parking garage stations, and the model predicts parking garage visits are 11% of visits. The estimates predict the choice of a work station is 25% of the visits when they are actually 15% of visits, and underrepresents grocery and shopping stations.

4.3.2 Robustness of Choice Set

To check for the robustness of the choice set specification, Table 8 compares the estimates from Table 5 with the alternative specifications of the choice set, since the true choice set for each driver is unknown. Table 8 shows estimates for alternative specifications of the choice set. The first group of columns contains the original specification from Table 5 where each driver's choice set includes all stations the driver visited more than one time over two years. The second group of columns expands the the choice set to include any station the driver ever visited. The third group of columns shrinks the choice set and only includes stations the driver visited more than twice.

The price estimates across all specifications of the choice set are relatively consist. Similarly, location characteristics are very similar across all specifications. Some of the business classification change as the size of the sample decreases, which is to be expected. As the number of alternatives changes, the frequency of each alternative occurring in driver choice sets changes, which may affect the coefficients estimated.

5 Counterfactuals and Policy Recommendations

This section uses the results from in Section 4 to perform two counterfactuals that have important policy implications. This section performs two counterfactuals. The first looks at the effects of the charging price subsidies on driver consumer surplus by comparing the actual consumer surplus observed in 2018 with a “counterfactual” surplus where charging prices remained zero. The second counterfactual calculates the dollar value each station provides drivers on the network by comparing total driver consumer surplus with and without each station.

5.0.1 Station Price Counterfactual

The charging price subsidy has been implemented in may different locations across the country without a good understanding of how it benefits drivers or its implications for future station congestion. While overall station usage is not beyond the charging capacity of the network in Kansas City in 2017 and 2018, Zhou and Li (2018) discusses problems of future charging capacity constraints for EV adoption. In light of these concerns, the counterfactual explores the value charging subsidies provide to drivers for every dollar spent on subsidies.

The counterfactual calculates the additional consumer surplus the charging subsidy provides for drivers on the Evergy network using the data and coefficients estimated in Section 4 by artificially setting the charging price in 2018 to zero. The consumer surplus of the artificial state of the world in 2018 where charging prices are zero is compared to the observed consumer surplus where the subsidy ended.

Figure 9 shows the number of actual, predicted, and counterfactual visits that occur on the network. The solid blue line show the actual visits that occur and the orange dotted line shows the number of visits the model predicts would occur in the real world. The green dotted line shows the number of visits the model predicts would occur in the "counterfactual" world where prices remained zero in 2018. The average number of visits per month in 2017 is shown by the red dotted line.

The dollar change in consumer surplus (CS) created for drivers by continuing the charging subsidy is calculated by

$$\Delta CS = \left[ln \sum_{j} e^{-\alpha_{it} p'_{jt} + \beta_{it} X_{ij}} - ln \sum_{j} e^{-\alpha_{it} p_{jt} + \beta_{it} X_{ij}} \right] \frac{1}{\alpha_{it}} \tag{7}$$

where p'_{jt} is zero for all stations and p_{jt} are the prices observed in 2018. The dollar value of the surplus is obtained by dividing by the price coefficient α.

Table 9 shows the consumer surplus for drivers in the observed state of the world, the "counterfactual" state of the world, and the difference between them. The total surplus for drivers in 2018 when prices artificially remain zero is \$151,816 for the 1,146 drivers. When the subsidy ends the total surplus falls to \$129,752. Maintaining the charging subsidy would increase the CS by about 17% or \$22,064 across 1,142 drivers. The foregone costs of continuing the subsidy in 2018 is total charging revenue in 2018. Total revenue from charging in 2018 was \$27,341, and for every dollar in forgone revenue the subsidy generates \$0.81 in driver consumer surplus.

Station subsidies need to be assessed accounting for costs and benefits, of the subsidy, potential long run benefits, and the behavior this subsidy incentivizes. The return to drivers from charging subsidies is less than the cost of implementing the subsidy. While this subsidy benefits EV drivers in the short term, it is not clear how this subsidy increases EV adoption in the future. Last, this subsidy incentivizes EV drivers to increase use of network stations, as is seen in Figure 9. This incentive may lead to station congestion and station critical mass difficulties as EV adoption grows, as is discussed in Zhou and Li (2018).

5.0.2 Station Counterfactuals

In addition to understanding how charging subsidies benefit drivers, the estimates from Section 4 also allow me to measure how drivers value the existence of stations on the network. Springel (2017) and Li et al. (2017) found that subsidizing the building of new stations is more cost effective than subsidizing the sale of electric vehicles. However, their analysis does not differentiate between stations or locations. This counterfactual calculates the value each station on the network provides to drivers over 6 months, and see how station characteristics affect station value.

Station value is calculated using the data and estimates from Section 4 to calculate the value of each station by individually removing them from the choice set to calculate their individual affect on consumer surplus. Consumer surplus is calculated as

$$\Delta CS = \left[ln \sum_{j} e^{-\alpha_{it} p_{jt} + \beta_{it} X_{ij}} - ln \sum_{j \neq n} e^{-\alpha_{it} p_{jt} + \beta_{it} X_{ij}} \right] \frac{1}{\alpha_{it}} \tag{8}$$

284 times, removing one station at a time. The loss in surplus from removing an existing station allows us to find the total value each station provides to all the drivers on the network. Because prices affect driver preferences for stations, this counterfactual is conducted using only 2017 data when all prices were zero.

The total value each station provides to all drivers from July 1, 2017 to December 31, 2017 varies from less than a dollar to more than 600 dollars. Figure 10a shows the histogram of station values and Figure 10b shows station values by business classification. While all groups have some low value stations, work, grocery, and parking garage stations have more stations with the high values, which are statistically different from apartment, entertainment, hotel, and industrial stations using a Mann-Whitney test at a significance level of 0.05.

Table 10 shows the number of stations by business classification in the top quartile of station value, which includes any station with a value of greater than \$144. Overall, 5 of the L3 stations exist in the top quartile, and grocery, work, and parking garage stations have the highest share of stations in this group while industrial, entertainment, and hotel stations have very few high value stations. Even though grocery and work stations serve a different numbers of unique drivers, they both remain high value stations.

Station value has implications for future endeavors to build charging stations. While building EV stations has been shown to increases adoption, not all stations are of equal value to drivers. Stations located at work, parking garage, grocery, and shopping stations provide the greatest value to drivers, which is consistent with the results from Section 3. While an area may have a large number of charging stations, some stations created almost no value to drivers, and not accounting for differences in station value to drivers could hinder the effectiveness of future station development.

5.1 Policy Implications

This paper has three policy implications for government subsidies and vehicle manufacturers. Charging station prices are an effective way to reduce future station congestion, charging subsidies may not be the most beneficial form of subsidy to drivers, and future station development should account for differences in station characteristics. Failure to account for driver price elasticity could lead to unnecessary congestion at charging stations and provide little benefit to drivers. A lack of understanding driver charging preferences can result in inefficient investment in EV charging.

First, price is an effective way to control station congestion and capacity constraints. Zhou and Li (2018) discusses problems of limited capacity for future charging in cities. This paper shows that drivers are very responsive to charging prices the use of charging prices may be a realistic option for decreasing future charging capacity constraints. As EV adoption continues to increase price subsidies my hinder adoption by increasing station congestion.

Second, subsiding EV charging may not be the most cost effective method for promoting EVs. Subsidizing EV charging costs more to the provider of the subsidy than it provides to the consumer. Alternative methods which eliminate this loss, such as subsidies on vehicle registration, reduced sales price, and investment in charging infrastructure may be of greater value to drivers. While the cost of station subsidies is relatively small over a six months, unlike developing more charging stations, this incentive does not build infrastructure for future EV drivers.

Third, future programs that invest in the development of EV charging should account for differences in driver charging preferences. EV charging stations are not created equal in the benefits they provide to drivers, and station investment should focus on building stations in locations where they will be most valued. Additionally, stations may be valued in different ways. Some stations serve a large population of drivers while others may create a significant benefit for only a few. Understanding these differences and implementing them is crucial for new station placement.

6 Conclusion

This paper looks at the effects of station characteristics and charging price subsidies on EV charging. I found that the elimination of the charging price subsidy decreased station charging on average by 55%, but the decrease was not uniform across all stations. The type of businesses near a station affect both the price elasticity of the station and total usage at a station. Stations located near grocery stores, work locations, and parking garages have the highest usage, and work and parking garage locations are less price elastic that other types of stations. Future policy approaches to advance EV adoption by governments or vehicle manufacturers should account for the important effects station characteristics have on usage and value to driver when expanding EV charging networks. Subsidizing charging prices may not be the most effective method for incentivizing EV adoption and may have a negative effect of on station congestion. Future work on the importance of station characteristics needs to be done to better understand differences in driver preference for level 2 chargers versus level 3 chargers and the potential differences this may have on EV adoption. Additionally, the market structure of EV charging needs to be better understood to further station development.

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Table 1: Driver Descriptive Statistics

# Drivers: 1094	mean	std	min	25%	50%	75%	max
# Visits	72.00	89.80	1.00	10.00	34.0	101.00	530.00
Total KWHs Charged	580.60	864.70	0.40	50.60	175.7	839.80	6962.40
Average Distance to Station (miles)	10.40	10.60	0.20	4.60	7.8	12.90	122.70
# Unique Stations Visited	8.00	8.20	1.00	3.00	6.0	10.00	160.00
Average Charging Fee (2018)	1.59	1.46	0.02	0.68	1.3	2.04	22.02

Note: This table shows descriptive statistics of individual driver's charging usage. **Source:** Author's calculation.

Table 2: Station Descriptive Statistics by Business Classification

	All	Grocery	Work	Industrial	Apartment	Parking	Shopping	Hotel
Visits	283.8	425.1	345.7	195.6	140.5	395.7	509.8	100.6
	(327.5)	(349.5)	(364.5)	(274.6)	(198.4)	(414.7)	(336.8)	(130.0)
KWHs Per Visit	7.4	5.5	8	7.1	6.7	8.8	6.9	7.7
	(3.9)	(3.5)	(3.6)	(3.5)	(3.7)	(2.6)	(2.5)	(3.0)
Total KWHs	2288.2	2560.8	2831.6	1795.3	1258.7	3743	3585.3	1019.3
	(2968.1)	(2944.8)	(3043.9)	(2870.9)	(1778.0)	(4195.3)	(2427.4)	(1938.8)
Visit Length (min)	104.1	51.4	128	142.6	103.6	123.3	91.7	106.7
	(54.8)	(27.5)	(46.4)	(66.1)	(58.1)	(45.2)	(35.5)	(35.4)
Unique Drivers	31.4	59.2	22.2	5.1	11.7	37.2	77.8	23.1
	(36.0)	(34.3)	(31.5)	(4.4)	(17.2)	(35.8)	(44.5)	(16.6)
Visit Frequency	14.4	7	25.5	34.2	11.9	21.8	7.3	6.8
	(23.4)	(4.5)	(34.3)	(41.5)	(16.7)	(31.0)	(4.2)	(13.4)
# Stations	278	50	42	25	18	24	14	9

Note: This table shows average descriptive statics of station usage by business type from July 1, 2017 to December 31, 2017 when all prices were zero. Standard errors are in parentheses. **Source:** Author's calculation.

Table 3: Stations that Remain Free and Stations that Become Not Free

	Remained Free				Become Not Free			
All Stations	2017	2018	%Δ	P Values	2017	2018	%Δ	P Values
Visits	169.7	163.4	-3.7%	0.4	175.2	88.1	-49.7%	1.13e-06
Total KWHs	1179.6	1207.6	2.4%	0.3	1403.7	690.7	-50.8%	1.93e-06
Visit Frequency	8.8	11.4	29.5%	0.07	8.5	7.3	-14.1%	1.22e-15
# Unique Drivers	30.4	27.7	-8.9%	0.3	33.8	23.0	-32.0%	7.89e-04
Charging Time (Min)	103.1	108.3	5.0%	1.30e-18	110.7	116.0	4.8%	7.52e-24
Customers Retained		11.1				8.2		
Customers Left		11.2				14.8		
New Customers		8.2				6.4		

Note: The figure shows the percent change in average station usage for stations that remain free and stations that become not free. **Source:** Author's calculation.

Table 4: Differences-in-Difference Results

	(1)	(2)	(3)
Difference-in-Difference Estimator			
$NOTFREE \times T$	-0.812^{***}	-0.891^{***}	-0.889^{***}
	(0.098)	(0.116)	(0.118)
Site Variables			
Level 2			-2.917^{***}
			(0.191)
Entertainment			-1.135^{***}
			(0.200)
Apartment			-1.732^{***}
			(0.332)
Hotel			-1.419^{***}
			(0.359)
Medicine			-0.425
			(0.257)
Other			-0.468^{*}
			(0.221)
Parking Garage			-0.447
			(0.337)
School			-0.987^{*}
			(0.383)
Shopping			0.311
			(0.264)
Work			-0.472
			(0.245)
Industrial Work			-0.949^{*}
			(0.372)
Spatial Variables			
ln(EV Station Density 1mi)		0.170	0.088
		(0.129)	(0.087)
ln(Total EVs in 10 mi)		0.383^{***}	0.365^{***}
		(0.094)	(0.046)
ln(Population Density)		0.034	
		(0.105)	
ln(Distance to Downtown)		0.039	
		(0.159)	
ln(Distance to Interstate)		0.200	
		(0.150)	
Control	3.629^{***}	0.292	0.153
	(0.049)	(0.211)	(0.184)
Constant	3.192^{***}	-0.632	3.631^{***}
	(0.047)	(0.853)	(0.405)
Month Fixed Effects	Yes	Yes	Yes
Station Fixed Effects	Yes	No	No
Observations	3,324	3,324	3,324
R^2	0.869	0.165	0.436

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$
Source: Author's calculation.

Table 5: Low and High Income Driver Mixed Logit Results

	All Stations		Low Income		High Income	
	mean	var	mean	var	mean	var
	β	σ	β	σ	β	σ
Price	-2.077***	2.272***	-1.922***	1.338***	-3.685***	6.843***
	(0.033)	(0.076)	(0.051)	(0.13)	(0.208)	(0.515)
Work	0.823***	0.0160	-0.0120	0.0170	0.828***	-0.0010
	(0.017)	(0.261)	(0.037)	(0.682)	(0.044)	(0.427)
Grocery	-0.0030	-0.0160	-0.139***	-0.0080	0.211***	-0.1760
	(0.013)	(0.23)	(0.027)	(0.476)	(0.042)	(0.349)
Parking	0.175***	0.0260	0.66***	-0.0360	-0.54***	0.010
	(0.024)	(0.31)	(0.041)	(0.526)	(0.067)	(0.655)
Shopping	-0.661***	-1.122***	-0.506***	-0.935***	0.137***	-0.0050
	(0.052)	(0.085)	(0.074)	(0.143)	(0.041)	(0.487)
Apartment	0.442***	0.721***	1.068***	-0.0650	-26.17*	-19.473*
	(0.052)	(0.139)	(0.046)	(0.505)	(11.564)	(7.653)
Medicine	0.356***	-0.0020	0.463***	-0.0050	0.616***	0.0160
	(0.021)	(0.246)	(0.048)	(0.592)	(0.044)	(0.425)
Distance to Driver's Home	-0.029***	0.016***	-0.011***	0.00	-0.082***	0.010
	(0.001)	(0.002)	(0.001)	(0.021)	(0.003)	(0.013)
# of Ports	-0.006***		-0.025***		0.018***	
	(0.001)		(0.002)		(0.002)	
Distance to Downtown	0.011***	-0.0020	0.029***	-0.00	0.009**	0.046***
	(0.001)	(0.005)	(0.001)	(0.009)	(0.003)	(0.004)
Station Density	0.007***	0.00	-0.0020	0.00	0.019***	-0.0010
	(0.001)	(0.003)	(0.001)	(0.004)	(0.002)	(0.006)
Level 2	-0.658***		-0.636***		-0.763***	
	(0.016)		(0.033)		(0.04)	
Av. Charging Time	0.01***	0.009***	0.01***	0.012***	0.013***	0.012***
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
Distance to Interstate	-0.028***	0.00	-0.056***	-0.00	-0.082***	-0.063*
	(0.003)	(0.013)	(0.005)	(0.019)	(0.009)	(0.025)
Log-Likelihood:	-162730		-42233		-31723	

Note: *p<0.05; **p<0.01; ***p<0.001
Source: Author's calculation.

Table 6: Urban and Rural Driver Mixed Logit Results

	All Stations		Near Downtown		Away from Downtown	
	mean	var	mean	var	mean	var
	β	σ	β	σ	β	σ
Price	-2.077***	2.272***	-1.433***	0.607***	-2.675***	2.556***
	(0.033)	(0.076)	(0.038)	(0.181)	(0.095)	(0.192)
Work	0.823***	0.0160	0.547***	0.0820	1.066***	-0.00
	(0.017)	(0.261)	(0.035)	(0.464)	(0.051)	(1.208)
Grocery	-0.0030	-0.0160	0.535***	0.449**	-0.0460	0.972***
	(0.013)	(0.23)	(0.041)	(0.17)	(0.039)	(0.117)
Parking	0.175***	0.0260	0.807***	0.436*	-0.907***	-0.010
	(0.024)	(0.31)	(0.051)	(0.208)	(0.099)	(1.716)
Shopping	-0.661***	-1.122***	0.176**	-0.3850	-1.654***	1.736***
	(0.052)	(0.085)	(0.054)	(0.238)	(0.16)	(0.19)
Apartment	0.442***	0.721***	0.73***	0.845***	-0.738***	0.1690
	(0.052)	(0.139)	(0.098)	(0.243)	(0.154)	(1.223)
Medicine	0.356***	-0.0020	1.007***	-0.2030	-0.482***	-0.0140
	(0.021)	(0.246)	(0.061)	(0.455)	(0.06)	(0.708)
Distance to Driver's Home	-0.029***	0.016***	-0.114***	0.178***	-0.009***	0.00
	(0.001)	(0.002)	(0.004)	(0.006)	(0.001)	(0.023)
# of Ports	-0.006***		-0.021***		-0.013***	
	(0.001)		(0.002)		(0.002)	
Distance to Downtown	0.011***	-0.0020	-0.043***	0.0060	0.019***	0.00
	(0.001)	(0.005)	(0.004)	(0.017)	(0.001)	(0.009)
Station Density	0.007***	0.00	-0.018***	-0.023***	0.0020	0.00
	(0.001)	(0.003)	(0.001)	(0.003)	(0.003)	(0.016)
Level 2	-0.658***		0.075*		-0.702***	
	(0.016)		(0.036)		(0.042)	
Av. Charging Time	0.01***	0.009***	0.011***	-0.01***	0.013***	-0.003***
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.001)
Distance to Interstate	-0.028***	0.00	-0.096***	0.0020	-0.028***	0.00
	(0.003)	(0.013)	(0.008)	(0.036)	(0.005)	(0.032)
Log-Likelihood:	-162730		-44672		-21781	

Note: *p<0.05; **p<0.01; ***p<0.001
Source: Author's calculation.

Table 7: Predicted Versus Actual Visits

Business Type	Predicted Stratified Share	Actual Share
Parking	0.11	0.09
Work	0.25	0.15
Other	0.53	0.48
Apartment	0.03	0.02
Shopping	0.01	0.06
Grocery	0.06	0.20

Note: The first columns shows the share of visits in each group predicted by the stratified data. The actual share of visits that occur in each group appear in the second column. **Source:** Author's calculation.

Table 8: Robustness Estimates

	Original Results		Minus Zero		Minus Two	
	mean	var	mean	var	mean	var
	β	σ	β	σ	β	σ
Price	-2.077***	2.272***	-1.983***	2.102***	-2.145***	2.198***
	(0.033)	(0.076)	(0.033)	(0.08)	(0.035)	(0.077)
Work	0.823***	0.0160	0.841***	0.0070	0.861***	0.0160
	(0.017)	(0.261)	(0.015)	(0.244)	(0.019)	(0.302)
Grocery	-0.0030	-0.0160	0.091***	0.010	0.03*	0.0070
	(0.013)	(0.23)	(0.012)	(0.22)	(0.015)	(0.257)
Parking	0.175***	0.0260	0.166***	0.0050	0.279***	-0.0020
	(0.024)	(0.31)	(0.022)	(0.279)	(0.027)	(0.361)
Shopping	-0.661***	-1.122***	-0.705***	1.306***	-0.304***	-0.788***
	(0.052)	(0.085)	(0.065)	(0.09)	(0.043)	(0.099)
Apartment	0.442***	0.721***	0.642***	0.0470	0.595***	0.703***
	(0.052)	(0.139)	(0.029)	(0.342)	(0.056)	(0.17)
Medicine	0.356***	-0.0020	0.554***	0.0030	0.383***	-0.0030
	(0.021)	(0.246)	(0.019)	(0.222)	(0.024)	(0.276)
Distance to Driver's Home	-0.029***	0.016***	-0.05***	0.039***	-0.024***	0.018***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
# of Ports	-0.006***		-0.006***		0.003**	
	(0.001)		(0.001)		(0.001)	
Distance to Downtown	0.011***	-0.0020	0.02***	-0.0040	0.007***	0.00
	(0.001)	(0.005)	(0.001)	(0.004)	(0.001)	(0.006)
Station Density	0.007***	0.00	0.003***	0.0010	0.004***	0.00
	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)	(0.003)
Level.2	-0.658***		-0.894***		-0.569***	
	(0.016)		(0.015)		(0.018)	
Av. Charging Time	0.01***	0.009***	0.009***	-0.008***	0.01***	0.01***
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
Distance to Interstate	-0.028***	0.00	-0.061***	0.0020	-0.011***	-0.0010
	(0.003)	(0.013)	(0.003)	(0.012)	(0.003)	(0.015)
Log-Likelihood:	-162730		-190440		-126280	

Note: *p<0.05; **p<0.01; ***p<0.001
Source: Author's calculation.

Table 9: Price Counterfactuals

Consumer Surplus when Price=0	\$151,816
Consumer Surplus when Price>0	\$129,752
Δ Consumer Surplus	\$22,064

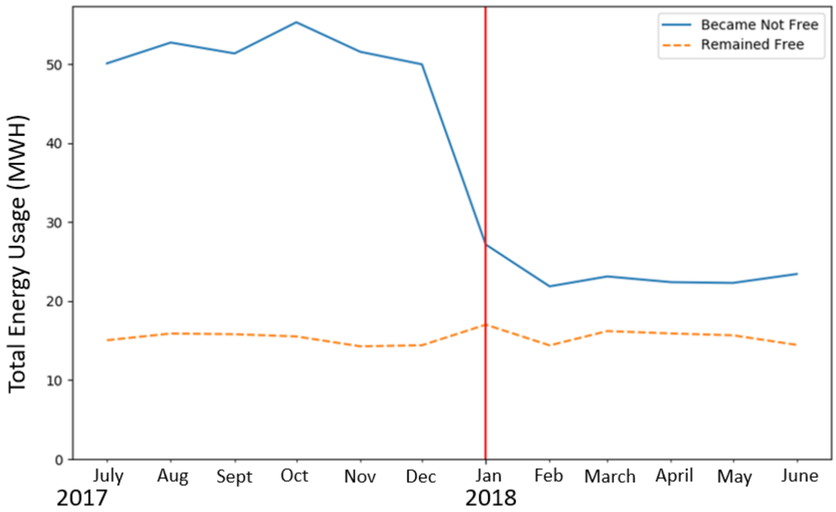
Note: This shows the observed consumer surplus and the counterfactual consumer surplus calculated from equation 7. **Source:** Author's calculation.

Table 10: Stations with Values in the Top Quartile

	Work	Parking	Grocery	Shopping	Apartment	Entertainment	Hotel
Q4 L3 Stations	0	1	4.00	0	0	0	0
Q4 L2 Stations	19	8	13	4	3	2	0
All Stations	42	23	50	14	15	23	8
Q4 Share	0.45	0.39	0.34	0.29	0.2	0.09	0

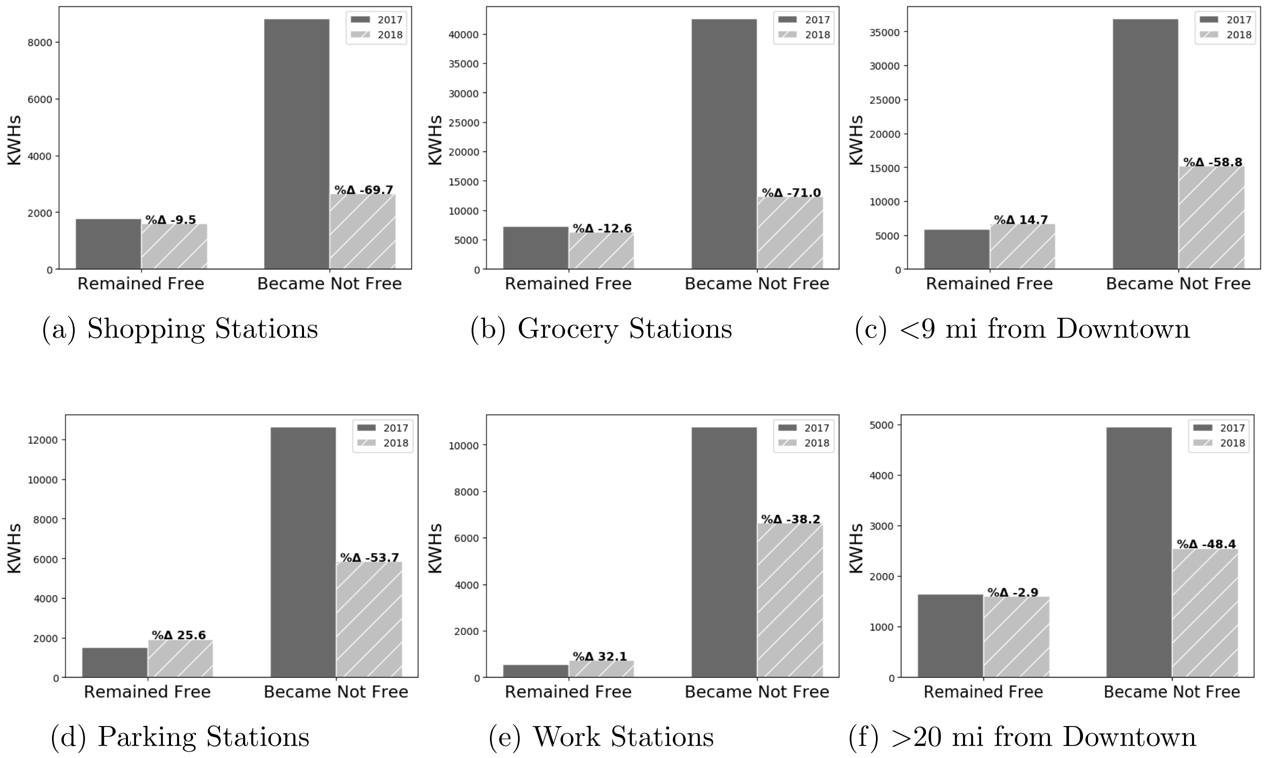
Note: This shows the stations with the highest values to drivers. **Source:** Author's calculation.

Figure 1: Charging Network Usage (MWH) Before and After the Subsidy Ended



Note: This figure shows total MWHs used at all stations on the network over time for stations that remained free in 2018 and stations that became not free. The vertical red line indicates when the subsidy ended and charging became not free. **Source:** Author's calculation.

Figure 2: Total Usage (KWH) by Station Business Classification and Location 2017 and 2018

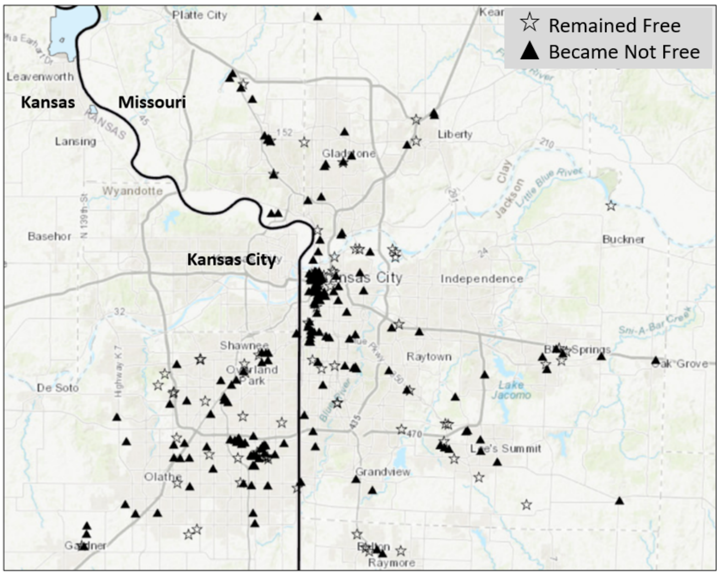


(a) Shopping Stations (b) Grocery Stations (c) <9 mi from Downtown

(d) Parking Stations (e) Work Stations (f) >20 mi from Downtown

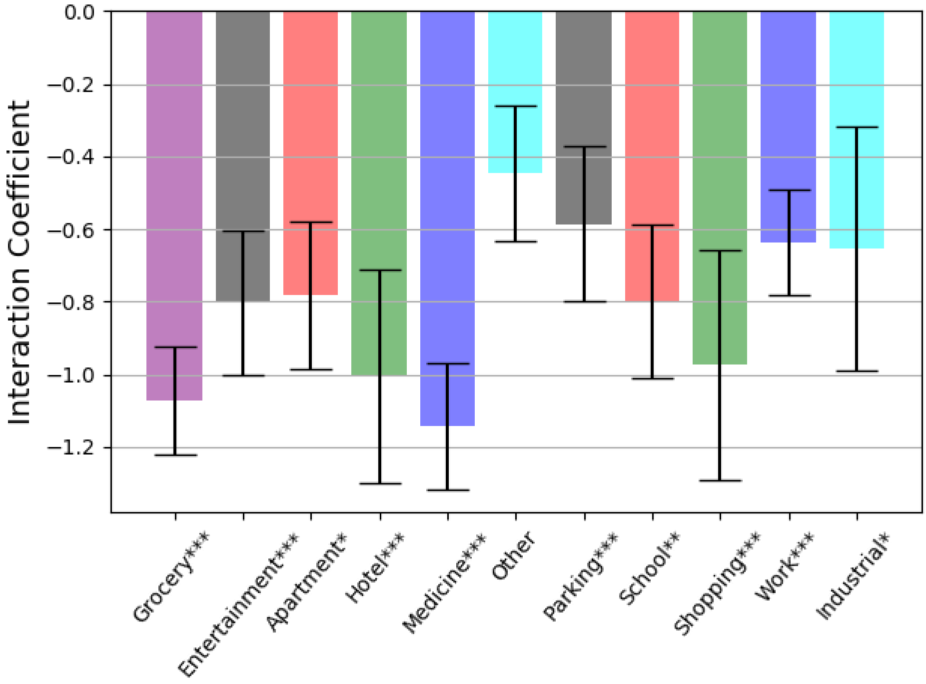
Note: These figures show total usage in 2017 and 2018 by station business classification and distance from downtown for stations that remain free and stations that become not free. **Source:** Author's calculation.

Figure 3: EV Stations in Kansas City



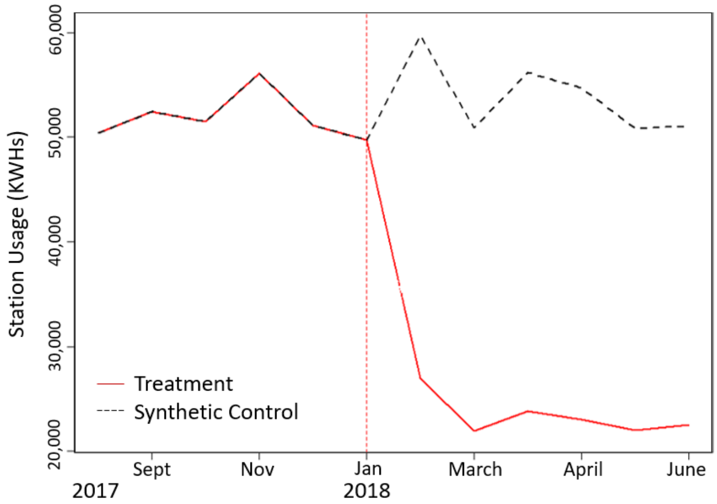
Note: This is a map of the Kansas City metro area with stations that remain free are shown as stars and stations that became not free are shown as black triangles. **Source:** Author's calculation.

Figure 4: Interaction Coefficients



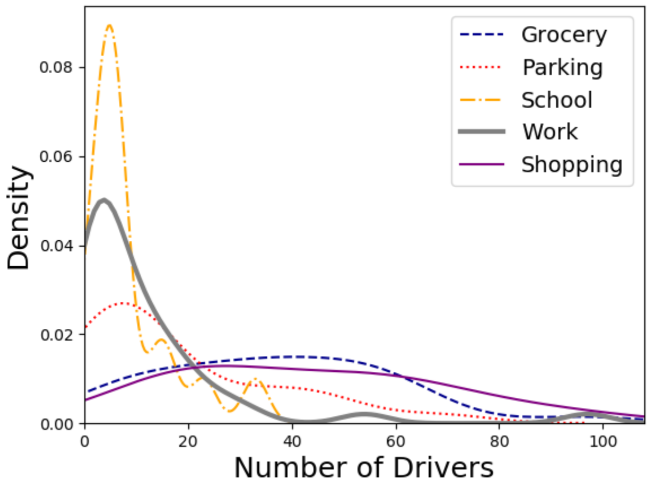
Note: This Figure shows coefficients for interactions between the difference-in-difference estimator and business types. The bars indicates 95% confidence intervals and $*$ indicates the change is statistically significant. **Source:** Author's calculation.

Figure 5: Synthetic Control



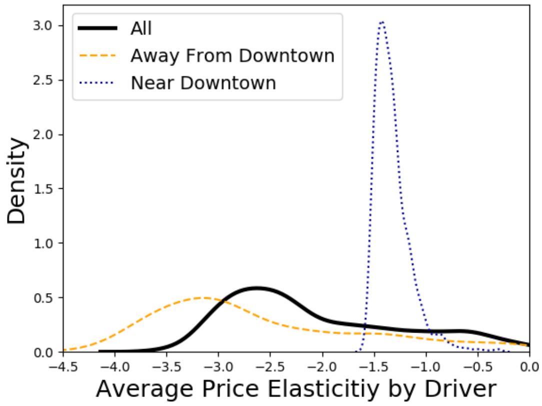
Note: This figure shows the actual usage and the synthetic control. **Source:** Author's calculation.

Figure 6: Unique # of Drivers at Each Station by Business Classification

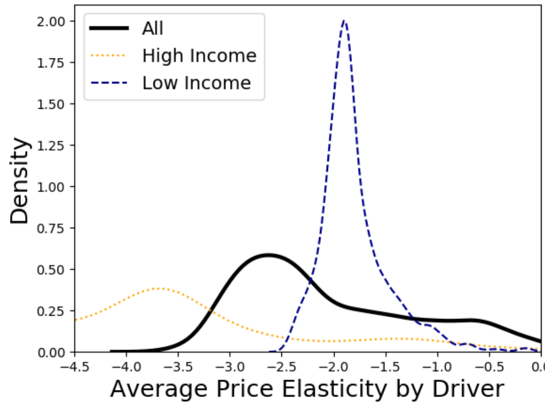


Note: This figure shows distributions of the number of unique drivers for each station by business classification. **Source:** Author's calculation.

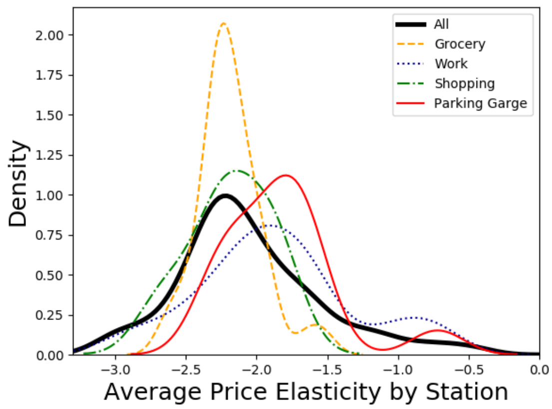
Figure 7: Driver and Station Elasticities



(a) Drivers by Distance to Downtown



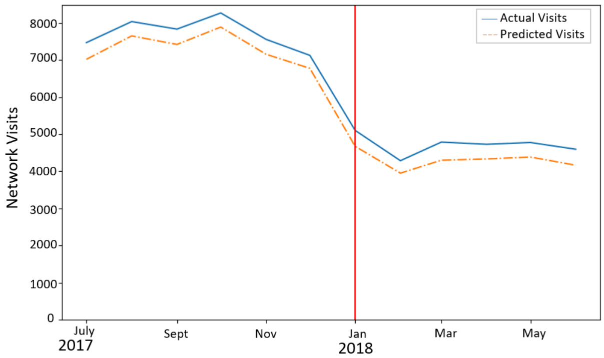
(b) Drivers by Income



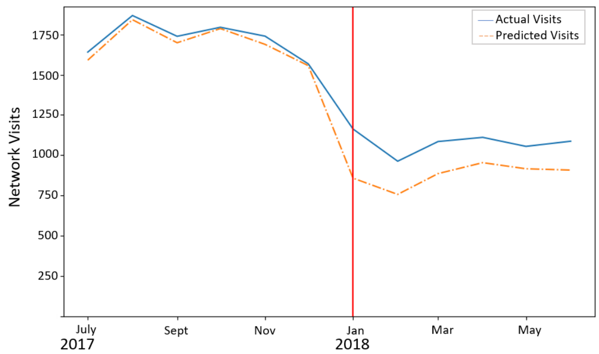
(c) Stations by Business Classification

Note: Figures a and b show individual average elasticity of drivers by drivers home location and income. Figure (a) looks at driver who live near downtown (less than 9 miles) and live far away from downtown (more than 20 miles). Figure (b) separates drivers by income: low income drivers live in zip codes with an average income of less than $76,000 and high income drivers live in zip codes with an average income of more than $118,000. Figure (c) shows average station elasticity by business classification. **Source:** Author's calculation.

Figure 8: Network Visits Actual and Predicted



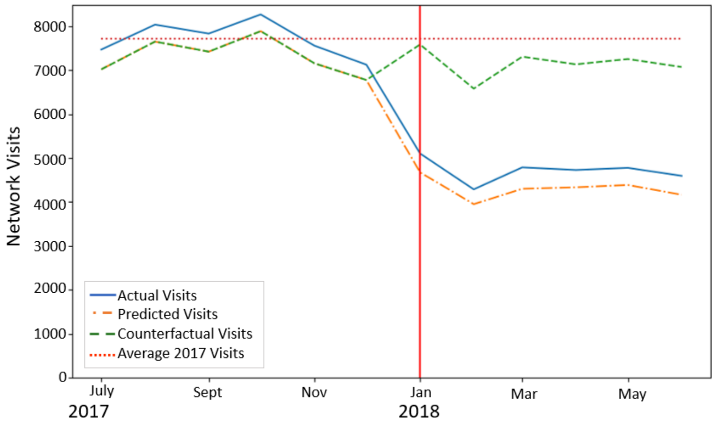
(a) Original Estimates



(b) Stratified Estimates

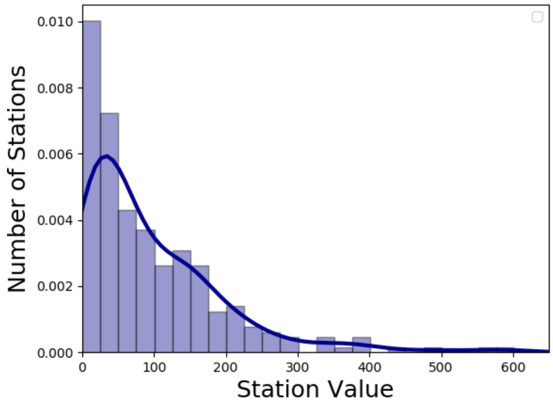
Note: Figure (a) shows actual charging visits on the network with the solid blue line and the number of visits predicted by the model with the orange dotted line. Figure (b) shows actual visits with the blue dotted line and shows the predicted visits by the stratified data with the orange dotted line. The vertical lines indicate the end of the subsidy. **Source:** Author's calculation.

Figure 9: Network Visits: Actual, Predicted, and Counterfactual

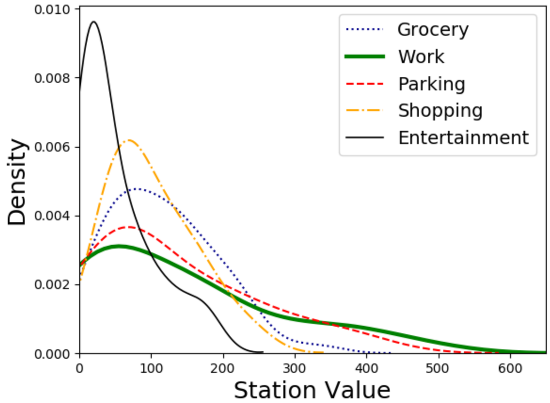


Note: The solid blue line shows actual visits on the network. The orange dotted line shows predicted visits. The green dotted line shows predicted visits if prices had remained zero. The red dotted line shows the average number of visits in 2017. **Source:** Author's calculation.

Figure 10: Individual Station Contribution to Consumer Surplus



(a) All Stations



(b) By Station Type

Note: Figure (a) shows the histogram of station values. Figure (b) shows the distribution of station values by business classification. **Source:** Author's calculation.