Preferences and Investments in Electric Vehicle Fast Charging: A Study of Tesla's Supercharging Network*

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Abstract

The two of the last three administrations in the United States made it a priority to combat climate change. To that end, several policies were introduced to support the electric vehicle (EV) industry. This paper studies Tesla's investment in the network of Supercharging stations as a tool to promote the attractiveness of its EVs. The model consists of three components: consumer demand for new vehicles, pricing competition among automakers, and Tesla's investment in the network. The demand model incorporates consumer heterogeneity reflecting fast charging accessibility in their home counties and along their travel routes. Tesla's investment decision features various locations in communities and along highway corridors. I follow the revealed preference approach used by Holmes (2011) and Houde et al. (forthcoming) to set-identify the investment cost parameters. The results show that consumers value both access to in-community and along-highway fast charging and both effects are equivalent to a 4 percent drop in vehicle prices. The counterfactual analysis shows that the EV purchase subsidy has an expansionary effect on the Supercharging network. The effect is larger for community locations and depends on the demographics of the location. The paper also shows that ignoring the Supercharging network or adjustments in the network underestimates the positive effect of the EV purchase subsidy on consumer welfare and emission reductions.

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1. Introduction

To combat climate change and reduce emissions, the Biden-Harris Administration sets a target that by 2030, 50% of all new vehicles sold in the United States should be electric vehicles (EV) along with 500,000 new EV charging stations. With that goal, the federal government has been heavily subsidizing the EV industry from various aspects. For example, the Inflation Reduction Act provides a $7,500 tax credit for new EVs and $4,000 for used EV from 2022 to 2032 and the Bipartisan Infrastructure Law provides $5 billion over 2022 to 2026 to help states create a network of EV charging stations especially along the Interstate Highway System. The policies have been increasingly focusing on fast charging network along highway corridors, aiming to give consumers confidence in EV long-distance trips.

However, work in the economics literature that studies EV fast charging is relatively scarce. Fast charging affects the EV industry from various dimensions and studying it would require scrutiny from multiple aspects. A first question to ask is whether and how fast charging affects consumers' EV adoption behaviors. A subsequent question is how that in turn affects firms' incentives to invest in fast charging infrastructure. A third question is whether and how the answers to the first two questions change under different policy environments. Finally, the most important question to ask is what the environmental impacts are. This paper investigates the role of fast charging in the EV industry by assessing the effectiveness of fast charging network in promoting EV sales and understanding how Tesla, the largest EV automaker in the US, uses its fast charging network (called Supercharging stations) as a tool to increase market penetration. This paper also studies how Tesla's incentives respond to government policies and the environmental impacts of such policies with a careful treatment of the fast charging network and long-distance trips made by EVs.

To that end, I develop a model of consumer demand and firms' competition in prices that is able to predict firms' profits for any given charging network configuration. Those profit predictions are then brought to a model of Tesla's investment decision on the expansion of the Supercharging network, which takes into account automotive profits and investment costs. Also incorporated throughout the model are existing policies, which can be turned off or modified to calculate policy effects.

I model consumers' demand for individual conventional and green vehicles using a random coefficient logit framework, while incorporating a rich structure on the tastes for the fast charging network. First, consumers value the network in two different use cases: they value stations within their community for charging during daily activities; they also value stations along the highway system for long-distance trips. Second, the values they attach to the highway charging network are idiosyncratic and depend on their long-distance travel patterns. This structural model of consumers' heterogeneous preferences for the fast charging network is made possible by utilizing an extensive dataset on simulated US household long-distance trips, whose routes are obtained from OpenStreetMap. Observing the consumer demand and the current charging network, car manufacturers engage in a Bertrand competition of vehicle prices to maximize static profits.

The demand and pricing model will be jointly estimated using Generalized Method of Moments. In addition to the orthogonality conditions derived from the demand and marginal cost instruments, I also include a micro-moment that matches the observed and model predicted popularity of EV models at the county level to better identify parameters on preferences for fast charging.

On the investment side, I maintain a very fine level of geographic details of highway and county locations, including more than 100 segments of the Primary Interstate Highways and more than 3000 counties in the contiguous US. Tesla chooses where to build Supercharging stations by maximizing the present discounted value of all automotive profit streams net of the Supercharger investment costs. The investment costs are modeled with several components: the cost of covering a county consists of a constant fixed cost, an estimated lifetime rent costs, costs of larger station sizes proxied by the county population and an unobserved cost component; the cost of covering a highway segment consists of a constant fixed cost for every station, an estimated lifetime rent costs, costs of larger station sizes proxied by the annual number of trips going through the segment and an unobserved cost component.

The optimal investment plan is the outcome of three trade-offs. The first trade-off is between covering a more populous county with higher investment costs and higher incremental automotive profits and covering a smaller county with lower costs and lower marginal profits. The second trade-off is the highway analogy of the first one - covering a heavily traveled highway with higher investment costs and higher marginal profits versus a less traveled highway with lower costs and lower marginal profits. The final trade-off is between a county and a highway: covering a county could be very effective in promoting sales among local residents while have little impacts on consumers elsewhere; on the other hand, covering a highway might have a smaller effect on individual consumers but might reach more people.

I use a revealed preference approach to infer the magnitudes on the two sides of the trade-offs, and recover the investment cost parameters using a moment inequality approach, following Holmes (2011) and Houde et al. (forthcoming). I observe the actual plan that Tesla chose, and consider alternative plans that deviate slightly from the actual plan. For example, if the actual plan covers a county 2 years before another county, the proposed alternative plan could reverse this order while keeping the rest of the plan unchanged, reflecting the first trade-off. Those alternative plans are the ones Tesla could have chosen but decided not to, which implies the value of the actual plan should be higher than the alternative ones. After subtracting the equilibrium automotive profits under the alternative network (with adjusting equilibrium prices), I find values of the cost parameters that render the observed plan more profitable than other plans. The inequalities derived from the revealed preference approach are linear inequalities in the cost parameters, and as a result, the (non-empty) set of parameters that satisfy all inequalities constitutes a connected and convex polygon, which will be fully characterized by its vertices.

The estimation results confirm that the accessibility of the fast charging network has a significantly positive effect on EV purchase, and both the stations within communities and stations along highway corridors are valued. In particular, the coefficients on local fast charging and highway fast charging are roughly equal, i.e. building a fast charging station in a consumer's local area has a similar effect to covering highways on all of her long-distance travel routes. Together with the estimated price coefficients, it implies that covering the local community or covering all long-distance travel routes of a consumer is equivalent to a 4 percent reduction in vehicle prices for an average consumer, or $2,256, evaluated at the average effective price of a Tesla vehicle. Moreover, lower effective prices and accessible EV fast charging are complements in boosting EV sales, which is key to understanding the indirect promotional effects of EV purchase subsidies on the fast charging network.

The estimated set of the investment cost parameters implies the median cost of a community Supercharging station is between $4.1 million and $6 million, and the median cost of a highway Supercharging station is between $2.03 million and $2.5 million. These estimates are the present discounted value of lifetime costs associated with a station, including the initial investment and all future operating and maintenance costs, and are consistent with engineering estimates. Note that the future costs constitute a significant proportion of the total costs (around 80%), highlighting that future costs are within Tesla's consideration when making investments. The county population and highway utilization also increase costs for community stations and highway stations respectively, indicating stations with more chargers are required for these locations and costs increase accordingly.

I then use the estimated model to evaluate the effects of the EV purchase subsidy on the roll-out of the Supercharging network. To do so, I need to solve the optimal investment plan for Tesla in the new policy environment. Since dynamics are important in Tesla's investment problem, I use a new method to calculate an approximation to the optimal network in the dynamic setting, whereas the previous literature finds an approximation to the optimal network in the static context. The method allows me to understand how Tesla would adjust its Supercharging network in response to a change in EV purchase subsidy and the consequent impacts on consumer welfare and emissions. The results show that increases in the purchase subsidy could stimulate Tesla's investments in fast charging both within communities and along highway corridors. The expansionary effects are larger for counties and more developed areas. It implies that if the government wants to develop fast charging along highways and in disadvantaged areas, extra subsidies targeting low-income households or charging infrastructure in those locations might be necessary. Moreover, through the expansionary effects on the fast charging network, the purchase subsidy achieves additional consumer welfare gains (an estimated $93 million increase due to a 20% increase in Tesla purchase subsidy from 2017 to 2020) and emissions reductions (an estimated 270 thousand tons of carbon dioxide emissions reduction, or $21 million worth of social value in the same scenario); any work that ignores the fast charging channel is likely to underestimate the benefits.

This paper relates to three strands of literature. First, there is a fast-growing literature on the EV market and the effects of government policies (Li (2019), Li et al. (2017), Springel (2021), Sinyashin (2021), Holland et al. (2016), DeShazo et al. (2017) and Xing et al. (2021)). I contribute to this literature by providing a rich and detailed model of EV fast charging which incorporates heterogeneous consumer preferences for fast charging and Tesla's dynamic investment decision in a high dimensional location space. The closest to this paper are Li (2019) and Sinyashin (2021). The main differences are Li (2019) assumes consumers from any geographic markets have identical value for the highway charging network and she has a static model of charging station investments; Sinyashin (2021) models consumer inconvenience costs of charging, which depends on the exogenous charging infrastructure within a local market and does not consider highway charging network. To my knowledge, this paper is also the first to provide cost estimates of charging infrastructure under a dynamic framework in the economics literature.

Second, this paper also contributes to the economy of density literature (Holmes (2011) and Houde et al. (forthcoming)). A main difficulty in this literature is that solving for the exact solution to the optimal network is impossible due to the fine level of geographic details, which poses a challenge in counterfactual analyses. I employ a similar modeling approach and partial identification strategy on Tesla's investment problem, and apply a new method to solve for an approximate solution in the dynamic setting, compared to an approximate solution in a simplified static environment in Houde et al. (forthcoming).

Finally, this paper relates to the literature on endogenous choices of product characteristics (Fan (2013), Sweeting (2013), Wollmann (2018), Eizenberg (2014) and Crawford et al. (2015)) by modeling the endogenous and dynamic choice of Tesla's Supercharging network and recovering the costs associated with improving product characteristics. This paper also speaks to how government policies can affect firms' choice of product positioning.

The rest of this paper is organized as follows. Section 2 gives an overview of the EV industry, introduces different types of EV and EV charging, and summarizes relevant government policies. Section 3 introduces the datasets. Section 4 lays out the model. Section 5 and Section 6 describe the identification and estimation strategies for the demand and pricing model, and Tesla's investment model respectively. The subsequent section presents the estimation results. The penultimate section conducts the counterfactual analysis and the final section concludes.

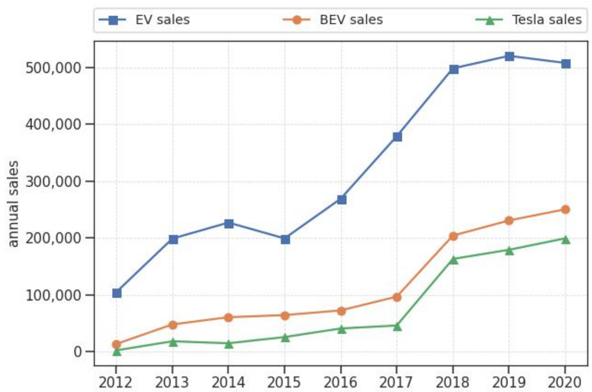
2. Institutional details

2.1 Overview of the EV market

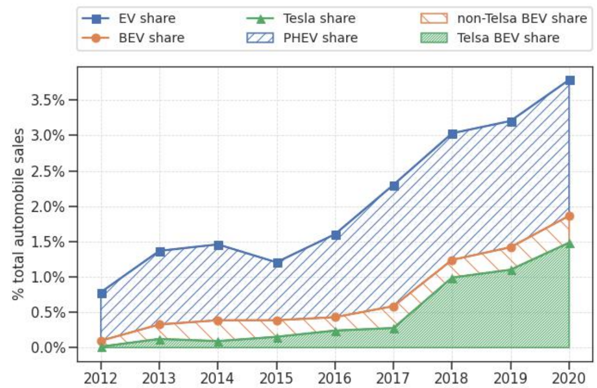
Since the introduction of Nissan LEAF and Chevrolet Volt in December 2010, the US EV market has grown exponentially in the last decade. In 2012, around 100,000 vehicles with an electric battery were sold in contiguous US and this number increased five-fold, reaching 508,174 units in 2020. Among them, plug-in hybrid EVs (PHEVs), which have both a rechargeable battery pack and a gasoline tank as a backup, made up for 90% of EV sales in 2012 but only half the sales by 2020. The rising EV type has been the battery EVs (BEVs), running solely on electricity stored in their battery packs, whose sales soared by almost 20 times, from 13,021 units in 2012 to 250,252 units in 2020. Figure 1 shows the growth of the EV market from 2012-2020.

Figure 1: EV Market Growth, 2012-2020

(a) EV Sales



(b) EV Shares Among Automobile Sales



Tesla is a major BEV manufacturer in the US. It introduced the flagship sedan Model S in mid 2012 and subsequently the SUV Model X in 2015, and strengthened its leading position in the BEV market by bringing up its most popular Model 3, selling an unprecedented 358,107 units in 3.5 years since its first delivery in mid 2017. This number is more than the sales of all non-Tesla BEVs from 2012-2020 combined. The four Tesla models (Model 3, S, X and Y) accounted for two-thirds of total BEV sales. Other major BEV models include Nissan LEAF, Chevrolet Bolt, Fiat 500e, Volkswagen e-Golf, among others. Table 1 shows the best-selling BEV models and their sales numbers.

Comparing to the US automobile industry as a whole, EVs accounted for 3.8% of all light-duty passenger cars and trucks sold in 2020. This share may still seem small, but this cannot mask the importance of EVs to the US economy. Industry experts project the market share of EVs will reach 30% by 2030, and 45% by 2035.[1] The federal and local governments have been playing a significant role in this issue. For example, the Biden-Harris Electric Vehicle Charging Action plan has set a target of 50% of electric vehicle sale shares in the

[1] https://www.statista.com/statistics/744946/us-electric-vehicle-market-growth/ and https://evadoption.com/ev-sales/ev-sales-forecasts/.

Table 1: Battery Electric Vehicle Sales

Make	Model	Sales	Share of total BEV sales	First year of sales
Tesla	Model 3	358,107	34.5%	2017
Tesla	Model S	168,832	16.3%	2012
Nissan	LEAF	136,682	13.2%	2011
Tesla	Model X	91,005	8.8%	2015
Chevrolet	Bolt	77,222	7.4%	2016
Tesla	Model Y	68,026	6.6%	2020
Fiat	500e	26,031	2.5%	2013
Volkswagen	e-Golf	18,860	1.8%	2014
BMW	i3	12,076	1.2%	2014
Audi	e-tron	11,888	1.1%	2019
Other BEV models		69,391	6.7%	NA

US by 2030.[2] California, the largest state in EV adoption, has an objective to achieve five million zero-emission vehicles (ZEVs) on the road by 2030 and requires that all new cars and passenger trucks sold in California be ZEVs by 2035.[3] Washington state has set a target that all vehicles of model year 2030 or later sold, purchased or registered in the state be electric, making it the state with the earliest all-electric target in the nation.[4]

2.2 Batteries and charging

Battery range is the distance a fully charged EV can travel. It varies with EV types, models and over time. PHEVs tend to have a smaller battery range, since they can run on their internal combustion engines when the battery is depleted. The median battery range of a PHEV is about 20 miles, making it best for daily commute and short trips. BEVs tend to have larger batteries, with a median of 111 miles. The battery capacities also vary greatly across BEV models and over time. Tesla stands out for its battery technology and long-range

[2] https://www.whitehouse.gov/briefing-room/statements-releases/2021/12/13/fact-sheet-the-biden-harris-electric-vehicle-charging-action-plan/.

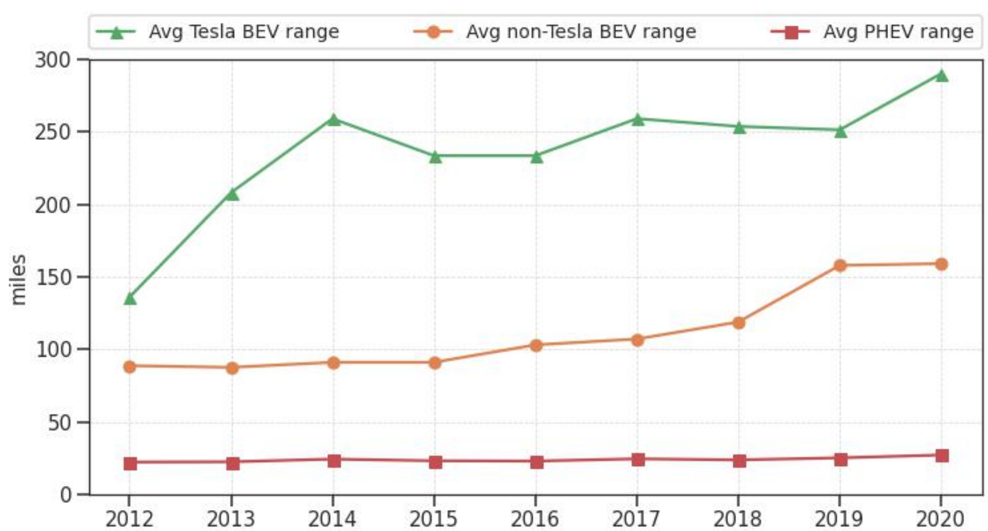
[3] https://www.cpuc.ca.gov/industries-and-topics/electrical-energy/infrastructure/transportation-electrification.

[4] https://electrek.co/2022/03/25/washington-passes-bill-targeting-all-electric-car-sales-by-2030-for-real-this-time/.

vehicles. Its 2020 Model X can travel 351 miles on a single charge, and all of Teslas models can surpass 300 miles of range with the basic version or the long-range version. On the other hand, models like Fiat 500e, Chevrolet Spark EV and Honda Fit EV can only go less than 100 miles.

EV ranges have also been rising steadily over time. Figure 2 plots the average EV range from 2012 to 2020. The average BEV range increased from 136 miles in 2012, to 290 miles in 2020 for Tesla models, and from 89 miles in 2012, to 159 miles in 2020 for non-Tesla models. Behind this increase is the improvement in battery technologies and declining battery costs. The estimated lithium-ion battery pack cost per kilowatt-hour was $712 in 2012, and dropped to $137 in 2020.[5] This decline was significant, since battery costs accounted for more than 30% of the selling price of BEVs on average.[6]

Figure 2: Average EV Battery Range (Miles), 2012-2020



One of oft-cited reasons why people delay buying EVs, especially in earlier years, is that they worry the battery will be depleted before reaching the destination or a charging station, referred to as the "range anxiety". The improvement in battery ranges has alleviated this

[5]https://www.statista.com/statistics/883118/global-lithium-ion-battery-pack-costs/.
[6]https://www.instituteforenergyresearch.org/renewable/electric-vehicle-battery-costs-soar/ and own calculation.

concern, together with the development of a robust and reliable charging network. There are three types of EV charging, level 1, level 2, and direct current fast charging (DC fast charging, or DCFC). Level 1 charging is the slowest - it can be used with any standard 120-volt outlet, replenishing between 3 and 5 miles of range per hour. Level 1 charging works better for PHEVs than for BEVs because of its slow speed and is mostly seen in residential areas. Level 2 charging adds an average of 25 miles of range per hour and requires installing a charger and plugging into a 240-volt outlet. It can fully charge an average BEV in about 8 hours, making it best for overnight charging. It can be seen at a wide variety of locations, including homes, workplaces, and public areas like stores and restaurants. All PHEVs and BEVs except Tesla use the same J1772 connector for Level 2 charging, and all Tesla cars include an adaptor with the purchase that allows Tesla models to charge using the J1772 connector. In this paper, I assume all EV models can charge at any level 2 charger universally.

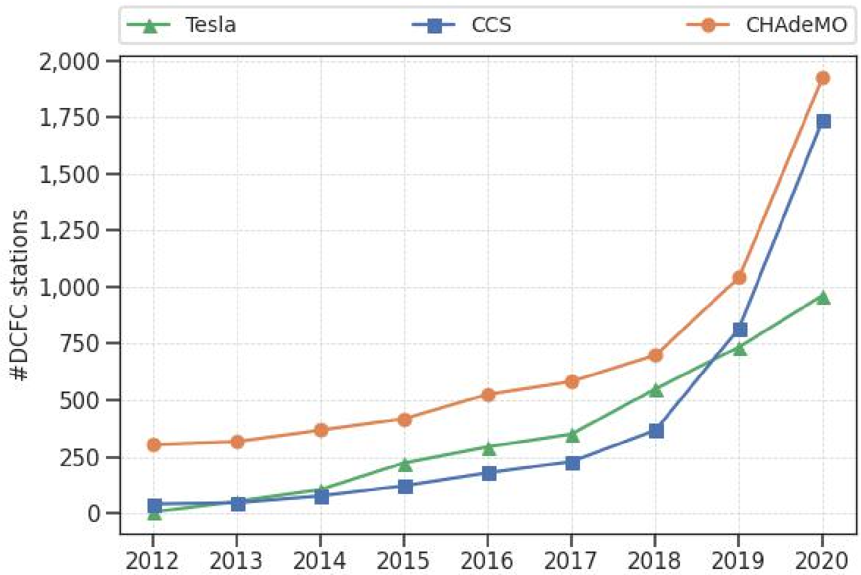
DC fast charging is the fastest type of charging, as its name stands. It can provide up to 250 miles of range per hour and can typically charge up to 80% in about 30 minutes. Fast charging is only available on some BEVs, and there are three incompatible standards, Tesla, Combined Charging System (CCS), and CHAdeMO. The Tesla DC fast charging stations, called Tesla Supercharging stations or Superchargers, can only be used for Tesla models.[7] CCS is mostly used among European and American automakers, including BMW, Ford, GM and Volkswagen. CHAdeMO is commonly seen in Japanese companies, such as Nissan and Mitsubishi.[8] Most CCS DCFC stations have CHAdeMO DCFC chargers available, and vice versa. However, Tesla Supercharging stations do not normally have the other two standards available. Figure 3 shows the number of DCFC stations in the US by standard.

The main use cases of DC fast charging include topping off the battery for intra-urban

[7] Tesla Superchargers use the CCS standard in Europe, and allows non-Tesla BEVs to use in selected countries. Currently, there are no reliable and widely available adaptors among the three fast charging standards in the US.

[8] The BEV models with DC fast charging are: Tesla Model 3, Tesla Model S, Tesla Model X, Tesla Model Y (Tesla standard); Audi e-tron, BMW i3, Chevrolet Bolt, Chevrolet Spark EV, Ford Focus Electric, Honda Clarity EV, Hyundai Ioniq EV, Hyundai Kona Electric, Jaguar I-PACE, Kia Niro EV, Kia Soul EV (since 2019), MINI Cooper Electric, Porsche Taycan, Volkswagen e-Golf (CCS standard); Kia Soul EV (before 2019), Mitsubishi i-MiEV and Nissan LEAF (CHAdeMO standard).

Figure 3: Number of DCFC Stations in the US, 2012-2020



travelers during the day and enabling inter-city long-distance travel through quick recharger. These correspond to the two types of locations where DCFC stations are usually built - in communities and along highway corridors. Since more miles are driven in a long-distance trip than a daily intra-urban trip, constructing a reliable DCFC network along major highways has become a recent emphasis by policymakers who try to reduce emissions and combat climate change. Programs exist in various states allowing the costs of establishing highway DCFC stations to be fully or partially subsidized.[9] Tesla moved first in deploying a fast charging network along the highway network - in fact, the first coast-to-coast trip across the US was completed by a Tesla Model S relying only on the Supercharging network in January 2014.[10] Figure 4 shows the maps of Tesla Supercharging stations and non-Tesla DCFC stations in 2014, 2017 and 2020.

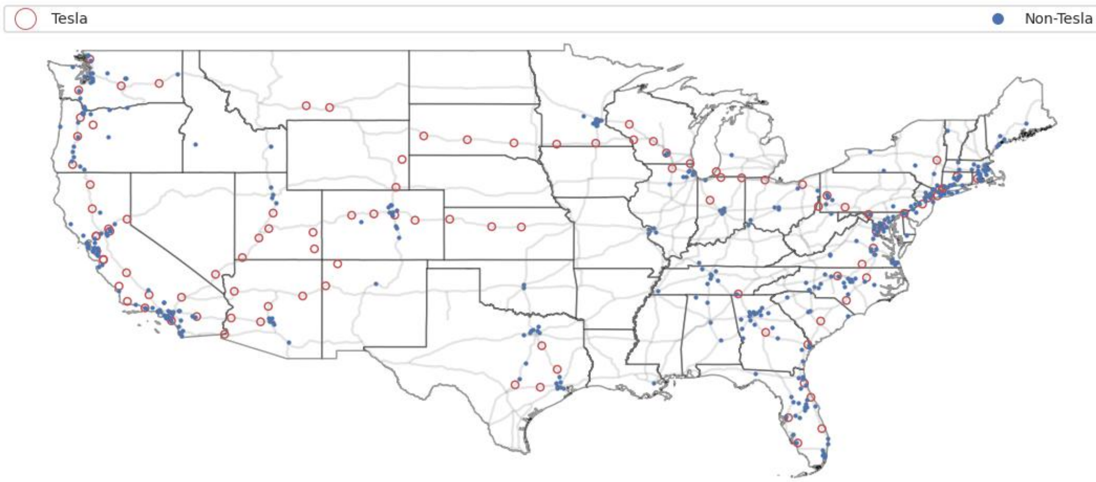
While Tesla Supercharging stations are solely built by the Tesla company, CCS and CHAdeMO DCFC stations are built by various entities. The ChargePoint Network accounts

[9]Based on my search on state level charging infrastructure subsidies, most states targeting DCFC stations (rather than EV charging stations in general) have some form of requirement that the DCFC stations need to be close to major highways.

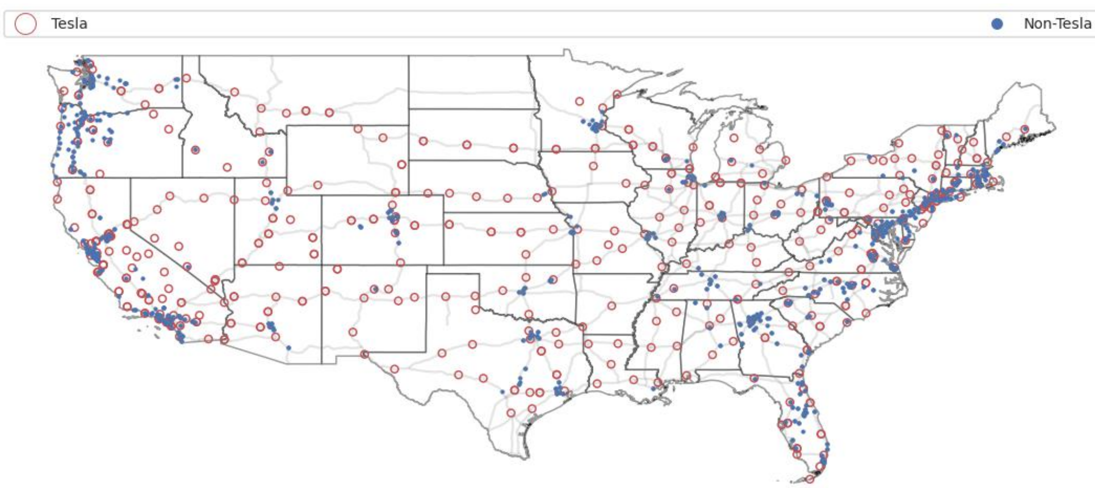
[10]https://www.tesla.com/blog/first-across-us-supercharger.

Figure 4: Tesla Supercharging stations and Non-Tesla DCFC stations in the US

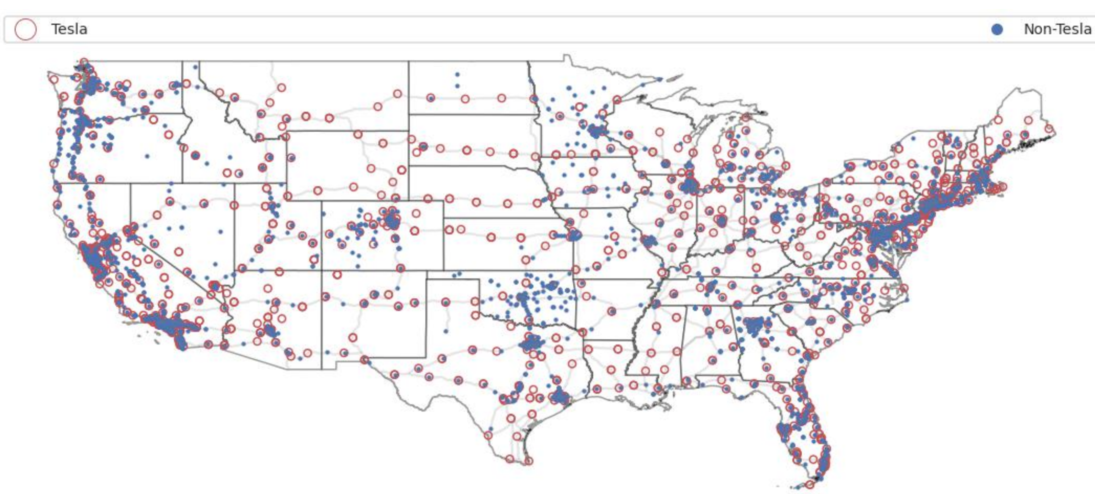
(a) 2014



(b) 2017



(c) 2020



for around 30% of non-Tesla DCFC stations, which operates in a decentralized way, like the "Airbnb" of DCFC charging. Anyone can host a ChargePoint DCFC station at their own preferred location, set their own charging prices, and enjoy the driver base and maintenance services ChargePoint provides. Following the ChargePoint Network is non-networked DCFC stations, accounting for another 25% of non-Tesla DCFC stations. The third place is Electrify America, which is a not-for-profit organization funded by the Volkswagen Diesel Emissions Environmental Mitigation Trusts,[11] owning 22% of non-Tesla DCFC stations. The remaining 22% are owned by various charging station companies including eVgo, Blink, Greenlots etc, each accounted for less than 10%. Given the numerous participants in building non-Tesla DCFC stations and the not-for-profit nature of some participant, non-Tesla DCFC stations will be thought of as competitively built in this paper.

2.3 Government involvements

Policymakers realized very early that the EV market is featured by the "chicken and egg" problem. That is, consumers are only willing to buy EVs if the charging infrastructure is well developed, and the charging stations are only profitable when EVs are widely adopted. To solve this dilemma and to speed up EV penetration, federal and state governments have been very active in this domain and allocated resources on various fronts. On the EV purchase side, the federal government offered up to $7,500 of federal income tax credits for new BEV and PHEV purchase since 2010;[12] some state governments[13] and utility companies provide purchase credits as well.

On the charging infrastructure side, state governments[14] and utility companies have re-

[11] In 2016, Volkswagen entered into a settlement to partially resolve alleged Clean Air Act violations by cheating federal emission tests, and agreed to spend $4.7 billion to mitigate pollution and make investments to support zero-emission vehicle technology, including building a network of fast charging stations.

[12] The credit phases out when a manufacturer sells 200,000 qualifying vehicles, and Tesla and GM reached the limit in 2020.

[13] California, Colorado, Connecticut, Delaware, Louisiana, Maine, Massachusetts, New York, Oregon, Pennsylvania, and Texas in my data period (2012-2020).

[14] California, Colorado, District of Columbia, Idaho, Maryland, New Mexico, Oklahoma, Pennsylvania, Rhode Island, Vermont and Washington in my data period (2012-2020).

bate programs of various generosities that help investors recoup the equipment costs. More recently, the Biden-Harris Administration announced in early 2022 that the National Electric Vehicle Infrastructure Formula Program will make available nearly $5 billion to help states build out a network of EV charging stations along designated highway corridors, particularly along the Interstate Highway System.[15] Monetary supports on charging infrastructure usually exclude Tesla-owned stations, since Tesla stations are proprietary assets of the company and can only be enjoyed by Tesla drivers.

On the manufacturing side, California initiated the ZEV mandate, which requires a growing proportion of the vehicles sold by large automakers be zero-emission.[16] Based on the total sales volume of fossil fuel vehicles in the previous year, each automaker is required to reach a credit each year by selling ZEVs, and the number of credits a qualifying clean vehicle earns depends on the type of ZEV and its battery range.[17] These credits can be stored for future use or traded among manufacturers. Tesla is the largest seller of these credits, because all of its sales are electric which earn credits but consume none. By 2020, 9 other states have opted into the ZEV program, including Connecticut, Maine, Maryland, Massachusetts, New Jersey, New York, Oregon, Rhode Island and Vermont. In this paper, the participation in this program is thought of as lowering the marginal costs of production of EVs (the extent depends on the number of credits an EV earns) but having no direct impacts on consumers (consumers will be indirectly affected through vehicle prices).

3. Data

My empirical analysis combines multiple data sources for estimation, including information on vehicle sales, vehicle characteristics, government subsidies on EV purchase and charging infrastructure, gasoline and electricity prices, EV charging stations, US Primary Interstate

[15] https://highways.dot.gov/newsroom/president-biden-usdot-and-usdoe-announce-5-billion-over-five-years-national-ev-charging.

[16] The vast majority of zero-emission vehicles sold are electric.

[17] For example, BEVs earn more credits than PHEVs.

Highways, US household travel patterns and travel routes, and US household demographics.

The US vehicle annual sales data is obtained from IHS Markit (formerly R.L.Polk), which accurately reflects new car registrations at each state's Department of Motor Vehicles. Each model is defined as a make-model-fuel type combination,[18] and the data contains sales numbers for passenger vehicle and light duty truck models. The panel includes 49 geographic areas (48 contiguous US states and Washington D.C.), and 9 years (2012-2020), totaling 441 markets. Consumers' choice sets are assumed to be all models with positive sales in a market, and the sizes of the choice sets range from 204 to 285, with an average of 252 models available in a market. To improve the granularity of the sales data, I also obtain the county-year level sales of each EV model for California and New York State which are published by the California Energy Commission[19] and New York State Energy Research and Development Authority[20] respectively. They are used to form a micro-moment which is key to identifying the preference parameters on DCFC infrastructure (see Section 5).

The geographic datasets (including maps of US Primary Interstates, EV charging station locations, and household travel patterns) warrant a more detailed discussion. There are 70 Primary Interstate Highways in the Interstate Highway System, whose maps are obtained from the Wikimedia Commons. The lengths of the Primary Interstates range from 12 miles to 3,020 miles, so I divide Interstates whose length is greater than 500 miles into segments, taking the end points of the segments to be intersection points with other Primary Interstates. Each segment is taken to be around 300 miles, but the length varies depending on where the intersections points are. This results in 112 Primary Interstate segments, with an average length of 352 miles.

The exact locations and open dates of all public EV charging stations (level 2 and DCFC) are accessed from the US Department of Energy Alternative Fuels Data Center. I define a

[18] The fuel types include BEV, PHEV, hybrid, gasoline, flex-fuel and diesel. For example, the gasoline version and electric version of Ford Focus are treated as two different models.

[19] https://www.energy.ca.gov/files/zev-and-infrastructure-stats-data.

[20] https://www.nyserda.ny.gov/All-Programs/chargeny/support-electric/data-on-electric-vehicles-and-charging-stations.

DCFC station to be along-highway if the straight-line distance between the station and the highway segment is at most 3 miles, and the station is called a community station otherwise. I define a highway segment to be covered by DCFC stations of some standard if there is at least one along-highway DCFC station of that standard every 100 miles. A county is defined as covered by DCFC stations of some standard if there is at least one community station of that standard in the county. These definitions are used on the demand side to model consumers' tastes for fast charging.

Household travel patterns are obtained from the Long-Distance Passenger Travel Demand Modeling Framework (rJourney) (Outwater et al. (2018)), which is a project sponsored by the Federal Highway Administration. It estimates a model of demand for long-distance trips using travel surveys in California, New York, Ohio, and Wisconsin and various data sources, and uses the model estimates to simulate single-day or multi-day business or leisure trips that are at least 100 miles for all US households. Existing papers on EV travel usually use the National Household Travel Survey (NHTS) to simulate travel behaviors (Sinyashin (2021)). I choose to use rJourney instead, because each NHTS respondent records all of their trips on a single day, which covers mostly commute trips and shorter trips around where most of their activities take place. The number of long-distance trips in the dataset is small, and if a respondent happens to be on a multi-day trip during the recording day, they will only log their driving pattern on that day, not on days before or after. The rJourney dataset focuses on long-distance trips and covers both single-day and multi-day trips, and thus is more suitable for the purpose of this paper. To obtain the travel route of each origin-destination pair, I use the OpenStreetMap to obtain whether and which Interstate segments are used for each route.

Model-year level vehicle characteristics are obtained from the Environmental Protection Agency (electricity range and fuel economy) and www.teoalida.com/ (MSRP, horsepower, country of origin, car classification and 5 vehicle size variables). Length, width, height, wheelbase and curb weight relate to the size of the vehicle and are highly correlated. I use the first component of the Principal Component Analysis to construct a size PCA variable. The EV battery pack costs are obtained from Statista.[21]

Panel information on federal and state level EV purchase rebates is collected from the Environmental Protection Agency[22] and state websites. The state level charging infrastructure subsidies are collected from state official records. Historical gasoline and electricity prices are obtained from the US Energy Information Administration. US household demographics including households' county of residence and annual income, and the fraction of college graduates in each county are acquired from American Community Survey through IPUMS.

4. Model

The model consists of two parts: a static model of consumer demand and automakers' pricing decisions in the spirit of Berry et al. (1995) (hereafter BLP) and Petrin (2002), and a dynamic model of Tesla's Supercharging investment decision in the spirit of Holmes (2011) and Houde et al. (forthcoming). In the first part, I use a random-coefficient logit model for consumer demand, which incorporates consumer preferences for fast charging networks in an innovative way. Consumers value fast charging in local neighborhoods and along highway corridors during long-distance trips, and the availability and convenience of both types of charging depend on consumers' home locations and travel patterns. Car manufacturers engage in static Bertrand competition and set national prices optimally. In the second part, Tesla has perfect foresight and faces a constrained dynamic optimization problem to choose which locations to cover with Supercharging stations each year. Section 4.1 lays out the demand model, Section 4.2 discusses firms' competition in prices, and Section 4.3 presents Tesla's investment model.

[21] https://www.statista.com/statistics/883118/global-lithium-ion-battery-pack-costs/.

[22] https://www.fueleconomy.gov/feg/taxevb.shtml.

4.1 Consumer demand

In each state and year, households choose from one of the following: buy a BEV, a PHEV, a non-electric vehicle, or not buy a new vehicle.[23] The choice set a consumer faces is assumed to be all vehicle models with positive sales in the state plus the outside option of not buying a new vehicle. The indirect utility consumer i obtains from product j in state s in year t is

$$u_{ijst} = \alpha_i \log(p_{jt} - \text{subsidy}_{jst}) + x'_{jst}\beta + f_{ijst}(N_t;\theta) + \xi_{jst} + \varepsilon_{ijst}, \tag{1}$$

where p_{jt} is the national level manufacturer's suggested retail price (MSRP) and subsidy_{jst} is the sum of all federal and state EV purchase tax credits an EV can enjoy; $p_{jt} - \text{subsidy}_{jst}$ is the effective price consumers pay for product j;[24] x_{jst} is a vector of vehicle characteristics (which might be specific to state s and year t);[25] N_t is the charging network at time t and $f_{ijst}(N_t;\theta)$ captures consumers' preferences for the DCFC network N_t, described in details below; ξ_{jst} is the unobserved product characteristic; and ε_{ijst} is an unobserved individual taste for the product that follows i.i.d. Type I Extreme Value distribution. α_i is an individual-specific price sensitivity coefficient that depends on the consumer's annual household income y_i, and is parametrized as

$$\alpha_i = \alpha_0 + \alpha_1 \log(y_i). \tag{2}$$

The outside option $j = 0$ is normalized to have utility $u_{i0st} = \varepsilon_{i0st}$.

[23] This could include buying a used vehicle, driving their existing vehicle, or relying on public transportation.

[24] I do not observe the out-the-door prices consumers actually pay for their new vehicle, which might include taxes, delivery fees less manufacturer's or dealer's discounts. Nor do I observe whether eligible consumers actually apply for the tax rebates or not. Hence, I assume consumers pay the MSRP less the EV rebates, which is a common assumption in the literature (Armitage and Pinter (2021) and Sinyashin (2021)).

[25] x_{jst} includes a constant, battery range of BEV, battery range of PHEV, year, the number of level 2 charging stations per household in the state, the energy cost of driving 100 miles (which depends on gasoline/electricity prices and vehicle efficiency), size PCA, horsepower, all-wheel drive, origin dummies (Europe, Asia or US), body type dummies (car, SUV, pickup truck or van), propulsion system dummies (BEV, PHEV or non-EV), the interaction terms between the propulsion system dummies and year, the interaction terms between propulsion system dummies and the fraction of college graduates in the state, and three-way interactions between the propulsion system dummies, year, and college graduate fractions.

Consumers are aware of the current DCFC network and care about it when they buy a BEV with fast charging capability. Let c be the county of residence for consumer i (county c is a county in state s), and the preference for the charging network $f_{ijst}(N_t;\theta)$ is written as

$$f_{ijst}(N_t;\theta) = \theta_1 \cdot \text{local coverage}_{jct} + \theta_2 \cdot \text{travel score}_{jct}, \tag{3}$$

where local coverage$_{jct}$ takes the value of one if there is at least one DCFC station that is compatible with j's charging standard and takes the value of zero if product j is not a BEV, does not have fast charging capability, or there are no DCFC stations of j's standard in county c. travel score$_{jct}$ is a continuous variable between zero and one that captures how DCFC-accessible the Primary Interstate Highway System is around county c. It is the fraction of trips an average household in county c can travel using the Interstate DCFC network and their BEV j (if product j is not a BEV or is not DCFC compatible, travel score$_{jct} = 0$). Formally, it is written as

$$\text{travel score}_{jct} = \sum_{d} w_c(d) \cdot \text{travelable}_{jct}(d). \tag{4}$$

In Equation (4), an average household in county c makes long-distance auto trips to various destination counties indexed by d. The weighting variable $w_c(d)$ is the ratio of the annual trips an average household in county c takes to destination d over the total number of long-distance trips the household takes. travelable$_{jct}(d)$ is a dummy variable and takes the value of one if j is a BEV with fast charging and all highway segments traveled along the route between counties c and d are covered by DCFC stations of j's standard.[26]

The two terms in Equation (3) reflect the two types of occasions where fast charging might be needed - short trips around where consumers live (for example commute trips or trips to restaurants nearby), and long-distance trips that span one or more days (for example road trips or auto business trips). This formulation is arguably more realistic and

[26]The highway segments and whether they are covered by DCFC stations are defined in Section 3.

less restrictive than some previous work, mainly in two ways. First, it allows for the fact that consumers do not just drive around where they live; they take longer trips and might take that into account when they buy new cars. Meanwhile, enabling long-distance trips with EVs has been emphasized by policymakers to achieve emissions reduction. It is important that charging needs during long-distance trips and the charging network along highways are incorporated. Second, the preference for the highway charging network is location-specific and depends on the home county of the consumer. A household living in New York almost for sure care more about whether they can charge on Interstate 95 than on Interstate 5,[27] and the contrary is true for most Los Angeles households. The idiosyncratic charging needs due to different travel patterns are allowed for using the trip information in the rJourney dataset, and Equations (3) and (4) help to map the same national fast charging network to how consumers feel differently about it in a structural and convenient way.

The market share of model j in state s in year t is calculated as

$$s_{jst} = \int \frac{\exp(\alpha_i \log(p_{jt} - \text{subsidy}_{jst}) + x_{jst}\beta + f_{ijst}(\theta) + \xi_{jst})}{1 + \sum_l \exp(\alpha_i \log(p_{lt} - \text{subsidy}_{lst}) + x_{lst}\beta + f_{ilst}(\theta) + \xi_{lst})} dG_{st}(y_i, c_i), \tag{5}$$

where $G_{st}(y_i, c_i)$ is the joint distribution of consumers' annual household income and residence county in state s and year t.

4.2 Pricing

I assume the observed prices are the equilibrium outcome of a Bertrand Nash game where multiproduct manufacturers set static national prices for each product they sell in a year. The marginal cost is assumed to be constant regardless of quantity, and across states, which is motivated from the observation that production usually takes place in a centralized setting.[28]

[27] Interstate 95 is the main north-south Interstate Highway on the East Coast going through Boston, New York City, Washington DC, Miami etc. Interstate 5 is the main north-south Interstate Highway on the West Coast going through Los Angeles, Sacramento, Portland, Seattle etc.

[28] For example, all Tesla vehicles sold in North America are produced in their factory in Fremont, California.

The log marginal cost of product j in year t is parametrized as

$$\log(MC_{jt}) = w'_{jt}\gamma + \gamma^{zev}\text{ZEV credits}_{jt} + \zeta_{jt}, \tag{6}$$

where w_{jt} is a vector of exogenous vehicle characteristics,[29] ZEV credits$_{jt}$ is the number of ZEV credits BEV j can earn in the ZEV states in year t (if product j is not a BEV or does not earn any credits, the value is zero),[30] and ζ_{jt} is the unobserved cost shifter.

The profit automaker f makes from vehicle sales in year t is

$$\pi_{ft} = \sum_{j\in\mathcal{J}_{ft}} \sum_{s} M_{st}(p_{jt} - MC_{jt})s_{jst}, \tag{7}$$

where $\mathcal{J}_{ft}$ is the set of products firm f sells in year t, M_{st} is the number of households living in state s in year t, and s_{jst} is the market share of product j as defined in Equation (5). The first order condition with respective to price is given by

$$\frac{\partial \pi_{ft}}{\partial p_{jt}} = \sum_{s} M_{st}s_{jst} + \sum_{l\in\mathcal{J}_{ft}} \sum_{s} M_{st}(p_{lt} - MC_{lt})\frac{\partial s_{lst}}{\partial p_{jt}}. \tag{8}$$

4.3 Tesla's Supercharging investment

Setup. I formulate Tesla's investment decision as whether and when to cover the counties and highway segments with Supercharging stations. Covering a county means the county has at least one in-community Supercharging station; covering a highway segment, which is a predetermined part on a Primary Interstate, is to have Tesla Supercharging stations at least

[29] w_{jt} includes a constant, year, imputed battery costs, size PCA, horsepower, all-wheel drive, miles per gallon equivalent (MPGe), origin dummies (Europe, Asia or US), body type dummies (car, SUV, pickup truck or van), and propulsion system dummies (BEV, PHEV or non-EV).

[30] ZEV credits can be traded freely for cash among automakers to comply with the ZEV mandate. The effective cost of a BEV in one of the ZEV states can be thought of as lowered by the market price of the credits it earns. For institutional details on the ZEV mandate, see Section 2.3. Note also that the ZEV credits apply only to the ZEV states and hence vary by whether the state has ZEV mandates, but the variable ZEV credits$_{jt}$ does not vary by state and is the credit amount in ZEV states. This is because the marginal cost is modeled at the national level. Therefore, γ^{zev} can be thought of as the monetary value of the ZEV credits, discounted by the fact that not all sales happen in ZEV states.

every 100 miles along the segment.[31] This formulation helps to translate Tesla's decision making from placing individual stations to covering locations, and the reasons for doing this are discussed next.

The main reason is because the goal of the paper revolves around the trade-offs between building stations on highways versus building them in communities, and which highways or counties to build stations. Understanding whether to build them next to restaurants or offices and on which highway exits is not the goal of this paper. Second, there will be numerous unobserved factors at the coordinate level affecting Tesla's decision making, which can be alleviated when zooming out to a less granular level.[32] Third, individual stations can be placed almost anywhere in the US (leaving aside some feasibility constraints), and hence finding the optimal geographic coordinates of stations is infinite-dimensional and intractable. On the other hand, there are around 3,000 counties and 112 Primary Interstate segments, and the decision on which locations to cover is finite-dimensional and more feasible. Finally, this location coverage formulation is also consistent with the demand model laid out in Section 4.1.

Some notations regarding Tesla's charging network are introduced next. Let $\mathcal{C}$ be the set of possible counties in which to build Supercharging stations, and $\mathcal{H}$ be the set of highway segments. Let $\mathcal{L} = \mathcal{C} \cup \mathcal{H}$ be the set of locations Tesla can cover with Supercharging stations, and $|\mathcal{L}|$ be the cardinality of set $\mathcal{L}$, and index a location in $\mathcal{L}$ by l. Denote the charging network in year t by N_t, which is a $|\mathcal{L}|$-vector of zeros and ones such that $N_{lt} = 1$ if and only if location l is covered by year t. Stack N_t for all years into $N = \{N_t\}_{t=0}^{\infty}$ for notational convenience. Denote the investment plan in year t by a_t, which is also a $|\mathcal{L}|$-vector of zeros and ones such that $a_{lt} = 1$ if and only if location l is newly covered in year t. Stack all a_t's to form $a = \{a_t\}_{t=0}^{\infty}$.

Timeline. Tesla is assumed to have perfect foresight, which is a common assumption in

[31] For details, refer to Section 3.

[32] For example, a specific location may not be suitable for building a parking lot, but a county should almost for sure have places for parking lots.

the literature (Holmes (2011) and Houde et al. (forthcoming)). The timing of the model is as follows:

(a) Before the start of year 0, no locations are covered yet, i.e. $N_{l,-1} = 0$ for all l. Tesla knows everything about the EV market that might affect its profits (including all the demand errors ξ_{jst}'s, marginal cost errors ζ_{jt}'s, and investment cost errors η_l's), and chooses an optimal investment plan a.

(b) At the beginning of each period t, the existing network is N_{t-1}. Investment a_t is made according to plan a. All investment costs are incurred and locations in plan a_t are covered. The network is now $N_t = N_{t-1} + a_t$.

(c) Car manufacturers (including Tesla) observe all information on demand and marginal cost in year t (including ξ_{jst}'s and ζ_{jt}'s), and engage in static Bertrand price competition. Equilibrium car prices p_{jt}'s are set.

(d) Consumers observe the current Tesla Supercharging network N_t and equilibrium car prices, and make car purchase decisions. Profits are earned by car manufacturers.

(e) Period t ends and period $t+1$ starts from step (b).

Investment costs. The costs of covering a location with Supercharging stations include the upfront costs (costs of hardware and materials, installation and construction costs, costs of permitting and labor costs) and operating and maintenance costs (site lease, site and equipment maintenance and labor costs). Since closures of stations are rarely observed in reality, I assume all opened stations will not be closed, and all covered locations will not be uncovered. Hence, at the time of the decision, Tesla should care about all the current and future costs associated with covering each location.

The (PDV of) cost of covering a county c is parametrized as

$$\text{cost}_c(\lambda) = \lambda_1 + \lambda_2 M_c + \text{rent}_c + \eta_c, \tag{9}$$

where M_c is the number of households in county c and rent_c is the PDV of rent payments that depends on the commercial per square foot rent and the imputed area of the station,[33] and η_c is an unobserved cost error. λ_1 is the average cost of covering a county including all upfront and future components but rents. The $\lambda_2 M_c$ term captures the fact that Tesla might build larger or more stations for counties with larger population. I do not directly include the number of stations or the number of chargers in the cost equation because those are choices made by Tesla and might be correlated with other unobserved factors that affect costs and thus introduce biases.[34] The population of the county is unlikely to change with the unobserved cost component, and thus can be treated as exogenous.

The (PDV of) cost of covering a highway segment h is parametrized as

$$\text{cost}_h(\lambda) = \lambda_3 \#\text{stations}_h + \lambda_4 \#\text{trips}_h + \text{rent}_h + \eta_h, \tag{10}$$

where $\#\text{stations}_h$ is the number of Tesla Supercharging stations on segment h, $\#\text{trips}_h$ is the total number of trips that go through segment h each year, rent_h is the PDV of rent payments calculated in a similar way as rent_c, and η_h is an unobserved cost error for segment h. Unlike Equation (9), Equation (10) directly includes the number of stations as a variable, and this is because Tesla usually places a station every 50 miles on the highway, and the number of stations on a segment depends almost solely on the length of the segment, which is exogenous. Bringing in the number of stations to the cost equation of segments should not cause biases. However, the size of each station (i.e. the number of chargers in each station) is an endogenous choice of Tesla that depends on their expectation on how busy the highway is and how often the chargers will be utilized. Hence, instead of including the number of chargers in the equation, I use the number of trips on the segments to proxy for how busy the segments are. The latter depends on the travel pattern of US households and the layout

[33]Each charger is assumed to take 160 square feet (the size of a standard parking space) and each station is assumed to need an additional 400 square feet for equipment. See https://techcrunch.com/2013/07/26/inside-teslas-supercharger-partner-program-the-costs-and-commitments-of-electrifying-road-transport/.

[34]For example, if the cost is lower in some county, Tesla might build larger or more stations in that county. This could bias the marginal cost of a station or the marginal cost of a charger towards zero.

of the US Highway System, and is unlikely to depend on Tesla's charging network.

In the cost specifications, the labor costs are not directly included in Equation (9) or (10), and are implicitly included as part of the fixed costs λ_1 and λ_3, which means they are more or less constant across locations (up to some unobserved errors) or at least not representable by the prevailing local wage rates. This is because building and maintaining Supercharging stations is a more centralized process that requires expertise, and the same team of people could be in charge of the process for all locations. Moreover, the stations require very little labor input for daily operations, unlike a Walmart store or an Amazon warehouse, which hires lots of local workers. Hence, I do not assume the labor costs associated with the stations are proportional to the local wage rates.

Tesla's value function. Tesla's value function consists of two parts: automotive profits from car sales and Supercharging investment costs. I do not include profits or losses from Supercharging activities in Tesla's value function for two reasons. On the one hand, I do not have detailed information on charger usage or prices; on the other hand, they do not seem to be Tesla's first-order concerns - Tesla models sold before 2017 were offered lifetime free charging at any Supercharging stations. If Tesla were to optimize profits from charging activities, any price below the marginal cost of charging (including but not limited to the cost of electricity) could not be optimal.

The value function of Tesla can be written as

$$\Pi(a) = \sum_{t=0}^{\infty} \rho^t \Big(\pi_t(N_t) - \sum_l a_{lt} \cdot \mathrm{cost}_l \Big), \tag{11}$$

where $\rho = 0.95$ is the time discount factor, $\pi_t(N_t)$ is Tesla's equilibrium automotive profits in year t when the Supercharging network is N_t, as defined in Equation (7). Here, the firm index f = Tesla is dropped for notational simplicity and the argument N_t is added to highlight that the profit depends on the endogenous charging network. As N_t changes, I allow the prices of BEVs with fast charging to adjust, and the new equilibrium prices are calculated through the pricing FOCs (Equation (8)). The equilibrium profit $\pi_t(N_t)$ is calculated under the new equilibrium prices. The PDV of all upfront and future cost components, cost_l, is as defined in Equations (9) and (10) for counties and highway segments respectively.

There are several complications that are ignored in this model. For example, Tesla might be financially constrained and cannot borrow freely. This might impede Tesla's ability to cover as many locations as they want each year. Alternatively, there might exist uncertainty on future demand or policy support, and Tesla might act cautiously and expand at the a slower rate than they otherwise would do. On the other hand, Tesla might take preemptive moves to secure a leading position, or Tesla might want to build trust among potential buyers, in which cases Tesla would have incentives to expand fast.

This paper is most interested in understanding the trade-offs associated with the choices to cover different locations. To that end and to minimize the potential biases caused by the real world complications mentioned above, Tesla's problem will be conditional on the number of locations covered each year (similar to Holmes (2011) and Houde et al. (forthcoming)). Tesla's Supercharging investment problem is characterized as the outcome of a constrained dynamic optimization problem with perfect foresight:

$$\begin{aligned} &\max_{a} \quad \Pi(a) \\ &\text{subject to } \sum_l a_{lt} = \sum_l a_{lt}^o \text{ for all } t, \end{aligned} \tag{12}$$

where $\Pi(a)$ is as defined in Equation (11), and a^o is the observed and optimal investment plan.

5. Identification and estimation of the demand and pricing model

The joint estimation procedure of the demand and pricing model is similar to Petrin (2002). The parameters are estimated using the method of efficient generalized method of moments (efficient GMM), which consists of three components. The first component is the orthogonality conditions between unobserved product characteristics ξ_{jst}'s and a vector of instruments Z_{jst}. The second component is the orthogonality conditions between the unobserved cost disturbances ζ_{jt}'s and another vector of instruments V_{jt}. The final component is a micro-moment that matches the model predicted and observed county penetration of BEV models with fast charging in California and New York State. The goal of the micro-moment is to help identify the non-linear parameters on consumer preferences for fast charging networks (i.e. θ_1 and θ_2). The three subsections describe the three components respectively.

The GMM algorithm is done 3 times, the first time using the weighting matrix of the 2-Stage Least-Squares regression, and the second and third times using the optimal weighting matrix calculated from the previous step. The results are very similar for the 2-step and 3-step GMM, implying a quick convergence. All the results presented in Section 7 are from the 2-step GMM. The standard errors are calculated following Hansen (2022) and Nevo (2000).

5.1 Demand side instruments

I assume the product characteristics are exogenous except the log effective price $\log(p_{jt} - \text{subsidy}_{jst})$ and the 3 variables related to EV charging (DCFC local coverage, DCFC travel score, and state level number of level 2 charging stations per household). The moment conditions are

$$\mathbb{E}[Z_{jst}\xi_{jst}] = 0, \tag{13}$$

where Z_{jst} contains the exogenous product characteristics and instruments for endogenous prices and charging variables. To select the instruments, I first propose a large candidate set of instruments, and then run first stage linear regressions of the endogenous variables on the exogenous product characteristics and proposed instruments for a diagnosis of weak instruments. Finally, I keep only the statistically and economically significant instruments in the moment conditions. The selected instruments come from 5 big categories, 3 targeting the effective prices and 2 targeting charging variables.

The instruments that help mainly to explain the effective prices are subsidies on EV purchase, cost shifters and BLP instruments. The federal tax credits on EV purchase and the average state rebate for EVs[35] are assumed to be exogenous and in the first category. The time trends in preferences for BEVs and PHEVs are already controlled for and the ξ_{jst}'s should only contain the temporary deviations from the time trend. On the other hand, government rebate programs require long-term planning, and the arrival times of the programs are likely to be random and uncorrelated with temporary demand shocks. The exogeneity of government EV subsidies is also a usual assumption maintained in the literature. The exogenous cost shifters include the number of ZEV credits a BEV can earn in a ZEV state, and the imputed battery costs of EVs. The former is a function of the battery range, and the latter is a function of the unit price of lithium ion battery packs and the battery capacity. All of them are heavily reliant on the battery technology and are assumed to be orthogonal to the demand errors. The BLP instruments describe the intensity of competition among manufacturers in the characteristic space. Since the characteristics themselves are assumed to be exogenous, any functions of them are exogenous too. 7 instruments are of this kind (after the selection of strong instruments), which contain information on the battery ranges, sizes, and fuel efficiencies of products produced by the same firm or other firms.

The instruments that are most relevant for the availability of charging infrastructure are government subsidies and the attractiveness of EVs. Whether the state subsidizes charging equipment, whether the state subsidizes DCFC charging equipment, and whether the DCFC subsidy highlights highway locations are assumed to be uncorrelated with the demand errors and included, for the same argument as the exogeneity of government EV purchase rebates. For the attractiveness of EVs, there is a slight distinction between instruments for level 2 charging availability and those for DC fast charging. The former is compatible across

[35]Since the MSRPs are set at the national level, not at the state level, a valid instrument for state rebates has to be constant across states. Hence, the average rebate across states is used, not the actual state-level rebate the consumers face.

BEV charging standards, and can be used for both BEVs and PHEVs. Hence, the overall popularity of EVs should matter to level 2 charging deployment. On the other hand, DC fast charging is only available on some BEVs and is incompatible across standards. As a result, only the attractiveness of BEVs of that standard should directly matter for the profitability of DCFC stations (the attractiveness of other EV models might matter indirectly for competition reasons). The included instruments for level 2 charging are the EV dummy interacted with whether the state has ZEV mandates, and with the average energy cost for EVs relative to all vehicles. The included instruments for DCFC availability are the BEV with DCFC capability dummy interacted with whether the state has ZEV mandates, with the average energy cost for BEVs of the same standard relative to all vehicles, and with the number of BEV models of the same standard sold.

5.2 Cost side instruments

The marginal costs are calculated by solving the pricing first order conditions in Equation (8). The calculation is slightly more involved than in BLP, because the prices are set at the national level, and each equation contains terms from all 49 markets in each year. After the marginal costs are recovered (for given non-linear parameters $(\alpha_0, \alpha_1, \theta_1, \theta_2)$), the GMM criterion function includes the orthogonality moments

$$\mathbb{E}[V_{jt}\zeta_{jt}] = 0, \tag{14}$$

where V_{jt} is the instruments and ζ_{jt} is the unobserved cost error as defined in Equation (6). Since the cost side variables w_{jt} are assumed to be exogenous, they constitute the first part of V_{jt}. The remaining part of V_{jt} are some demand shifters uncorrelated with the cost errors, including the average gas to electricity price ratio interacted with the BEV, PHEV and non-EV dummies, the average local coverage, and the average travel score.[36] The construction of

[36]Since the marginal cost equation is at the national level while the original forms of the demand shifters are at the state level, the averages of those demand shifters across states are taken to form cost

charging stations is irreversible, as closures of stations are rarely observed in the data, and as a result, the decision to build stations should take into account long-term variables, not just the current-year profitability. The unobserved cost errors are short-term errors, as the time trends are already controlled for. Hence, the average local coverage and average travel score should be valid instruments that are uncorrelated with the cost errors.

5.3 Identifying charging preferences and the micro-moment

First, the case without any micro-moment is discussed. The non-linear parameters on DCFC charging preferences (θ_1, θ_2) are identified through the market-level variations (i.e. across states and over time) in local coverage and travel score. A rich set of controls are included in the demand specification to address market-level differences in EV preferences that are not due to DCFC charging availability. Through those controls, we allow for distinct time trends for buying vehicles of different fuel types, differentiating preferences across states for vehicles of different fuel types explainable by the fraction of college graduates in the state, and the state-time varying tastes for vehicles of different fuel types. For example, if well educated consumers are first adopters of green cars and other consumers catch up over time, this can be explained by the coefficients in those controls and will not be wrongly attributed to development of DCFC infrastructure through the correlation (not causation) between DCFC development and BEV market shares. For the complete list of demand controls, refer to footnote 25.

If the micro-moment were not added, (θ_1, θ_2) would be solely identified from the relationship between state-year level DCFC availability and state-year level consumers' responses (after properly controlling for other covariates), whereas the valuable information contained in the county-year level relationships cannot be utilized. Since the local coverage and travel score variables are at the county level and the model is capable of predicting county level market shares, what is needed is the observed county-level market shares, which can be

side instruments.

matched with the model predicted ones to better identify (θ_1, θ_2). To that end, the county-level market shares of EV models are collected for California and New York State, and are matched with model predicted market shares to form a micro-moment in the GMM criterion function.

More specifically, the micro-moment matches the observed and model predicted market penetration (i.e. sum of market shares from 2012-2020) of each BEV model with fast charging in each county.[37] Let pen^o_{cj} and $\text{pen}_{cj}(\alpha, \theta)$ be the observed and model predicted market penetration of model j (which is a BEV model with fast charging). Let $g_{cj} = (\text{pen}^o_{cj} - \text{pen}_{cj}(\alpha, \theta))^2$ be the squared difference between the two values, which is non-negative and approaches zero when (α, θ) approaches the true value. Let $\bar{g}$ be the average value of g_{cj}, and the micro-moment can be written as

$$W^{mm} \cdot \bar{g}^2, \tag{15}$$

where W^{mm} is the weighting matrix (in this case, a scalar) of the micro-moment.[38]

6. Identification and estimation of Tesla's investment decision

The parameters on the investment side that remain to be identified and estimated are $\lambda = (\lambda_1, \lambda_2, \lambda_3, \lambda_4)$, as defined in Equations (9) and (10). I follow Holmes (2011) and Houde et al. (forthcoming) and take a revealed preference approach that any feasible alternative investment plan is not more profitable than the observed plan a^o. This assumption gives rise to inequality constraints and leads to a moment inequality estimator for λ. This approach circumvents solving the infinite horizon dynamic programming problem of location choices,

[37] The reason why I do not match the market shares in individual years is because I observe there are some discrepancies between the state-year level sales from the IHS Markit dataset and the county-year sales datasets, and the discrepancies are significantly reduced when sums are taken across years. This is likely because they use different methods in attributing registration records to years.

[38] In the first-step GMM, $W^{mm} = 1$. In later steps, W^{mm} is updated to be the inverse of the estimated variance of g_{cj} from the previous step.

which is infinite dimensional (even with a finite horizon problem, the dimensionality is very high given the large set of possible locations).

6.1 Forming the moment inequalities

To form those inequalities, I only consider plans that are minimally perturbed from the observed plan, i.e. where the coverage years of two locations are swapped. The benefit is twofold. First, I cannot fully control for the financial constraints and other dynamic considerations Tesla faces (Section 4.3 has a discussion on this). Small deviations that hold fixed the number of locations covered each year are more likely to be feasible and within Tesla's consideration. Hence, they are more robust to the real world complications. Second, with such bilateral swaps, only profit streams between the two coverage years are affected, avoiding making assumptions on the distant future profit streams and reducing computation burden.

Denote the two locations being swapped by l and l', and the two coverage years by t and t' where $t < t'$. Denote by $a^{l,l'}$ the alternative plan where the coverage year of location l (l') becomes t' (t) and everything else is the same as a^o. Let $N_\tau(a)$ be the Supercharging network in year t under plan a. The revealed preference approach states

$$\Pi(a^o;\lambda) - \Pi(a^{l,l'};\lambda) \geq 0, \tag{16}$$

where $\Pi(\cdot;\lambda)$ is as defined in Equation (11). Plugging in the functional form of the value function to the inequality, the constraint can be written as

$$\begin{aligned}\Pi(a^o;\lambda) - \Pi(a^{l,l'};\lambda) = &\sum_{\tau=t}^{t'-1} \rho^\tau \Big[\pi_\tau\big(N_\tau(a^o)\big) - \pi_\tau\big(N_\tau(a^{l,l'})\big)\Big] \\ &- (\rho^t - \rho^{t'})\Big[\text{cost}_l(\lambda) - \text{cost}_{l'}(\lambda)\Big] \qquad \geq 0 \end{aligned} \tag{17}$$

There are two types of locations, counties and highway segments, and as a result, there are four types of bilateral swaps - switching two counties, switching two segments, switching an early-covered county and a late-covered segment, and switching an early-covered segment and a late-covered county. The identification argument is discussed separately for each type of swaps below.

Switch two counties. The inequality can be written as

$$Y^{c,c'} - \lambda_2 X_2^{c,c'} + \epsilon^{c,c'} \geq 0, \tag{18}$$

where $Y^{c,c'}$ is the discounted difference in automotive profit flows net of rents between the actual and alternative plan, where the automotive profits are calculated using the estimates from the demand and pricing model:

$$Y^{c,c'} = \sum_{\tau=t}^{t'-1} \rho^\tau \left[\hat{\pi}_\tau\big(N_\tau(a^o)\big) - \hat{\pi}_\tau\big(N_\tau(a^{c,c'})\big) \right] - (\rho^t - \rho^{t'}) \cdot (\text{rent}_c - \text{rent}_{c'}), \tag{19}$$

$X_2^{c,c'}$ is the discounted difference in number of households between county c and c':

$$X_2^{c,c'} = (\rho^t - \rho^{t'}) \cdot (M_c - M_{c'}), \tag{20}$$

and $\epsilon^{c,c'}$ captures the unobserved components in the value difference, due to unobserved investment cost errors η_c and $\eta_{c'}$, using the estimated demand parameters not the actual ones, and any model misspecification or other factors not included in the model.

Equation (18) shows how λ_2 is partially identified. Ignore the error term $\epsilon^{c,c'}$ for now. $Y^{c,c'}$ and $X_2^{c,c'}$ are directly calculable from the demand model and the data, and the range of λ_2 can be derived from the inequality. For illustration, consider the case where county c (covered first) is smaller in size than county c' (covered next). The actual plan would have a lower investment cost than the swapped one if larger counties are more costly to cover (which is the case given the estimated range of λ_2 in Section 7.2), and the profit flows and rent costs might be different too. Suppose the PDV of profit flows net of rent costs is lower for the actual plan as well. The fact that the alternative plan is not chosen means that the higher investment cost in the alternative plan cannot be fully compensated for with the higher profits net of rent costs, which leads to a lower bound for λ_2. Mathematically, $X_2^{c,c'}$ is negative in this case, and the inequality implies $\lambda_2 \geq \frac{Y^{c,c'}}{X_2^{c,c'}}$. If $Y^{c,c'}$ is negative, $\frac{Y^{c,c'}}{X_2^{c,c'}}$ is a meaningful lower bound for λ_2, and the more positive $\frac{Y^{c,c'}}{X_2^{c,c'}}$ is, the more information the revealed preference contains, and the tighter the lower bound is.

The case where county c is larger in size than county c' is similar. The actual plan would have a higher investment cost than the swapped one (if larger counties are more costly to cover). Suppose the PDV of profit flows net of rent costs is higher for the actual plan as well. The fact that the alternative plan is not chosen means that the lower investment cost in the alternative plan cannot fully compensate for the lower profits net of rent costs, which leads to an upper bound for λ_2. Mathematically, $X_2^{c,c'}$ is positive in this case, and the inequality implies $\lambda_2 \leq \frac{Y^{c,c'}}{X_2^{c,c'}}$. If $Y^{c,c'}$ is positive, $\frac{Y^{c,c'}}{X_2^{c,c'}}$ is a meaningful upper bound for λ_2, and the smaller $\frac{Y^{c,c'}}{X_2^{c,c'}}$ is, the more information the revealed preference contains, and the tighter the upper bound is.

The arguments above omit the error term $\epsilon^{c,c'}$. If the error term is non-zero, focusing on single inequalities could make the identified range for λ_2 unrealistically small, or even non-existent. Consider the first case where $X_2^{c,c'}$ is negative. The lower bound for λ_2 should be $\lambda_2 \geq \frac{Y^{c,c'}+\epsilon^{c,c'}}{X_2^{c,c'}}$. If the realized $\epsilon^{c,c'}$ is very negative but is ignored, the lower bound will be mistakenly large. Similarly, in the second case where $X_2^{c,c'}$ is positive, the true upper bound for λ_2 is $\lambda_2 \leq \frac{Y^{c,c'}+\epsilon^{c,c'}}{X_2^{c,c'}}$; but if the realized $\epsilon^{c,c'}$ is very positive but is ignored, the upper bound will be mistakenly small. A solution to this is to take averages across inequalities to make the average of the errors vanish.[39]

Formally, let $Z^{c,c'}$ be a vector of non-negative instruments that are uncorrelated with

[39] If the $\epsilon^{c,c'}$'s were independent across swaps, then the average of the errors would approach zero as the number of swaps increases. However, two distinct swaps might involve the same county, breaking the independence assumption. This dependence will be taken care of when calculating the standard errors using Bootstrap.

$\epsilon^{c,c'}$. Then, λ_2 can be estimated using the following moment inequality conditions:

$$\mathbb{E}[Z^{c,c'} \cdot (Y^{c,c'} - \lambda_2 X_2^{c,c'})] + \mathbb{E}[Z^{c,c'} \cdot \epsilon^{c,c'}] \geq 0 \tag{21}$$

The second term $\mathbb{E}[Z^{c,c'} \cdot \epsilon^{c,c'}] = 0$ under the assumption, and hence the inequality becomes

$$\mathbb{E}[Z^{c,c'} \cdot Y^{c,c'}] - \lambda_2 \cdot \mathbb{E}[Z^{c,c'} \cdot X_2^{c,c'}] \geq 0 \tag{22}$$

Switch two segments. The inequality is

$$Y^{h,h'} - \lambda_3 X_3^{h,h'} - \lambda_4 X_4^{h,h'} + \epsilon^{h,h'} \geq 0, \tag{23}$$

where $Y^{h,h'}$ is the discounted difference in profit flows from car sales net of rents between the actual and alternative plan:

$$Y^{h,h'} = \sum_{\tau=t}^{t'-1} \rho^\tau \Big[\hat{\pi}_\tau\big(N_\tau(a^o)\big) - \hat{\pi}_\tau\big(N_\tau(a^{h,h'})\big)\Big] - (\rho^t - \rho^{t'}) \cdot (\text{rent}_h - \text{rent}_{h'}), \tag{24}$$

$X_3^{h,h'}$ is the discounted difference in the number of Supercharging stations between segment h and h':

$$X_3^{h,h'} = (\rho^t - \rho^{t'}) \cdot (\#\text{stations}_h - \#\text{stations}_{h'}), \tag{25}$$

$X_4^{h,h'}$ is the discounted difference in the annual number of trips between segment h and h':

$$X_4^{h,h'} = (\rho^t - \rho^{t'}) \cdot (\#\text{trips}_h - \#\text{trips}_{h'}). \tag{26}$$

The identification argument for λ_3 and λ_4 is similar to that for λ_2 in the swap-two-counties case, except that there are now two parameters to identify, and the identified set should be a region in the $\mathbb{R}^2$ space, instead of a 1-dimensional interval range for a single parameter.

Let $Z^{h,h'}$ be a vector of non-negative instruments. The moment inequality conditions are

$$\mathbb{E}[Z^{h,h'} \cdot Y^{h,h'}] - \lambda_3 \cdot \mathbb{E}[Z^{h,h'} \cdot X_3^{h,h'}] - \lambda_4 \cdot \mathbb{E}[Z^{h,h'} \cdot X_4^{h,h'}] \geq 0. \tag{27}$$

Switch a county and a segment. The remaining two cases where an early-covered county and a late-covered segment, and an early-covered segment and a late-covered county are swapped are very similar. The details are left for Appendix A.

Unifying the four types. A unifying way to write the moment inequalities for all four types of swaps is presented below.

Let l and l' be the indices for the two locations swapped in the alternative plan. Let $Z^{l,l'}$ be a vector of non-negative instruments that are uncorrelated with $\epsilon^{l,l'}$. The moment inequality conditions write

$$\mathbb{E}[Z^{l,l'} \cdot Y^{l,l'}] - \sum_{k=1}^{4} \lambda_k \cdot \mathbb{E}[Z^{l,l'} \cdot X_k^{l,l'}] \geq 0, \tag{28}$$

where

$$\begin{aligned}
Y^{l,l'} &= \sum_{\tau=t}^{t'-1} \rho^\tau \Big[\hat{\pi}_\tau\big(N_\tau(a^o)\big) - \hat{\pi}_\tau\big(N_\tau(a^{l,l'})\big)\Big] - (\rho^t - \rho^{t'}) \cdot (\text{rent}_l - \text{rent}_{l'}),\\
X_1^{l,l'} &= (\rho^t - \rho^{t'}) \cdot \big[\mathbb{1}(l \text{ is a county}) - \mathbb{1}(l' \text{ is a county})\big],\\
X_2^{l,l'} &= (\rho^t - \rho^{t'}) \cdot \big[M_l - M_{l'}\big],\\
X_3^{l,l'} &= (\rho^t - \rho^{t'}) \cdot \big[\#\text{stations}_l - \#\text{stations}_{l'}\big], \text{ and}\\
X_4^{l,l'} &= (\rho^t - \rho^{t'}) \cdot \big[\#\text{trips}_l - \#\text{trips}_{l'}\big].
\end{aligned}$$

(Here, let $M_l = 0$ for segments, and $\#\text{stations}_l = \#\text{trips}_l = 0$ for counties for the sake of rigor.)

6.2 Instruments

The county size M_l, number of stations on a segment $\#\text{stations}_l$ (which is roughly a step function of the segment length), and number of annual trips going through the segment $\#\text{trips}_l$ are assumed to be uncorrelated with $\epsilon^{l,l'}$. I consider the groupings instruments similar to Holmes (2011) and Houde et al. (forthcoming). A naive version of the grouping instrument would take the value of 1 if a swap (l, l') belongs to a group, and 0 otherwise. To make the magnitudes across swaps more comparable, the naive instrument will be multiplied by ρ^{-t}, so that the values are rescaled to the present value in the year when the swap begins. That is, the grouping instrument takes the value of ρ^{-t} (where t is the coverage year of location l) if a swap (l, l') belongs to a group, and 0 otherwise. The groups are defined based on the swap type, and the values of M_l, $\#\text{stations}_l$ and $\#\text{trips}_l$, and are defined in Table B1 in Appendix B. There are 50 groups, referred to as the basic instruments.

In addition, $X_k^{l,l'}$ is a function of the exogenous variables M, #stations and #trips, and hence are uncorrelated with $\epsilon^{l,l'}$. Any functions of $X_k^{l,l'}$ are valid instruments too. Besides the basic instruments, I also include Order-1 instruments, where the basic instruments are interacted with the non-negative $X_{k+}^{l,l'}$, defined as $X_{k+}^{l,l'} = X_k^{l,l'} - \min_{l,l'}\{X_k^{l,l'}\}$. For each basic instrument (i.e. each group), there are 4 Order-1 instruments, corresponding to $k = 1, 2, 3, 4$. Order-2 instruments are the interactions between the basic instruments and $X_{k+}^{l,l'} \cdot X_{m+}^{l,l'}$. For each basic instrument, there are 10 Order-2 instruments. There are 50 basic instruments, 200 Order-1 instruments, and 500 Order-2 instruments. I apply different sets of instruments for estimation, and the results for the basic instruments, the basic instruments plus Order-1 instruments, and the basic instruments plus Order-1 and Order-2 instruments are presented in Section 7.2. With Order-1 and Order-2 instruments, the identified set of λ narrows down.

6.3 Characterizing the identified set of λ

The identified set of λ, Λ, is such that all (the sample analog of) the moment inequality conditions are satisfied and can be written as

$$\Lambda = \Big\{\lambda \in \mathbb{R}^4 : \quad \big(\frac{1}{\#\text{dev}} \sum_{(l,l')} Z_g^{l,l'} Y^{l,l'}\big) - \sum_{k=1}^{4} \lambda_k \big(\frac{1}{\#\text{dev}} \sum_{(l,l')} Z_g^{l,l'} X_k^{l,l'}\big) \geq 0, \quad \text{for all } g\Big\}, \tag{29}$$

where #dev is the number of (l, l') pairs, or the number of deviations considered.

Note that all the constraints are linear inequalities of λ. Hence, the identified set has the following good properties. If the identified set is non-empty (which is the case in this paper), it will be a convex and connected 4-dimensional polygon, and can be fully characterized by its vertices. These vertices are the extreme points of the identified set. The identified set is the convex hull of these vertices. That is, a point is in the identified set if and only if it can be represented by a linear combination of the vertices. In Section 7.2, the set of estimated investment cost parameters will be represented by the vertices of the set. If one is interested in knowing the estimated range of a single parameter λ_k, it is the interval between the minimum and maximum values of the k-th coordinates of the vertices.

6.4 Confidence region

I also calculate the 95% confidence region for the identified set. I follow Holmes (2011) and use a subsampling procedure with Bootstrap samples to correct for the fact that different deviations may involve the same location and hence are correlated. I obtain the mean and variance-covariance matrix of the components in the inequalities (Equation (29)) and draw 1000 simulations from the multivariate normal distribution with the estimated mean and variance-covariance matrix. I then calculate the identified set with each draw, and find the points that are inside the simulated identified set 95% of the times to form the 95% confidence region. The procedure is described in detail in Appendix C.

7. Estimation results

7.1 Demand and MC parameters

The demand and MC parameters are jointly estimated using the GMM framework with the demand side moments (Equation (13)), the MC side moments (Equation (14)) and the micro-moment (Equation (15)). Table 2 shows the estimated demand parameters, and Table 3 presents the estimated MC parameters.

All the coefficients on vehicle characteristics in the demand model come out significant and have the expected signs: all else equal, consumers prefer vehicles with a smaller fuel/electricity cost, a higher horsepower, a larger size, and all-wheel drive. American vehicles are preferred to European ones or Asian ones, and Asian vehicles are slightly more preferable than European ones. Cars and SUVs are more preferred to pickup trucks and passenger vans. Consumers value EVs with a larger battery range, more so for BEVs than for PHEVs, and consumers are more likely to buy EVs if the level 2 charging infrastructure in the state is more developed. The trend parameters convey confirmative messages too. The overall preference for buying a new vehicle declines over year, but increases for EVs. If 2012 is treated as the starting year, consumers first prefer conventional vehicles over EVs, especially over BEVs. This could be due to their lack of confidence in the BEV technology or the future development in the early years. Over time, their preferences for EVs are slowly catching up. Looking at the geographic variations, states with more college graduates tend to be early adopters of the new technology, especially for BEVs. Over time, other states are catching up.

Price sensitivity The negative price coefficient α_0 implies consumers like lower prices, and the average own-price elasticity is -3.45, which is in line with the estimates in the prior literature on automobiles.[40] The sensitivity to prices also decreases with consumer income, as indicated by the positive α_1. The average own-price elasticities for consumers with income

[40]The estimated own-price elasticity is -3.28 in Goldberg (1995), -2.7 in Li (2019), and -6.26 in Sinyashin (2021).

Table 2: Demand Parameter Estimates

	Estimate	Standard error	Significance
Coefficients on log effective price			
Const. (α_0)	-6.643	0.247	***
Log household annual income (α_1)	0.241	0.019	***
Coefficients on fast charging availability			
Local coverage (θ_1)	0.058	0.032	*
Travel score (θ_2)	0.057	0.020	***
Vehicle characteristics - general			
Constant	30.400	0.738	***
Energy cost per 100 miles	-0.093	0.003	***
Horsepower	0.005	0.000	***
Size PCA	0.367	0.007	***
Origin - Asia	-0.103	0.013	***
Origin - Europe	-0.135	0.026	***
All-wheel drive	0.726	0.027	***
Body type - car	0.666	0.031	***
Body type - SUV	0.796	0.029	***
Body type - pickup	-0.008	0.039	
Vehicle characteristics - EV			
BEV battery range	0.018	0.001	***
PHEV battery range	0.015	0.001	***
State level 2 stations per household	8675.440	802.202	***
Trends			
Year	-0.141	0.009	***
BEV	-6.156	0.532	***
PHEV	-2.974	0.358	***
Year×BEV	0.388	0.104	***
Year×PHEV	0.404	0.073	***
BEV×college	5.566	2.260	**
PHEV×college	2.983	1.682	*
Year×BEV×college	-2.621	0.447	***
Year×PHEV×college	-2.468	0.330	***

Note: This table presents the demand estimates of the BLP model.
*p<0.1; **p<0.05; ***p<0.01.

in each of the four quartiles are -4.17, -4.00, -3.87 and -3.35 respectively.

Preference for fast charging The preference for fast charging parameters are both positive and significant, and $\hat{\theta_1} \approx \hat{\theta_2}$, implying consumers value local coverage and highway coverage almost equally. That is, consumers receive the same utility when their county has a DCFC station or when all their long-distance trip routes are covered with DCFC stations.[41] The average semi-elasticity of market share with respective to local coverage is 0.1343, and with respective to travel score is 0.1340. Moreover, the second derivatives of market share with respect to log price and local coverage or travel score are consistently negative, i.e.

$$\frac{\partial^2 s_{jct}}{\partial \log(p_{jt} - \text{subsidy}_{jct})\ \partial \text{local coverage}_{jct}} < 0, \text{ and}$$
$$\frac{\partial^2 s_{jct}}{\partial \log(p_{jt} - \text{subsidy}_{jct})\ \partial \text{travel score}_{jct}} < 0, \tag{30}$$

implying that building DCFC stations becomes a more effective tool to boost sales when prices are lower and in that sense better fast charging infrastructure and lower vehicle prices are complements.

Marginal costs and markup Estimated marginal costs (net of ZEV credits) can be calculated from the pricing FOCs (Equation (8)). Table 3 presents the parameter estimates for the $\log(MC)$ equation (Equation (6)). The estimates all have the expected signs: marginal costs increase with time, size, horsepower, all-wheel drive and MPGe. Vehicles from Europe are more costly than those from Asia or America, and cars and SUV tend to be more costly than pickup trucks and passenger vans.[42] EVs are more costly to produce than conventional vehicles, and BEVs are slightly more costly than PHEVs. Battery costs contribute to a non-negligible part of total marginal costs, and ZEV credits effectively reduce BEV costs.

[41] From firms' perspective, it is easier to build a single station in a county than to cover all highways nearby with DCFC stations. Hence, if Tesla just wants to stimulate purchases in a single county, it is more likely to build a Supercharging station in the county directly. However, there will be a positive effect on other counties if a highway segment is covered. Tesla might want to cover highway segments whenever they boost sales from multiple counties nearby. This rationale will be revisited and manifested in the counterfactual analysis.

[42] This could be because there is a larger fraction of high-end luxury cars and SUVs than luxury pickups or vans.

Table 3: log(MC) Parameter Estimates

	Estimate	Standard error	Significance
Vehicle characteristics - general			
Constant	9.9805	0.0198	***
Year	0.0059	0.0015	***
Size PCA	0.0522	0.0045	***
Horsepower	0.0032	0.0001	***
All-wheel drive	0.1650	0.0175	***
MPGe	0.0055	0.0007	***
Origin - Asia	0.0577	0.0110	***
Origin - Europe	0.3097	0.0138	***
Body type - car	0.1071	0.0188	***
Body type - SUV	0.0668	0.0179	***
Body type - pickup	-0.2584	0.0198	***
Vehicle characteristics - EV			
BEV	0.1578	0.0679	**
PHEV	0.1236	0.0254	***
Imputed battery cost (in thousands)	0.0169	0.0026	***
Number of ZEV credits	-0.0720	0.0194	***

Note: This table presents the marginal cost estimates of the BLP model.
*p<0.1; **p<0.05; ***p<0.01.

Table 4 presents the distribution of estimated MCs, margins and markups. The estimates are in general consistent with numbers in automakers' public financial reports. For example, Tesla reports its automotive gross margin to be around 25% in its Form 10-K, compared to my median estimate of 26.9%.[43] The markups range from 37.3% at the 10th percentile to 47.3% at the 90th percentile for all vehicles, and are lower for PHEVs and the lowest for BEVs. The markups range from 30.1% (10th percentile) to 41.4% (90th percentile) for PHEVs, and from 24.2% (10th percentile) to 40.3% (90th percentile) for BEVs. This can be explained by the relatively limited demand for EVs compared with conventional vehicles,

[43]Note that Tesla treats the sales of ZEV credits as part of its revenue, while I treat it as a reduction in costs. If the margin reported by Tesla is adjusted to fit my definition, this will increase the margin, making it even closer to my estimates.

even under various policy supports. Tesla is more successful than other BEV manufacturers, earning markups between 33.1% (10th percentile) and 41.6% (90th percentile), by providing a more extensive charging network and larger battery ranges.

Table 4: Distribution of Estimated MCs and Markups

	10th	**25th**	**Median**	**75th**	**90th**
All vehicles					
MSRP	18,698	23,073	29,725	38,939	52,900
MC (net of ZEV credits)	13,065	16,032	20,821	27,014	37,083
Margin	5,544	6,798	8,902	11,761	16,304
Markup	37.3%	41.7%	43.5%	45.3%	47.1%
PHEVs					
MSRP	25,620	27,338	39,995	66,775	95,740
MC (net of ZEV credits)	19,062	20,364	29,190	48,165	67,692
Margin	6,093	6,822	11,248	18,649	27,586
Markup	30.1%	32.1%	35.3%	39.1%	41.4%
BEVs					
MSRP	25,000	29,600	36,620	42,400	69,870
MC (net of ZEV credits)	20,233	23,688	26,168	32,659	51,282
Margin	4,788	6,208	8,528	10,688	18,679
Markup	24.2%	26.5%	29.5%	35.7%	40.3%
Tesla BEVs					
MSRP	40,995	53,950	68,000	79,745	82,750
MC (net of ZEV credits)	30,724	39,707	50,302	56,861	60,294
Margin	10,141	14,891	18,463	21,875	23,100
Markup	33.1%	35.2%	36.7%	38.7%	41.6%

Note: This table presents the distribution of the vehicle prices (Manufacturer's Suggested Retail Price), estimated marginal costs less any ZEV credits, estimated margin (difference between MSRP and MC), and estimated markup (margin over MC). The 10th, 25th, 50th, 75th and 90th percentiles of the distributions are presented.

7.2 Supercharging station costs

Following the moment inequality approach described in Section 6, the investment cost parameters λ in Equations (9) and (10) are estimated. I use the basic instruments, and optional Order-1 and Order-2 instruments for the estimation. The sets of estimated λ are non-empty in all cases. Every estimated set is a convex polygon in the $\mathbb{R}^4$ space, and is fully characterized by specifying all vertices of the polygon. The coordinates of those vertices, and thus the full characterization of the estimated sets, are presented in Appendix D. The extreme points of those vertices give rise to the lower and upper bounds for each individual parameter λ_k, as shown in Table 5. The extreme points in the confidence region are shown in the last two columns of Table 5.

The estimated ranges for all cost parameters are positive,[44] as expected, indicating that covering a county is costly and the cost increases with county sizes, and that each station on the highway is costly and the cost increases with highway usage. As more instruments are added to the constraints, the ranges shrink but the changes are not dramatic, which is reassuring that the instruments are exogenous and valid.[45] In what follows, I will focus on the results with the full set of instruments.

With the vertices of the estimated set of λ, I could calculate the cost bounds for covering each county and each segment, and each station.[46] The distribution of costs are presented in Table 6. The way to read the table is the following: across all the counties that are covered during the data period, the estimated cost is at most between \$3.41 million and \$5.39 million

[44]Holmes (2011) restricts the signs of the parameters in the inequality constraints to ensure the results are sensible. I do not include those restrictions, and the signs all turn out as expected.

[45]Imagine if the estimated ranges narrowed by a lot or even became non-existent when Order-1 instruments were added to the basic instruments, this would imply the Order-1 instruments brought a lot of new constraints. However, multiplying the basic groupings instruments by some variable orthogonal to the errors should not bring too much new information, unless the variable were actually correlated with the errors and the new constraints were wrong.

[46]The calculation is done by plugging in the coordinates of each vertex, and the attributes of the location (rental costs, number of households, number of stations on the segment, and/or number of annual trips). The maximum and minimum costs across these vertices are the estimated upper and lower bounds of the costs. The cost function is linear in λ, which guarantees the cost evaluated at any point in the estimated set of λ is within the range evaluated at the vertices.

Table 5: Investment Cost Parameter Estimates

Panel A: Basic instruments				
	Estimated range		**95% Confidence region**	
	Min	**Max**	**Min**	**Max**
Dummy for county (λ_1), in millions	2.398	4.790	0.813	5.566
# households in county (λ_2)	8.630	11.584	8.300	12.564
# stations on segment (λ_3), in millions	0.953	1.635	0.166	1.922
# trips on segment (λ_4)	0.247	0.657	0.129	0.991

Panel B: Basic + Order-1 instruments				
	Estimated range		**95% Confidence region**	
	Min	**Max**	**Min**	**Max**
Dummy for county (λ_1), in million	2.413	4.666	0.788	5.474
# households in county (λ_2)	8.630	11.584	8.347	12.524
# stations on segment (λ_3), in million	0.953	1.585	0.283	1.865
# trips on segment (λ_4)	0.290	0.657	0.184	0.968

Panel C: Basic + Order-1 + Order-2 instruments				
	Estimated range		**95% Confidence region**	
	Min	**Max**	**Min**	**Max**
Dummy for county (λ_1), in million	2.427	4.567	1.010	5.258
# households in county (λ_2)	8.630	11.584	8.340	12.388
# stations on segment (λ_3), in million	0.953	1.545	0.339	1.786
# trips on segment (λ_4)	0.323	0.657	0.226	0.962

Note: This table presents investment cost parameter estimates. The estimated set is a convex polygon and the extreme points in each dimension are shown in Columns 2 and 3. The 95% confidence region is calculated using the method detailed in Appendix C. The extreme points in the confidence region along each dimension are shown in Columns 4 and 5.

for 25% of the counties, and at most between \$4.29 million and \$6.12 million for half of the counties.[47] The median cost of a community Supercharging station is between \$4.1 and \$6 million, while the median cost of an along-highway Supercharging station is between \$2.03 and \$2.5 million. A community station is estimated to be around twice as costly as an along-highway station. This could be due to higher rents, higher costs associated with

[47]To be more accurate (but at the risk of repetition), the table reads the estimated minimum cost is at most \$3.41 million for 25% of the counties, and at most \$4.29 million for half of the counties; the estimated maximum cost is at most \$5.39 million for 25% of the counties, and at most \$6.12 million for half of the counties.

upgrading the power grids in populous areas, more costly and tedious permitting process, higher management costs, higher electricity costs,[48] and any other challenges related to high population density.

Table 6: Investment Cost Distributions (in Millions)

	10th	25th	Median	75th	90th
Cost of covering a county					
Lower bound	2.97	3.41	4.29	6.14	9.29
Upper bound	5.04	5.39	6.12	7.88	11.97
Cost of a community Supercharging station					
Lower bound	2.92	3.28	4.10	5.83	8.81
Upper bound	5.00	5.27	6.00	7.55	11.23
Cost of covering a highway segment					
Lower bound	4.11	7.28	9.26	12.25	17.03
Upper bound	5.02	8.97	11.28	14.93	20.03
Cost of an along-highway Supercharging station					
Lower bound	1.47	1.77	2.03	2.43	2.95
Upper bound	2.01	2.25	2.50	2.85	3.67

Note: For each location, the bounds of the investment cost are calculated from the estimated set of investment cost parameters, as described in footnote 46. The 10th, 25th, 50th, 75th and 90th percentiles of those bounds are presented in this table.

Note that the costs are the discounted lifetime costs (evaluated at a 0.95 discount factor), including both the upfront costs like the equipment costs and installation costs, and the flow operating costs like the rent and maintenance costs. That is why these numbers may look larger than numbers from other sources that just include the upfront setup cost. For example, a report by the Idaho National Laboratory (INL) gives engineering estimates on the cost of DCFC stations (Francfort et al. (2017)). Depending on the station capacity and whether the station has a photovoltaic system, the estimated upfront cost ranges from \$0.38 million to \$2.03 million, while the annual operating cost ranges from \$0.16 million to \$0.51 million.

[48]The electricity cost is likely to be higher for community stations if they are utilized more and drivers pay less than the cost of electricity on average, which is plausible given Tesla offered free charging for models sold before 2017 and had various programs to subsidize charging since 2017.

With a discount factor of 0.95, the discounted lifetime cost ranges from \$3.64 million to \$12.32 million. Three remarks follow: First, operating costs constitute a significant part of the overall lifetime costs (they are at least 5 times as costly as the upfront costs), and should not be ignored in cost calculations. Second, the INL estimates are for non-Tesla DCFC stations, which might be higher than Tesla Supercharging stations. Tesla might have a larger bargaining power in the procurement process or might be more efficient than other charging companies. Third, these are engineering costs, not economic ones - any non-monetary costs are not included. Hence, these number should only serve as an orders-of-magnitude check. My estimated costs of Supercharging stations are similar in magnitudes to those numbers.

Few papers in the literature estimate the costs of charging stations. An exception is Li (2019), who uses a static investment model and recovers the charging station costs from firms' first order conditions with respect to charging stations. She estimates a DCFC station costs about \$10,000 per year on average, which converts to a discounted present value of \$0.2 million using a 0.95 discount factor. This number is significantly lower than the estimates in the Idaho National Laboratory report and than my estimates, and a potential reason could be that her model is static. With a dynamic environment, firms cannot undo an investment or collect scrap values from selling existing investments (at least the closures of stations are not observed in the data). Hence, an investment could pay off in the long run. If the model is wrongly assumed to be static and ignores the fact that the investments can generate long-lasting benefits, the present value of marginal profit streams of the investments are underestimated by 20 times (if the discount factor is 0.95 and the marginal flow profits are constant over time). The implied costs of the investments will be biased towards zero by a similar factor. This demonstrates the advantage of my approach, and highlights the importance of having a dynamic model of investments in the context of EV charging.

8. Counterfactual analysis

In this section, I use the estimated model to understand how Tesla's Supercharging investment decision interacts with the government EV purchase subsidy and estimate the effect of the purchase subsidy on the Supercharging network, consumer welfare and the environment.

Specifically, I reduce the purchase subsidy by 20%[49] for Tesla vehicles from 2017 to 2020[50] and compare the differences between the actual Supercharging network and the network under the reduced subsidy. The overall changes in consumer welfare[51] and long-distance miles driven by Tesla vehicles are calculated, which are then decomposed into the direct effect of the subsidy and the indirect effects through changes in the Supercharging network. Finally, changes in EV miles are translated into carbon dioxide (CO_2) emissions and the social value of the avoided emissions is assessed. Appendix E presents the algorithm that obtains the equilibrium investment decision under the new environment. The results for a 10% subsidy change are available upon request.

The results show that the 20% purchase subsidy increase provides more incentive to Tesla's investment and has an expansionary effect on the Supercharging network. 18% of the locations in the network would experience an acceleration in investment timing. The subsidy increase induces a direct $5.01 billion increase in consumer surplus during 2017 to 2020 through improved utility of Tesla vehicles due to lower effective prices. Moreover, the improvements in the Supercharging network yield a further $93 million gain in consumer surplus. While the direct gain in consumer surplus can be viewed as a transfer from the government to consumers and is welfare neutral, the indirect increase in consumer surplus through network improvements is the byproduct of the subsidy and is the net gain from the policy.

[49]The average federal and state subsidy is $5,193 per Tesla vehicle during 2017 to 2020. The 20% reduction in subsidy is $1,039.

[50]I decide to introduce the subsidy change since 2017 because that is when Tesla started to greatly expand its Supercharging network and when the best-selling Tesla Model 3 was introduced.

[51]The changes in consumer welfare are calculated using the Compensating Variation approach (Small and Rosen (1981)).

In addition to the indirect gain in consumer surplus, the environmental impacts are socially beneficial and are the key motivation for government interventions. My model is capable of assessing the long-distance miles driven by EVs, which can then be converted into CO_2 emissions and associated social value of avoided emissions. The long-distance miles driven by Tesla vehicles is calculated as the lengths of all the long-distance trips each household with a Tesla can drive using the Supercharging network,[52] and is determined by the following factors: the number of Tesla vehicles sold, the average driving needs of Tesla owners and the average fraction of trips that can be traveled using the highway Supercharging network. The purchase subsidy increases Tesla vehicle sales and EV miles directly through lower prices, which is the common channel of environmental impact studied in the literature. Additionally, through the stimulating effect on Tesla's investment, miles driven can increase in three ways: First, the more accessible network increases the attractiveness of Tesla vehicles and hence increase Tesla car sales. Second, as the network becomes accessible, those who drive more will be attracted to buy Tesla cars (the selection effect). Finally, with a better highway network, more routes are now be travelable with Tesla cars. Note that the average life span of a EV is 12 years, so the annual effects are multiplied by 12 to get an estimated lifetime effect on miles driven. Table 7 shows the effects of the different channels on long-distance miles driven by Tesla vehicles.

A 20% change in the purchase subsidy from 2017 to 2020 increases Tesla long-distance miles by 6.2 billion miles directly and 0.8 billion miles indirectly. Assuming a gasoline vehicle emits an average of 0.97 pound of CO_2 per mile while a BEV produces an average of 0.33 pound (in the electricity generation process)[53] and the social cost of CO_2 emissions is \$51 per ton (the US governments current interim estimate), the direct and indirect effects translate into a reduction in CO_2 emissions by about 2 million and 0.27 million tons respectively, or

[52]For the trips that are not travelable using the Supercharging network, I assume the household uses conventional vehicles (e.g. other vehicles the household owns or a rented car).

[53]The Alternative Fuels Data Center calculates a national average of 11,435 pounds of CO_2 equivalent produced by a gasoline vehicle per year and 3,932 pounds by a BEV per year using an average annual vehicle miles driven of 11,824 miles, which converts to 0.97 pound per mile for gasoline cars and 0.33 pound per mile for a BEV. See https://afdc.energy.gov/vehicles/electric_emissions_sources.html.

Table 7: Effect Decomposition of 20% Tesla Purchase Subsidy Change on Lifetime Tesla Long-distance Miles (in Million)

	2017-2020 total	2017	2018	2019	2020
Direct effect	6,245.2	312.8	1,830.4	2,369.6	1,732.4
Total indirect effect	828.6	15.4	325.0	262.4	225.9
Indirect effect on sales	117.5	4.6	53.1	38.2	21.6
Driving pattern for Tesla owners	228.7	9.5	10.0	44.4	164.8
Highway travelability	482.4	1.2	261.9	179.8	39.5

Note: This table presents the increases in long-distance miles traveled by Tesla vehicles by increasing the Tesla purchase subsidy from 80% of the actual levels to the actual levels from 2017 to 2020. The direct effect captures the increases in Tesla vehicles on the road due to lower effective prices, and the indirect effect is any additional effect caused by equilibrium adjustments to Tesla's Supercharging network. The indirect effect consists of three parts: (a) more Tesla vehicles are purchased due to a more extensive Supercharging network, (b) the composition of Tesla drivers changes - they tend to be those with more driving needs now, and (c) more routes can be travelable with a Tesla vehicle with a better network. Columns 3-6 show the lifetime impact of the change in subsidy in 2017-2020 respectively, and Column 2 shows the overall impact of the 4 years of change combined.

equivalently $159 million and $21 million of social value. For any work studying the effects of EVs on emissions that ignores the fast charging network and how consumers drive their EVs, the effects on emissions reduction through changing fast charging network will be wrongly omitted, and in this case, this leads to not counting $21 million worth of social value achieved by a 20% change in Tesla purchase subsidy in 4 years.

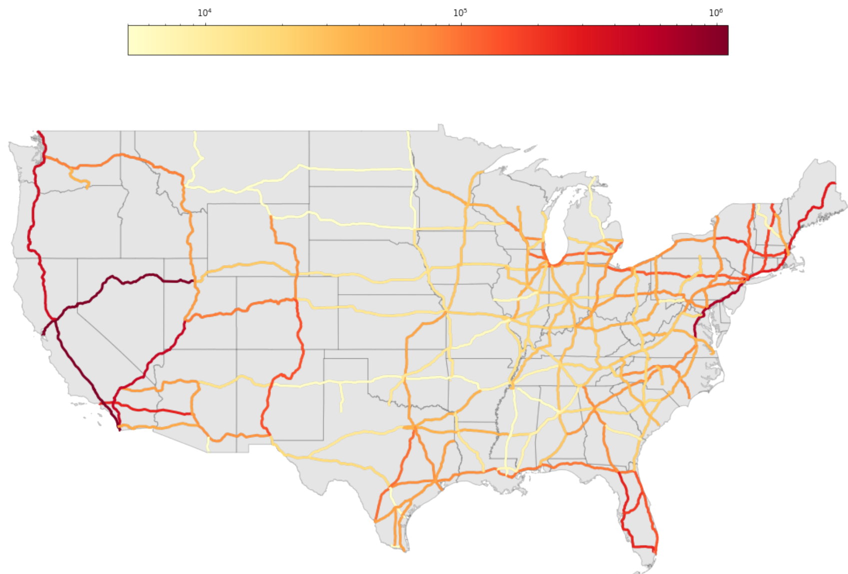
Heterogeneous stimulating effects on Supercharging network I also evaluate the differential effects of the change in the purchase subsidy on different parts of the Supercharging network. The stimulating effect of the subsidy on fast charging is larger for community charging stations than for highway stations - the investments in 26% of county locations and 12% of highway locations are accelerated, and the difference in the fractions is statistically significant. Among the locations that experience investment acceleration, the average investment timing advances by 1.44 years for counties and 1.2 years for highway segments. It implies that if the government aims at developing an extensive network of highway fast charging which is at least as convenient as community charging, additional policy supports that target highway charging are needed, which is consistent with the recent policy focus on subsidizing highway fast charging infrastructure.

Finally, the spatial variations of the effect on the network is evaluated. Since the number of locations in the sample during this period is small and it is hard to distinguish real patterns from idiosyncratic errors using this small sample, I zoom out to all the possible locations in the US (3106 counties and 112 highway segments), and calculate the immediate changes to the marginal profit of covering each location with and without the change in the subsidy. That is, I hold fixed the network as observed except for one location of interest, and calculate Tesla's values with and without covering that location, whose difference gives the marginal value of covering that location. This marginal value is calculated twice, at the two different levels of subsidy. The change in the marginal value captures the immediate change in Tesla's investment incentives following the policy change, as shown in Figure 5.

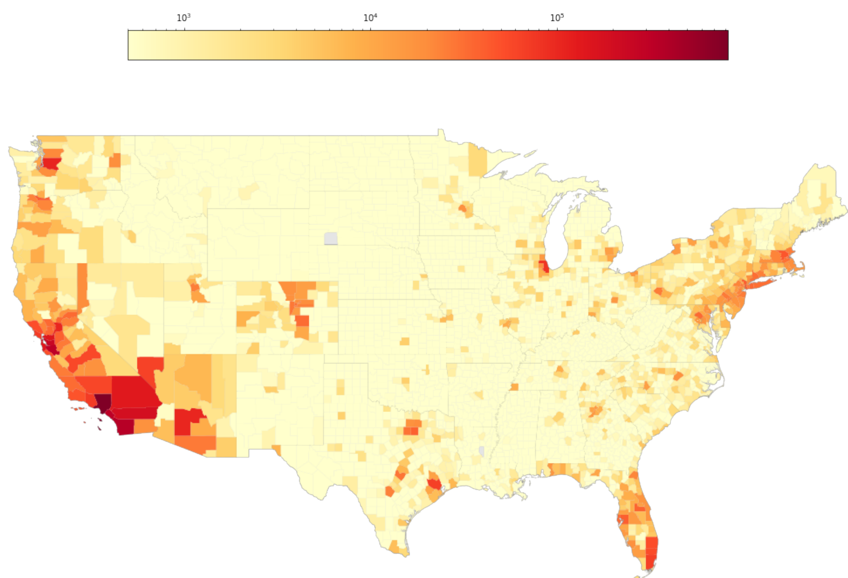
Figure 5 shows that the purchase subsidy has the most stimulating effect on Tesla Supercharging stations mostly on the west coast and in the northeast. Supercharging development in the following states benefits the most from the purchase subsidy: California, Colorado, Connecticut, Florida, Massachusetts, New York, Oregon and Washington. A regression analysis is conducted to understand what location characteristics are associated with more stimulating effects, and the results are shown in Table 8. Segments and counties that are more developed benefit more: locations with higher income and larger pre-period EV adoption, more traveled segments and larger counties enjoy more stimulating effect. It implies that with the same level of purchase subsidy for all consumers, disadvantaged areas will be further left behind due to lacking the incentives for fast charging network development. If the government wants to stimulate EV development in disadvantaged and underserved areas, they need to be subsidized more than developed areas (for example extra EV purchase subsidies to low-income households or extra charging infrastructure subsidies in disadvantaged areas).

Figure 5: Immediate Changes in Tesla's Investment Incentives

(a) Highway locations



(b) County locations



Note: The two graphs above show the immediate changes in marginal profit of covering each location in 2020 where Tesla purchase subsidy increases from 80% of the actual levels to the actual levels. That is, holding everything at the 2020 level (demand and coverage status of other locations in particular), the marginal profit of a location under a given policy environment is the difference in profit from Tesla car sales in 2020 between covering and not covering the location under the given policy environment. The changes in marginal profit captures the effect of the 20% subsidy change on Tesla's investment incentives and tendencies. Darker color means the subsidy has larger stimulating effects.

Table 8: Strength of the Subsidy Stimulating Effect on Supercharging Network

Variables	**Segments**	**Counties**
Constant	-468.5***	-8.152***
	(163)	(1.55)
Median income (in thousand dollars)	4.2265**	0.0445**
	(2.084)	(0.020)
Pre-period EV adoption (%)	1003***	22.95***
	(128)	(1.42)
Traffic volume (in thousand trips)	0.0201***	
	(0.003)	
County size (in thousand households)		0.1167***
		(0.002)
Number of observations	112	3106

Note: This table shows the regression results of the immediate changes in marginal profits of covering a location on various location characteristics. The endogenous variable is as defined in the note of Figure 5 (in thousand). The exogenous variables are the median household income in the county/in nearby counties for a segment, the 2012-2016 EV penetration rates in the county/in nearby counties for a segment, the annual number of trips going through the segment and the number of households in the county.
*p<0.1; **p<0.05; ***p<0.01.

9. Conclusion

This paper studies how fast charging networks affect BEV sales and how Tesla expands its Supercharging network, and understands how the Supercharging network responds to changes in EV purchase subsidies. I build and estimate a random coefficient logit model of demand and a model of oligopolistic competition in pricing, which are subsequently taken into a dynamic investment model in Tesla's Supercharging network. The cost parameters in the investment model are set-identified using the revealed preference approach. The counterfactual analysis investigates the effects of a 20% change in EV purchase subsidy on the Supercharging network, consumer surplus and emissions. The results show that purchase subsidy could stimulate Tesla's investments in fast charging both within communities and along highway corridors. The stimulating effects are larger for counties, and more developed areas. It implies that if the government wants to develop fast charging along highways and in disadvantaged areas, extra subsidies targeting low-income households or charging infrastructure in those locations might be necessary. Moreover, through the expansionary effects on the fast charging network, the purchase subsidy achieves additional consumer welfare gains and emissions reductions; any work that ignores the fast charging channel is likely to underestimate the benefits.

The main contributions of this paper are twofold. It contributes to the understanding of preferences for and the deployment of EV fast charging. This paper studies the EV industry with detailed modeling on fast charging both on the demand side and on the investment side. Two types of fast charging use cases are incorporated - charging during daily activities around where drivers live and during long-distance trips that are far from home, and two types of fast charging stations are distinguished - within communities and along highway corridors. Consumers are allowed to have heterogeneous values on the charging network because they reside at different places and have idiosyncratic travel patterns. The model provides a rich yet manageable way to think about how fast charging stations are used and deployed in real world. To my knowledge, this is the first paper to allow for a high-dimensional national fast charging network and a location-specific taste for charging. Moreover, this paper is one of the few papers in the economics literature to provide a cost estimate of the fast charging stations and the first to estimate that in a dynamic framework. The dynamic approach is preferred to the static one in that it recognizes that investments are irreversible and have long-term profit implications, avoiding biased estimates which are likely to arise in static models.

Methodology-wise, this paper builds on the economy of density literature (Holmes (2011) and Houde et al. (forthcoming)) and uses a new method to calculate an approximation to the optimal network in the dynamic setting in the counterfactual analysis, while the existing approach looks at static snapshots in the development process and solves for an approximation to the optimal static solution.

This paper has two major limitations. First, the current investment model focuses on Tesla and takes the fast charging stations of the other standards as exogenous and fixed. These charging station companies might well respond to changes in Tesla's charging network and/or policy changes. A fully-fledged model would incorporate endogenous roll-outs of CCS and CHAdeMO stations, which might pose a challenge for computation complexity. Another limitation is that some realistic features of charging stations are abstracted away from the model, including charging station utilization rates and congestions, optimal station size, charging fee structure design and profits from charging activities. New datasets on those topics are needed to develop an all-round understanding on EV fast charging, which are left for future research. I plan to use the framework presented in this paper to compare the effects on fast charging network development under various policies, including subsidies on charging infrastructure, ZEV mandates, full compatibility among charging standards, and other composite policy designs.

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Appendix A. Details on moment inequalities for county-segment swaps

This appendix describes the identification of λ in the two cases where the coverage years of a county and a segment are swapped.

Switch an early-covered county and a late-covered segment. The inequality is

$$Y^{c,h'} - \lambda_1 X_1^{c,h'} - \lambda_2 X_2^{c,h'} - \lambda_3 X_3^{c,h'} - \lambda_4 X_4^{c,h'} + \epsilon^{c,h'} \geq 0, \tag{A1}$$

where $Y^{c,h'}$ is the discounted difference in profit flows from car sales net of rents between the actual and alternative plan:

$$Y^{c,h'} = \sum_{\tau=t}^{t'-1} \rho^\tau \Big[\hat{\pi}_\tau\big(N_\tau(a^o)\big) - \hat{\pi}_\tau\big(N_\tau(a^{c,h'})\big)\Big] - (\rho^t - \rho^{t'}) \cdot (\text{rent}_c - \text{rent}_{h'}), \tag{A2}$$

$X_1^{c,h'}$ is the change in discount factor (since county c is covered in different years):

$$X_1^{c,h'} = (\rho^t - \rho^{t'}), \tag{A3}$$

$X_2^{c,h'}$ is the discounted difference in the number of households for county c:

$$X_2^{c,h'} = (\rho^t - \rho^{t'}) \cdot M_c, \tag{A4}$$

$X_3^{c,h'}$ is the discounted difference in the number of Supercharging stations for segment h':

$$X_3^{c,h'} = (\rho^t - \rho^{t'}) \cdot (-\#\text{stations}_{h'}), \tag{A5}$$

$X_4^{c,h'}$ is the discounted difference in the number of annual trips for segment h':

$$X_4^{c,h'} = (\rho^t - \rho^{t'}) \cdot (-\#\text{trips}_{h'}). \tag{A6}$$

$(\lambda_1, \lambda_2, \lambda_3, \lambda_4)$ will be jointly identified in this case, and the identified set (using only swaps of this kind) will be a region in $\mathbb{R}^4$. The moment inequality conditions are

$$\mathbb{E}[Z^{c,h'} \cdot Y^{c,h'}] - \lambda_1 \cdot \mathbb{E}[Z^{c,h'} \cdot X_1^{c,h'}] - \lambda_2 \cdot \mathbb{E}[Z^{c,h'} \cdot X_2^{c,h'}] - \lambda_3 \cdot \mathbb{E}[Z^{c,h'} \cdot X_3^{c,h'}] - \lambda_4 \cdot \mathbb{E}[Z^{c,h'} \cdot X_4^{c,h'}] \geq 0. \tag{A7}$$

Switch an early-covered segment a late-covered county. The inequality is

$$Y^{h,c'} - \lambda_1 X_1^{h,c'} - \lambda_2 X_2^{h,c'} - \lambda_3 X_3^{h,c'} - \lambda_4 X_4^{h,c'} + \epsilon^{h,c'} \geq 0, \tag{A8}$$

where $Y^{h,c'}$ is the discounted difference in profit flows from car sales net of rents between the actual and alternative plan:

$$Y^{h,c'} = \sum_{\tau=t}^{t'-1} \rho^{\tau} \left[\hat{\pi}_{\tau}\big(N_{\tau}(a^o)\big) - \hat{\pi}_{\tau}\big(N_{\tau}(a^{h,c'})\big) \right] - (\rho^t - \rho^{t'}) \cdot (\text{rent}_h - \text{rent}_{c'}), \tag{A9}$$

$X_1^{h,c'}$ is the change in discount factor (since county c' is covered in different years):

$$X_1^{h,c'} = (\rho^t - \rho^{t'}) \cdot (-1), \tag{A10}$$

$X_2^{h,c'}$ is the discounted difference in the number of households for county c':

$$X_2^{h,c'} = (\rho^t - \rho^{t'}) \cdot (-M_{c'}), \tag{A11}$$

$X_3^{h,c'}$ is the discounted difference in the number of Supercharging stations for segment h:

$$X_3^{h,c'} = (\rho^t - \rho^{t'}) \cdot \#\text{stations}_h, \tag{A12}$$

$X_4^{h,c'}$ is the discounted difference in the number of annual trips for segment h:

$$X_4^{h,c'} = (\rho^t - \rho^{t'}) \cdot \#\text{trips}_h. \tag{A13}$$

$(\lambda_1, \lambda_2, \lambda_3, \lambda_4)$ will be jointly identified in this case, and the identified set (using only swaps of this kind) will be a region in $\mathbb{R}^4$. The moment inequality conditions are

$$\mathbb{E}[Z^{c,h'} \cdot Y^{c,h'}] - \lambda_1 \cdot \mathbb{E}[Z^{c,h'} \cdot X_1^{c,h'}] - \lambda_2 \cdot \mathbb{E}[Z^{c,h'} \cdot X_2^{c,h'}] - \lambda_3 \cdot \mathbb{E}[Z^{c,h'} \cdot X_3^{c,h'}] - \lambda_4 \cdot \mathbb{E}[Z^{c,h'} \cdot X_4^{c,h'}] \geq 0. \tag{A14}$$

Appendix B. Definition of basic instruments

Table B1 tabulates the 50 basic instruments, i.e. groups, used to form the moment inequalities in Equation (28).

Appendix C. Calculate the confidence region for the estimated set of λ

This appendix describes how to obtain the 95% confidence region for the identified set of λ. Recall the identified set Λ is characterized by Equation (29):

$$\Lambda = \Big\{\lambda \in \mathbb{R}^4 : \quad \big(\frac{1}{\#\text{dev}} \sum_{(l,l')} Z_g^{l,l'} Y^{l,l'}\big) - \sum_{k=1}^{4} \lambda_k \big(\frac{1}{\#\text{dev}} \sum_{(l,l')} Z_g^{l,l'} X_k^{l,l'}\big) \geq 0, \quad \text{for all } g\Big\}, \tag{29}$$

where g is the index for instruments. For notational simplicity, I write deviation $\frac{1}{\#\text{dev}} \sum\limits_{(l,l')} Z_g^{l,l'} Y^{l,l'}$ as $\bar{w}_{0g}$ and $\frac{1}{\#\text{dev}} \sum\limits_{(l,l')} Z_g^{l,l'} X_k^{l,l'}$ as $\bar{w}_{kg}$ in this appendix. Now Equation (29) becomes

$$\Lambda = \Big\{\lambda \in \mathbb{R}^4 : \quad \bar{w}_{0g} - \lambda_1 \bar{w}_{1g} - \lambda_2 \bar{w}_{2g} - \lambda_3 \bar{w}_{3g} - \lambda_4 \bar{w}_{4g} \geq 0, \quad \text{for all } g\Big\}. \tag{C15}$$

Stack $\bar{w}_{0g}$ across instruments to form vector $\bar{w}_0 = \{\bar{w}_{0g}\}_g$. Do the same for $\bar{w}_1, \bar{w}_2, \bar{w}_3$ and $\bar{w}_4$. Write $\bar{w} = (\bar{w}_0, \bar{w}_1, \bar{w}_2, \bar{w}_3, \bar{w}_4)$ in a long vector format.

To construct the confidence region, an intermediate step is to obtain the joint distribution of $\bar{w}$. From the Central Limit Theorem (for dependent random variables), the joint distribu-

Table B1: Definition of Groups

Panel A: Location class definitions

County class I	Define county classes I1, I2, I3 and I4 by M_c being in $(0, 10^5)$, $[10^5, 5 \times 10^5)$, $[5 \times 10^5, 10^6)$ or $[10^6, \infty)$.
County class II	Define county classes II1, II2, II3 and II4 by the quartiles of M_c, with II1 being the bottom quartile and II4 being the top quartile.
Segment class III	Define segment classes III1, III2, III3 and III4 by $\#\text{stations}_h$ being in $\{1, 2, 3\}$, $\{4\}$, $\{5, 6\}$ or $\{7, 8, 9, 10, 11, 12\}$.
Segment class IV	Define segment classes IV1, IV2, IV3 and IV4 by the quartiles of $\#\text{trips}_h$, with IV1 being the bottom quartile and IV4 being the top quartile.

Panel B: Swap grouping definitions

Swap group category	**Group counts**	**Description**
Swap Type 1 - Switch two counties:		
County size increasing	3	c in class Ii, c' in class I$(i+1)$ for $i = 1, 2, 3$
County size decreasing	3	c in class I$(i+1)$, c' in class Ii for $i = 1, 2, 3$
Swap Type 2 - Switch two segments:		
Segment stations increasing	3	h in class IIIi, h in class III$(i+1)$ for $i = 1, 2, 3$
Segment stations decreasing	3	h in class III$(i+1)$, h in class IIIi for $i = 1, 2, 3$
Segment trips increasing	3	h in class IVi, h in class IV$(i+1)$ for $i = 1, 2, 3$
Segment trips decreasing	3	h in class IV$(i+1)$, h in class IVi for $i = 1, 2, 3$
Swap Type 3 - Switch early-covered county and late-covered segment:		
Based on county size	4	c in class IIi for $i = 1, 2, 3, 4$
Based on segment stations	4	h in class IIIi for $i = 1, 2, 3, 4$
Based on segment trips	4	h in class IVi for $i = 1, 2, 3, 4$
Based on year difference	4	$t - t = 1, t - t = 2, t - t = 3,$ or $t - t \geq 4$
Swap Type 4 - Switch early-covered segment and late-covered county:		
Based on county size	4	c in class IIi for $i = 1, 2, 3, 4$
Based on segment stations	4	h in class IIIi for $i = 1, 2, 3, 4$
Based on segment trips	4	h in class IVi for $i = 1, 2, 3, 4$
Based on year difference	4	$t - t = 1, t - t = 2, t - t = 3,$ or $t - t \geq 4$

tion of $\bar{w}$ can be approximated by a normal distribution with mean and variance-covariance matrix to be estimated. The difficulty lying in the estimation of the variance-covariance matrix is that the deviations (l, l') are not independent because some of them share the same location. In fact, there are 295 locations involved in the 36,546 deviations. To correct for the dependence across deviations, I use a subsampling procedure to estimate the variance-covariance matrix, following Holmes (2011).

More specifically, for each simulation s, I randomly select $\frac{1}{3}$ of county and segment locations in my sample (the location subsample), and look at the subsample of deviations that involve only locations in the location subsample. I then calculate $\bar{w}^{(s)}$ in this deviation subsample. The subsamples are drawn with replacement $S = 1,000$ times, and the $\bar{w}^{(s)}$ draws are used to form the variance-covariance matrix in the subsample:

$$\text{var-cov}(\bar{w})_{\text{sub}} = \frac{1}{S-1} \sum_{s} (\bar{w}^{(s)} - \bar{\bar{w}})(\bar{w}^{(s)} - \bar{\bar{w}})', \tag{C16}$$

where $\bar{\bar{w}} = \frac{1}{S} \sum_s \bar{w}^{(s)}$ is the mean of $\bar{w}^{(s)}$ across subsamples.

The variance-covariance matrix of the whole sample is[54]

$$\text{var-cov}(\bar{w}) = \frac{1}{3} \cdot \text{var-cov}(\bar{w})_{\text{sub}}. \tag{C17}$$

Next, I draw 1,000 times from the normal distribution with mean $\bar{w}$ and variance-covariance var-cov$(\bar{w})$ and calculate the identified set for each draw. The 95% confidence region consists of points that are in the identified set at least 95% of the times. The extreme values of the 95% confidence region in each dimension are presented in Table 5.

[54]Holmes (2011) shows the rate of convergence is a function of the number of locations, not the number of deviations.

Appendix D. Full characterization of estimated set of λ

The estimated set for λ is a convex polygon and can be characterized by its vertices. Table D2 shows the coordinates of these vertices for the three sets of instruments respectively.

Table D2: Vertex coordinates of estimated set of λ

Vertex id	$\boldsymbol{\lambda_1}$	$\boldsymbol{\lambda_2}$	$\boldsymbol{\lambda_3}$	$\boldsymbol{\lambda_4}$
Basic instruments				
1	3,867,022	8.630	1,439,531	0.247
2	4,789,789	8.630	1,634,548	0.471
3	3,811,304	8.630	1,113,661	0.613
4	3,364,854	11.584	1,350,334	0.408
5	3,833,958	11.584	1,449,474	0.521
6	3,336,529	11.584	1,184,672	0.594
7	3,829,856	8.630	1,424,848	0.255
8	2,818,896	8.630	953,127	0.657
9	3,219,940	8.630	953,127	0.657
10	2,613,177	11.584	1,053,361	0.572
11	2,398,361	11.584	953,127	0.657
12	2,483,577	11.584	953,127	0.657
Basic + Order-1 instruments				
1	3,830,729	8.630	1,405,294	0.290
2	3,841,378	8.630	1,134,391	0.607
3	3,326,225	11.584	1,320,348	0.439
4	3,731,681	11.584	1,407,502	0.533
5	3,331,374	11.584	1,189,354	0.592
6	4,665,594	8.630	1,584,749	0.483
7	4,412,981	9.437	1,536,872	0.497
8	4,579,940	8.630	1,536,872	0.497
9	4,527,982	8.630	1,536,872	0.497
10	3,683,592	8.630	1,347,533	0.321
11	2,833,469	8.630	953,127	0.657
12	3,173,468	8.630	953,127	0.657
13	2,533,313	11.584	1,009,080	0.609
14	2,412,708	11.584	953,127	0.657
15	2,460,943	11.584	953,127	0.657
Basic + Order-1 + Order-2 instruments				
1	3,827,127	8.630	1,384,958	0.323
2	3,859,728	8.630	1,151,131	0.603
3	3,290,936	11.584	1,292,448	0.468
4	3,626,307	11.584	1,364,826	0.544
5	3,305,496	11.584	1,188,022	0.593
6	4,567,251	8.630	1,544,688	0.492
7	4,205,438	9.787	1,475,689	0.514
8	4,448,640	8.630	1,475,689	0.514
9	4,370,262	8.630	1,475,689	0.514
10	3,547,602	8.630	1,275,911	0.382
11	2,847,917	8.630	953,127	0.657
12	3,129,934	8.630	953,127	0.657
13	2,458,690	11.584	967,777	0.645
14	2,426,933	11.584	953,127	0.657
15	2,439,733	11.584	953,127	0.657

Appendix E. Counterfactual approach: obtaining the equilibrium network

The appendix describes the method to obtain the equilibrium network in a new environment. To be consistent with the counterfactual analysis in the main text, I describe the case where the environment and the network are unchanged before 2017 and only change in 2017 and onward.

The counterfactual scenario in the main text is a 20% reduction in purchase subsidy compared with the actual scenario, and it is shown that the reduction causes delay in investment timing. That is, a subset of locations actually covered during 2017-2020 will be covered in the counterfactual scenario. Hence, the candidate set of locations that might be covered in the counterfactual can be taken as the locations in the actual network. In other cases where more locations are expected to be covered, a candidate set of locations needs to be specified. It usually includes locations covered in an extended period or locations of competitors.

With the candidate set of locations ready, we can now proceed with the algorithm.

Start with an initial investment plan $a^{(0)}$ (I take it to be the actual plan). For each location, find the optimal coverage year (from 2017-2021) while the other locations are covered according to $a^{(0)}$.[55] Denote the plan formed by the optimal coverage year of each location by $a^{(1)}$. Now, for each location, find the optimal coverage year while the other locations are covered according to $a^{(1)}$. Obtain the updated plan $a^{(2)}$. Repeat this process until convergence, i.e. $a^{(r+1)} = a^{(r)}$. The converged plan $a^{(r)}$ is the equilibrium investment plan.

Note that the obtained investment plan is an approximation to the optimal plan in that

[55] Calculating the value difference between 2021 and any year before only requires the profit streams up to 2020 and hence it can be done with in-sample information. If the optimal coverage year is 2021, it means that covering before the end of the data period is definitely not optimal. On the other hand, if the optimal coverage year is not 2021 (say it is 2018), it does not mean covering in 2018 is necessarily better than any other year in the future. A sufficient condition for 2018 to be the exact optimal is that the marginal profit of covering that location in any year after 2020 is at least as high as that in 2020, which is likely to hold given the growing popularity of EVs. If the optimal coverage year is 2021, it generally means 2021 or beyond, or not covered before the end of the period of interest.

any perturbations to the plan involving a single location are not profitable; joint perturbations of multiple locations might be profitable. It might happen when multiple locations are complements - an example is when sales increase substantially when a county and the neighboring highway are both covered.