Competition For a New Automobile Technology and Impact of Station Build-out

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Abstract

The transition from gas-powered to electric vehicles (EVs) remains a central challenge for environmental policy. Despite federal and state subsidies, EV adoption remains limited, with range anxiety—stemming from sparse charging infrastructure—acting as a key deterrent. This thesis develops and estimates a dynamic game of product entry among all automakers using parametric approximations to firms' value functions and estimate the sunk cost of introducing a new EV model. Additionally, to account for Tesla's unique product positioning, I allow Tesla to provide exclusive charging stations for its users and estimate the annual fixed cost to maintain each station. I estimate demand from micro-data on household purchase patterns, from the National Highway Transportation Survey (NHTS), and highlight the complementarity between the size of the charging network available to a consumer and their utility from operating an EV, indicating that expanding the charging network increases consumer utility from EVs, encouraging new model introductions and amplifying EV adoption through a feedback loop between infrastructure growth and model variety. Results indicate that during the period 2010-2019, Tesla consistently had a higher likelihood of EV entry than the rest, while non-Tesla firms exhibited divergence in entry likelihoods over time. To evaluate the impact of a large scale policy expanding the network of charging stations, I conduct a counterfactual analysis simulating the National Electric Vehicle Infrastructure (NEVI) program as an unanticipated shock in 2010. Simulation results indicate that this large-scale expansion of charging infrastructure to have significantly increased model availability, accelerated EV adoption, but diminished Tesla's market power by reducing the value of its exclusive charging network, leading to a more evenly distributed EV market.

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Contents

Chapter 1

Introduction

A competitive and innovative automotive industry is at the center of a new industrial policy that aims to allow greater transition from polluting gasoline vehicles to battery-operated electric vehicles ("EV"). Automobiles contribute to "29 percent of total U.S. greenhouse gas emissions",[1] making the transition to EVs a critical concern for environmental policy. Recent legislative actions, including the Infrastructure Investment and Jobs Act and the Inflation Reduction Act were passed into law with provisions to bolster adoption of electric vehicles (EVs). The Infrastructure Investment and Jobs Act, signed into law in November 2021, allocated $7.5 billion to expand the network of charging stations, to alleviate *range anxiety* and facilitate long-range EV travel.[2]. The Inflation Reduction Act of 2022 has provisions to reinforce Section 30D of the Internal Revenue Code, also called the Federal EV Tax Credit, providing $7,500 in tax credits for purchases of new EVs and up to $4,000 for used EVs, as well as well reversing the tax-credit phase out that certain manufacturers were subjected to having hit 200,000 units in EVs sold.[3] Prior to these recent legislative efforts, various policies both at the federal as well as at the level of various states have been enacted to

[1] *See* "Carbon Pollution from Transportation", United States Environment Protection Agency, available at https://www.epa.gov/transportation-air-pollution-and-climate-change/carbon-pollution-transportation

[2] *See* "Bipartisan Infrastructure Law," U.S. Department of Energy, available at https://www.energy.gov/bil/bipartisan-infrastructure-law

[3] *See* "The Inflation Reduction Act Drives Significant EV Adoption," U.S. Department of Energy, available at https://www.energy.gov/articles/inflation-reduction-act-drives-significant-ev-adoption

improve the rate of adoption of EVs.[4]

Despite these efforts, EVs comprise a modest portion of vehicle sales—only 8% quarterly and a mere 1% of the total vehicle stock—attributable in part to *range anxiety*, which arises from an insufficient network of charging stations.[5] [6] Against this backdrop, Tesla has been relatively successful, accounting for 50-75% of all EV sales between 2012 and 2022, likely due to its exclusive charging network.[7] From its early days, Tesla adopted the policy of providing stations exclusive to its users, which became a key channel of differentiation compared to other EVs and a significant source of market power. In contrast, incumbent firms like General Motors, Ford, and Hyundai have had to rely on the proliferation of stations provided by third-party charging station providers. The sluggish growth of these third-party networks has, until recently, served as a significant bottleneck, hindering the introduction of more and updated EV models over the years.

Additionally, incumbent firms like General Motors, Ford, Hyundai, etc. predominantly rely on sales from vehicles that run on Internal Combustion Engines (ICEs), i.e. gas vehicles, and therefore, have to take into account for the potential reallocation of demand within the firm's own product lineup having introduced a new EV. Introducing newer models of EVs makes them engage in a strategic tradeoff, typical of any multi-product oligopolist, where they have to compare the profits from the sales of this new product introduced with respect to sales *lost* or cannibalized into their existing set of products. Within the class of firms that sell gas vehicles, the degree of potential cannibalization could also vary significantly across firms depending on factors such as existing market share, quality of goods as well as the quality of the potential EV to be introduced. The tradeoff incumbent firms face between incremental profits from introducing a technological novel good and cannibalization into existing products

[4] *See*: Policies to promote electric vehicle deployment, Global EV Outlook 2021, IEA, available at https://www.iea.org/reports/global-ev-outlook-2021/policies-to-promote-electric-vehicle-deployment

[5] *See* Global EV Outlook 2023, International Energy Agency, available at https://www.iea.org/reports/global-ev-outlook-2023/executive-summary

[6] *See* The long road to electric cars, Reuters, available at https://www.reuters.com/graphics/AUTOS-ELECTRIC/USA/mopanyqxwva/

[7] Cox Automotive

have been investigated in other settings such MRI adoption in US hospitals, microprocessors, hard disk drive, etc. (Schmidt-Dengler et al. (2006), Igami (2017), Igami (2017), Goettler and Gordon (2011))

In this thesis, I model and estimate a forward looking game of entry in EV models, played among auto-manufacturers within the United States. Electric vehicles, despite being a technologically novel good and providing a promising way to address air pollution from vehicular emissions, are vertically almost *inferior* compared to gas vehicles on account of limitations on the driving range of the battery and a lack of sufficient network of charging stations. Potential consumers of EVs suffer from *range anxiety* on account of this limitation, which stifles sales of existing models of EVs as well deters firms from introducing newer models, further stifling growth of EV adoption. Given the complementarity between the size of the charging network available to a consumer and their utility from operating an EV, increasing the availability of charging stations is expected to drive greater adoption of EVs by consumers. As a result, firms introduce newer varieties of EVs that results in compounding effect on sales, driven by both the increase in charging stations and the expansion of available models.

Tesla's position as the market leader within this subsegment could potentially be explained by the network of charging stations it maintains exclusively for its users. Compared to an equivalent non-Tesla EV with similar characteristics, a Tesla EV would be vertically *superior* due to the added convenience of these exclusive stations. Additionally, since Tesla does not sell any gasoline vehicles and offers a limited number of models in its portfolio, concerns about cannibalization are arguably lower than those faced by other firms. This highlights the importance of evaluating Tesla's ex-ante likelihood of entry and comparing it against the likelihood of entry from other firms.

Any public build-out program of charging stations could potentially diminish Tesla's market power by subsidizing entry for its competitors. An extensive network of charging stations that is publicly accessible deters Tesla's entry by reducing the incremental value derived from its exclusive charging network. As such a program effectively addresses range anxiety for all EV users, Tesla's market advantage could be eroded, providing a relative benefit to firms that may have more significant concerns about cannibalization. Therefore, the ex-ante impact of such a policy is potentially ambiguous and requires empirical evaluation.

I use micro-data from National Highway Transportation Survey (NHTS) that records purchases of vehicles at the household level. Additionally, NHTS records information on households' incomes as well as their respective travel need, which allows me to define range anxiety and rationalize its contribution to the utility of a new vehicle being purchased. Using data on individual household's information on purchase of new vehicle, income, travel requirements, etc., I apply the Conditional Logit model (McFadden (1974)) to estimate the utility function that rationalizes the purchase patterns at the level of households as observed. Within a conditional logit framework, each household has access to all possible vehicles available in a given year, and the vehicle it chooses to purchase maximizes its utility relative to all available options. Utility from a vehicle depends on range anxiety, among other things such as price, mileage, etc., and is held to be zero for vehicles that can run on gas. For battery operated electric vehicles, range anxiety depends on household's respective travel requirements, battery range of the respective EV and the relevant number of charging stations in the respective household's state of residence. A detailed description of the demand system as conceptualized is provided in Chapter 5.1.

To analyze the aspect of the competition as characterized within this setting, I formulate a forward-looking game played among automakers. The automakers compete not only in prices, maximizing current variable profits by choosing Bertrand Nash prices, but also compete in entry of new models electric vehicles (EVs). Firms maximize lifetime profits deciding whether or to expand their respective product offerings by introducing a new EV model. Introducing a new EV allows firm a greater differentiation in product offerings but simultaneously, involves considerations of cannibalization into the sales of its existing offerings, in addition incurring the sunk cost to introduce the new product. In the dynamic competitive setup as presented in this thesis, firms compare the expected lifetime profitability from having introduced a new EV or not, and optimize accordingly. A detailed description of the competition structure is provided in Chapter 5.2.

Beyond considerations of the sunk costs of developing a new EV model as well as the potential cannibalization of sales from existing offerings, the size of the available charging network is also a crucial factor in the decision to introduce an EV model. Given the distribution of households' daily travel requirements and the characteristics drawn for the potential new EV, firms could potentially be deterred from introducing a new EV model on account of lack of a sufficiently large network. Given Tesla's absence of reliance on the sales of gas vehicles, addressing range anxiety has been utmost important to it. From very early on, Tesla has provided an exclusive charging network it provides to its users, and have gradually expanded it, supporting the sales of both its existing and new products. The model as presented in this thesis capture this characteristic feature of the US EV landscape, and allows Tesla to offer charging stations exclusively to its users. According to the model, each period, Tesla not only chooses the prices of existing goods and whether to introduce a new EV model or not, but also decides availability of charging station in each individual US state. For a detailed description on Tesla's decisions to build charging stations, refer to Chapter 5.2.3.

To rationalize firms' decision to introduce new models of EVs, I model the competition under the assumption that all auto-manufacturers play Markov perfect stationary strategies (Maskin and Tirole (1988) and Ericson and Pakes (1995)). In this model, firms take actions maximizing lifetime profits, but can set new prices every period, without paying any additional costs, for each of the products offered by them in the market. This makes that prices chosen for respective products at a given period to not have bearing on the decisions taken in the next period, and therefore can be solved for the static problem typical of a Bertrand Nash game. The decision to introduce an EV or not is modeled as a discrete decision and for a typical firm, given its expectations of market structure and behavior of other firms, it chooses the path that provides a higher payoff. I assume model entry decisions have payoff shocks that follows a distribution that allows me to map the optimal decision regarding model introduction in the space of choice probabilities. For a detailed description on characterization of equilibrium, refer to Chapter 5.3.

Introducing a new line of vehicles generates payoffs from future time periods, making dynamic competition the appropriate way to capture strategic interactions in the context as presented in this thesis. Estimating a model with differentiated products within a dynamic framework has its challenges on account of dealing with the large state space that includes all the necessary information as the industry evolves. To solve for the value function that rationalizes the forward looking game, I follow Sweeting (2013) to apply parametric approximation to the value function to solve for the game. Using parametric policy iteration procedure (Benitez-Silva et al. (2000)), repeatedly solving for a set of choice probabilities that show convergence, the value function is rationalized as linear combination of polynomials whose coefficients are recovered as those that attempt to approximate the value function at those choice probabilities. For detailed description of the solution method used to solve for the dynamic game, refer to Chapter 6.3.

Results indicate that the utility a household receives from the purchase of an electric vehicle reduces as the household's respective range anxiety goes up. Range Anxiety of a household for a given electric vehicle, increases with the increase in household's traveling requirement, and decreases with the increase in the EV's battery range as well as with the increase in relevant charging network available in the household's state of residence. Given utility is negatively related to Range Anxiety, one can expect as battery ranges offered by electric vehicles improve or the network of charging station expands or both, utilities from EVs would increase leading to the increase in their adoption. Tesla users have accessibility to both Tesla's exclusive network as well as the third-party network of charging stations available to all, limiting the extent of range anxiety. Given the excess stations Tesla users have access to, Tesla users have to be compensated less than non Tesla users for the increase in their traveling requirements. As the size network increases, the value of each additional station goes down. However, given Tesla users accessibility both Tesla as well as non-Tesla stations, the value of an additional station is incrementally more devalued than non-Tesla stations. For a detailed discussion of results pertaining to demand estimation and marginal rate of substitution, refer to Chapter 7.1 and Chapter 7.2.

Firms can set new prices every period, without paying any additional costs, for each of the products offered by them in the market, making the pricing sub-game in this model akin to that of the Bertrand Nash pricing sub-game of a typical static problem. According to my estimates, Battery operated EVs roughly 30% more expensive to produce than gas vehicles, however they are cheaper than hybrid electric vehicles, plausibly on account hybrid EVs' reliance on both internal combustion as well as electrical engine systems. My estimates also indicate the battery operated EVs have lower marginal costs than both gas vehicles as well as hybrid EVs, with the markup for hybrid EVs being the highest. For a detailed discussion of marginal costs and markups, refer to Chapter 7.3.

To estimate the two key parameters that characterize the forward looking oligopolistic nature of the model as presented in this thesis - sunk cost of EV entry and fixed cost for maintaining a Tesla station, I implement a Grid Search over potential parameter values, and select those which maximizes the likelihood of data as observed. The Grid Search I implement to solve for the dynamic parameters involves solving for the model for sunk cost of EV entry between 500 million USD and 10 billion USD in increments of 100 million USD, and fixed cost of maintaining a Tesla stations between 10,000 USD and 500,000 USD in increments of 10,000 USD. For a detailed discussion on the estimation of dynamic parameters, refer to Chapter 6.4. With discount factor $\beta = 0.95$, the sunk cost of introducing an EV model is estimated at \$4.34 billion and the fixed cost of maintaining a Tesla station is estimated at \$83,000.[8] For a detailed discussion on the estimated sunk cost of model entry and fixed cost for maintaining a Tesla station, refer to Chapter 7.4.

[8] Solving dynamic model require us to assume values of the discount term as given. The discount term which "weighs" payoffs from the future time periods has to be assumed at a given value on account of not being separately identifiable from the expected value function characterizing the future payoff stream.

For the counterfactual exercises conducted in this thesis, I first simulate the entry game over multiple draws of EV characteristics across all firms and evaluate how the respective probabilities of entry into new EV models evolve over the years. Each period, each firm independently draws vehicle characteristics at random from the convex hull of characteristics observed in the data for EVs in the subsequent period. Based on this realization, the firm then decides whether to introduce a new EV model with those characteristics. Under the assumption of perfect foresight, I simulate 100 draws for each firm and estimate the probability of entry into a new EV model for every year from 2010 to 2019. The results indicate that during this period, Tesla is consistently more likely than other firms to introduce a new EV, with this difference widening from 2010 to 2016, after which most of the differences diminish. Among non-Tesla firms, in the early years (2010–2011), most firms exhibit similar likelihoods of introducing an EV. However, as time progresses, divergence emerges: firms like BMW, General Motors, and Tata increase their likelihood of introducing a new EV model, while firms like Ford and Honda experience a decline in their likelihood of entry. For a detailed discussion on this counterfactual exercise, refer to Chapter 8.1.

Another counterfactual exercise I present in this thesis involves evaluating the impact of a large-scale national policy aimed at expanding the network of charging stations across the United States, by engaging in a full model simulation between 2010-2020. The National Electric Vehicle Infrastructure (NEVI) Formula Program is a federal initiative aimed to provide funding to facilitate states to expand their respective network of charging stations. For my counterfactual study, I evaluate the hypothetical impact had the policy been implemented in 2010, with stations being built as planned in the current policy as an unanticipated shock in 2010 across the respective states. With the stations being built as a shock, I forward simulate the model taking into account the full sequence of model dynamics including new EVs being introduced, stations being maintained by both the third-party operators and Tesla, as well as estimate the resulting demand. The results from the model simulation indicates the policy to have had more than doubled the EV model offerings compared to what is observed in data. The evolution of third-party stations in the counterfactual analysis follows a similar pattern as observed in data, but scaled bigger with the size of the third-party network in counterfactual being almost thrice the size as observed in the data. Interestingly enough, Tesla's network in counterfactual is less than 5% of the overall network compared to 30-60% as observed in data, indicating a decline in value from exclusivity on account of the sizeable public network being built for all. In the counterfactual, EV sales grow steadily during the period, crossing 25% in 2020, with no clear market leader and Tesla delegated a mid rank in terms of EV sales. For a detailed discussion on this counterfactual exercise, refer to Chapter 8.2.

Widespread EV adoption suffers from a "Failure to Launch" problem, with payoff to one side of the market is contingent on complementary behavior from other side. Firms are reluctant to offer EV models without the presence of a sufficiently large network of charging stations leading to meager sales figures in EVs, while investment on charging infrastructure remains modest on account of a limited EV driver bases and product offerings. This creates coordination failure typical in evolving two-sided platforms with important cross-group externalities: the value of EV ownership increases with the availability of charging stations, and the value of investing in stations increases with the stock of EVs on the road.

This thesis contributes to understanding the dynamics of a two-sided platform by analyzing the interaction between the availability of charging infrastructure and the entry incentives of automakers. I explicitly quantify how range anxiety, driven by the density of charging stations, affects household demand for EVs, and in turn, how this shifts firms' forward-looking incentives to introduce new EV models. By modeling Tesla's behavior — introducing EVs and building stations — unlike other firms which rely on third-party providers, the analysis captures how strategic control over the platform side can alter competitive outcomes. Moreover, through counterfactual simulations, the study evaluates how public infrastructure expansions could mitigate the failure to launch, accelerate EV model introductions, and reshape the market structure of the automobile industry.

This thesis is organized as follows. Chapter 2 reviews the related literature and discusses how this thesis contributes to the field. Chapter 4 overviews the data sources used in this study and provides descriptive statistics of the key variables that are used in this thesis. Chapter 5 outlines the structure of the model, detailing both household behavior on the demand side and the competitive dynamics among auto manufacturers. Chapter 6 covers the identification of model parameters and the estimation strategies used to recover them. Chapter 7 presents the estimation results for the model parameters. Chapter 8 details the counterfactual analysis conducted and presents the corresponding results. Finally, Chapter 9 provides the conclusion.

Chapter 2

Related Literature & Contribution

This chapter provides an overview of the contribution this thesis makes to certain topics and themes. First, the thesis contributes to the literature evaluating policy incentives that have been institutionalized with a goal to promote EV adoption. DeShazo et al. (2017) investigates California's EV rebate program that provides higher incentives to lower income households, and find that they are effective in promoting equity in EV adoption across households with differential incomes. Similarly, Xing et al. (2021) finds that as much as EV tax credits are effective in promoting sales, targeting low income households would be more cost-effective and potentially lead to more equitable outcomes in EV adoption. Tal and Nicholas (2016) show that 30% of the EV sales could potentially be attributed to federal tax credits, however recommending tailoring the credits to household income and vehicle type to maximize impact. Muehlegger et al. (2018) finds that the Enhanced Fleet Modernization Program (EFMP) in California led to an uptick in EV adoption among low- and middle-income households.

Environmental impacts are a crucial theme in evaluating EV policy effectiveness. Holland et al. (2016) shows that environmental gains from EV replacement is differential across locations, dependent on how clean the respective regional electricity grid is. Sinyashin (2021) finds that subsidy schemes that are tailored to the characteristic such as driving range of a given EV, enhances environmental benefits as well as social welfare. Muehlegger and Rapson (2020) underscores the important of accounting for appropriate counterfactuals in estmating benefits from EV adoption, finding that EV incentives lead to replacement of relatively fuel-efficient gasoline cars, which dampens net environmental gains. In a recent paper, Allcott et al. (2024) evaluates the impact of the Inflation Reduction Act (2022) and finds that targeted credits could significantly increase policy benefits while balancing trade and environmental objectives.

My thesis also contributes to the literature evaluating the importance of charging network on EV adoption. Similarly, Li et al. (2017) quantifies network effects from charging stations and find that subsidizing charging stations would potentially be twice as effective in promoting EV growth compared to purchase subsidies. Li et al. (2019) demonstrates that a uniform charging standard if mandated can reduced double incidence of investments in charging network, expand EV market and potentially lead to overall welfare gain. Springel (2021) implements a two-sided approach and finds that subsidies for charging stations is more effective than tax rebates to drive EV adoption, especially at lower income and spending levels. Zhou and Li (2018) finds that markets failing to reach critical mass in deployment of charging station stifles the growth of EV adoptions, with more than half of the MSAs within the United States failing to reach this critical mass. Jenn et al. (2018) quantifies that \$1,000 in purchase subsidies boosts EV sales by 2.6%, compared to 4.7% increase in EV sales from equivalent non monetary incentives.

To rationalize firms' decision to introduce new models of EVs, I design a forward-looking game played among them. Following Maskin and Tirole (1988) and Ericson and Pakes (1995), I model the competition under the assumption that all auto-manufacturers play Markov perfect stationary strategies. As an alternative to the conventional way to solve for forward-looking game theoretical models using forward simulation (Rust (1987); Bajari et al. (2007)), I follow Sweeting (2013) to apply parametric approximation to the value function to solve for the game. Some other empirical applications that have also used parametric approximation to solve for dynamic models include but are not limited to Fowlie et al. (2016), Barwick and Pathak (2015) and Hendel and Nevo (2006) (Also see Arcidiacono et al. (2013), Farias et al. (2012) and Benitez-Silva et al. (2000) for a more theoretical exposition).

In analyzing the impact of policies on the variety of products available in the market in equilibrium, this relates to the literature on endogenous product positioning (Fan (2013), Sweeting (2013), Wollmann (2018), Eizenberg (2014), and Crawford et al. (2015)). Endogenizing firm responses to the introduction of new EV models in response to policies or competition or both, this paper contributes to this literature by presenting a model of competition in which firms uniquely position themselves in the product space by deciding whether to introduce an EV model or not. Additionally, Tesla can further enhance its product positioning by modifying its network of charging stations.

Whitefoot et al. (2017) and Klier and Linn (2012) allow for firms endogenously choosing vehicle attributes in response to changing fuel economy standards. Some recent work has been conducted in exploring endogenous product selection or position within the EV landscape. Remmy et al. (2022) evaluating the German market for automobiles, allows firms to adjust price and range of their respective EV model in response to subsidies and the presence of indirect network effects and finds firms adjust to price subsidies by offering lower-range EVs whereas expanding the size of charging network leads to negligible changes in product attributes offered. In another paper, Zhao (2022) endogenizes Tesla's charging network, investigating the complementarity of purchase subsidies and Tesla's charging network. Hutchens (2024) endogenizes gas stations' decisions to enter the EV charging market in response to policies that promote EV adoption.

There are various work within Industrial Organization that rationalize evolving market structure by the virtue of firms adopting new technology. Firms incur sizable sunk costs to introduce new products/technology for benefits often delayed into the future, which makes forward looking approach to rationalize complementarity of policy changes and industry level dynamics appropriate. Schmidt-Dengler et al. (2006) rationalizes timing of MRI adoption in

US hospitals. De Groote and Verboven (2019) investigates the role of investment subsidies to promote adoption of photo-voltaic(PV) systems. Igami (2017) explains the incumbent-entrant innovation gap in the transition from 5.25 to 3.5-inch generation within the hard disk drive (HDD). Goettler and Gordon (2011) explains the role of competition in explaining innovations within the microprocessors industry.

Chapter 3

Industry Background

Automotive Industry

The focus of this thesis is the automotive industry, with a particular focus upon Electric Vehicles. The auto industry plays a crucial role in the US economy contributing 3% - 3.5% of the overall Gross Domestic product within the United States.[1] During 2022, the automotive industry drove more than a trillion dollar of contribution into the US economy, at 4.9% of the US economy.[2] The automotive industry is directly responsible for the employment of 1.7 million American workers and indirectly contributes to more than 8 million jobs.[3] The Auto Industry also plays a key role in driving innovation and research within the US economy, contributing $32.8 Billion in R&D in 2022.[4] Within the United States, the auto-manufacturers include - BMW, DaimlerAG, Ford, Geely, General Motors, Honda, Hyundai, Mazda, Renault-Nissan-Mitsubishi Alliance, Stellantis, Subaru, Tata, Tesla, Toyota and Volkswagen.

[1] *See*: Contribution of the Automotive Industry to the Economies of all Fifty State and the United States, Center for Automotive Research, available at https://www.cargroup.org/publication/contribution-of-the-automotive-industry-to-the-economies-of-all-fifty-state-and-the-united-states.

[2] *See*: 2022 Industry Report, Alliance for Automotive Innovation

[3] *See*: How The Auto Industry Predicts (And Shapes) The U.S. Economy, Trent Boberg, Oct 09, 2024, available at https://www.forbes.com/councils/forbestechcouncil/2024/10/09/how-the-auto-industry-predicts-and-shapes-the-us-economy/.

[4] *See*: Press Release, Alliance for Automotive Alliance, January 29, 2025, available at https://www.autosinnovate.org/posts/press-release/auto-innovators-data-driven-report-release

Given the pervasiveness of automobiles around us, the auto industry plays a significant and sizable role in contributing towards global pollution through vehicular emissions. Automobiles that run on Internal Combustion Engines (ICEs) particular contribute towards air pollution account of their emissions releasing toxic gases into the atmosphere, including carbon dioxide, nitrogen oxides, particulate matter, and volatile organic compounds. These emissions have a detrimental quality on human life not only raising temperature globally by contributing to global warming, but also the toxicity of these compounds that are released through emissions causes a wide variety of diseases.

According to the Environmental Protection Agency (EPA), the automotive industry, "Greenhouse gas (GHG) emissions from transportation account for about 28 percent of total U.S. greenhouse gas emissions, making it the largest contributor of U.S. GHG emissions."[5] A 2013 study at Massachusetts Institute of Technology (MIT) estimates about 53,000 premature deaths every year to be directly attributable to air pollution from traffic congestion.[6] The International Council on Clean Transportation (ICCT) reported "that global transportation emissions in 2010 and 2015, respectively, contributed 361000 and 385000 particulate matter and ozone-attributable premature deaths."[7] Another study at the Harvard T.H. Chan School of Public Health have found a sizable relationship between improving vehicular emissions standard and reduced mortality from air pollution.[8]

Given the severity of air pollution that the auto industry contributes to not just within the United States, but globally as well, addressing and potentially fixing it remains one of

[5] *See*: Transportation and Climate Change, United States Environmental Protection Agency, May 14, 2024, available at https://www.epa.gov/transportation-air-pollution-and-climate-change/carbon-pollution-transportation

[6] *See*: Study: Air pollution causes 200,000 early deaths each year in the U.S, MIT News, August 29, 2013, available at https://news.mit.edu/2013/study-air-pollution-causes-200000-early-deaths-each-year-in-the-us-0829

[7] *See*: A Global Snapshot of the Air Pollution-Related Health Impacts of Transportation Sector Emissions in 2010 and 2015, International Council on Clean Transportation, 2019, available at https://theicct.org/wp-content/uploads/2021/06/Global$_{h}ealth_{i}mpacts_{t}ransport_{e}missions_{2}010 - 2015_{2}0190226.pdf$

[8] *See*: Decreased vehicle emissions linked with significant drop in deaths attributable to air pollution, Harvard T.H. Chan School of Public Health, December 14, 2021, available at https://hsph.harvard.edu/news/decreased-vehicle-emissions-linked-with-significant-drop-in-deaths-attributable-to-air-pollution/

the key challenges of the modern century. Given Electric Vehicles run on electric engines and do not rely on Internal Combustion Engines, Electric Vehicles provide a promising solution to the problem of air pollution cause by the automotive industry, especially at the vehicular level, potentially achieving significant reductions in Greenhouse gases and other pollutants that are released from combustion engines. Despite EVs ultimately relying on power that could potentially be produced from fossil fuels, growing reliance on renewable sources of power, and development of efficient electricity markets, combined with zero tailpipe emissions at the vehicular level provides a promising path forward to significantly reduce the carbon footprint of the automotive industry. According to the data collected by International Energy Agency (IEA), in 2023, an EV's emission during its entire lifetime is less than 50% on average than the lifecycle emission of an equivalent gas vehicle.[9] Taking the current mix of electricity grid within the United States into consideration, Union of Concerned Scientists reports that "battery electric vehicle produces roughly half the global warming pollution than a comparable gasoline or diesel vehicle."[10] Electric Vehicles are able to convert 77% of electric energy from the electricity grid to the wheels, whereas conventional gas vehicles have a comparable efficiency of 12%-30% to convert energy from gasoline to the wheels.[11] According to the American Lung Association, a complete electrification of the vehicular fleet within United States can lead to a reduction of 57,200 emergency room visits related to asthma.[12] A study from California found that increasing 20 Zero Emission Vehicles per 1000 population for a given zipcode led to a fall of 3.2% annual asthma hazard ratio, measured using local hospital patient admission data (Garcia et al. (2023)).

[9] *See:* In most cases, electrifying cars reduces their emissions, Science Feedback, 20 September, 2024 available at https://science.feedback.org/in-most-cases-electrifying-cars-reduces-their-emissions/

[10] *See:* Driving Cleaner How Electric Cars and Pick-Ups Beat Gasoline on Lifetime Global Warming Emissions, Union of Concerned Scientists, Jul 25, 2022, available at https://www.ucsusa.org/resources/driving-cleaner

[11] *See*: Electric Vehicles, Clean Energy Alliance, 2025, available at https://thecleanenergyalliance.org/energy-saving-tips-2/electric-vehicles/

[12] *See*: Boosting Health for Children: Benefits of Zero-Emission Transportation and Electricity, American Lung Association, Feb 2024, available at https://www.lung.org/getmedia/dec4362b-0467-4609-9639-2e62301409a4/EV-Boosting-Health-for-Children.pdf (2024)

Evolution of Electric Vehicles

Despite the advent of electric vehicles be traced to late 19^{th} century, the modern EV produced for mass consumption has its roots in 1990s with innovations in battery technology and the growing acknowledgment of the need of a suitable alternative to gas vehicles. General Motors, in 1996, introduced the EV1 which was a subcompact electric vehicle that ran either on a lead acid battery or nickel metal hybrid battery. According to the EPA, the GM EV1 provided a range of 78 miles with the lead acid battery and a range of 142 miles with nickel metal hybrid battery, respectively. Despite spending more than 1B$ in development, GM decided to cease all production of EV1 in 1999, having built just over a 1000 units.[13] EV1s untimely demise, driven by GM's loss of faith in the future of electric vehicles, led Martin Eberhard and Marc Tarpenning to set Tesla Motors, a Silicon Valley startup in 2003.[14] In 2008, it introduced *Roadster*, a luxury electric sports car with a range of 200+ miles, representing a breakthrough in the industry.

Tesla's introduction of *Roadster*, despite being an expensive, niche and a prototype model, marks a watershed moment for the industry, as it changed the perception of the industry to consider electric vehicles to be able to potentially replace gas vehicles. Following Tesla's lead, many manufacturers announced and subsequently introduced plans to produce electric vehicles for the masses. In 2011, within the United States, Nissan introduced the *Leaf*, the first commercially available battery operated EV with a modest range of 73 miles,[15] shortly followed by Mitsubishi who introduced the *i-MiEV* with a range of 62 miles and Daimler who introduced the *Smart ED* which had a range of 63 miles. Within a year, in 2012, Tesla introduced its commercially available model, *Model S* with a battery range of 250 miles. The same year, Ford introduced *Focus*, Honda introduced *Fit* and Toyota introducing the Rav4

[13] *See*: This little electric car made history. 25 years ago, GM stopped making it, OPB, Dec. 6, 2024, available at https://www.opb.org/article/2024/12/06/what-happened-to-the-general-motors-ev1

[14] *See*: The EV1 may have been first, but its demise launched Tesla, Haggerty, 23 January 2020, available at https://www.hagerty.com/media/car-profiles/ev1-may-have-been-first-demise-launched-tesla/

[15] Mitsubishi had introduced the first battery operated EV i-MiEV in Japan in 2009.

Table 3.1: Battery operated Electric Vehicles Introduced (2010-2019)

Year	Make	Model
2011	Daimler AG	ED
2011	Mitsubishi	i-MiEV
2011	Nissan	Leaf
2012	Ford Motor Company	Focus
2012	Honda	Fit EV
2012	Tesla	Model S
2012	Toyota	RAV4 EV
2013	General Motors	Spark EV
2013	Stellantis	500e
2014	BMW Group	i3
2014	Daimler AG	B-Class
2014	Hyundai Motor Group	Soul
2015	Tesla	Model X
2015	Volkswagen Group	e-Golf
2016	General Motors	Bolt
2017	Honda	Clarity BEV
2017	Hyundai	Ioniq EV
2017	Tesla	Model 3
2018	Tata Motors	I-Pace
2018	Volkswagen Group	e-tron
2019	Hyundai	Niro EV
2019	Hyundai	Kona Electric

EV. The EV market, which had seemed stifled over the last couple of decades, with the start of 2010, had finally found its momentum, which newer models being introduced every year. What seemed like a niche, not too long ago, was poised to become a serious alternative to gas vehicles. Table 3.1 presents a full list of Battery Operated EVs introduced between the period 2010-19, the period of study as focused in this thesis.

Evolution of Charging Stations

With growing lineup of electric vehicles to purchase from, this period also witnessed an increasing proliferation of charging stations to support the growing EV market. Many anec-

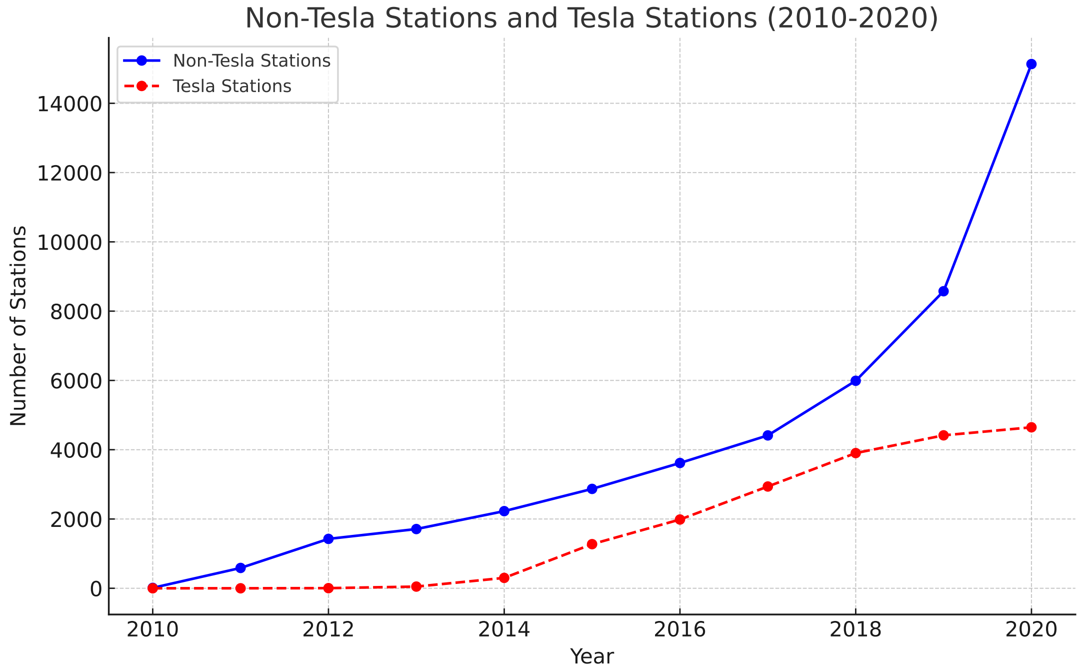


Figure 3.1: This figure reports total number of stations within the United States between 2010-20.

dotal evidence suggests lack of charging stations to be a key concern driving consumers' hesitance towards greater EV adoption due to *Range Anxiety*. Multiple surveys consistently highlight range anxiety to be a key factor dissauding potential EV users. According to 2019 survey by AAA, 58% of potential EV purchasers are worried about running out of charge while driving and 60% of potential EV purchasers are worried that there are not enough charging stations around them.[16]

Figure 3.1 provides the number of stations within the United States between 2010-20 as the network of charging stations has evolved. Tesla differentiates itself from other manufacturers by maintaining a network of stations which is exclusive to its users. The non-Tesla Stations are non-exclusive, i.e., they are accessible to EVs from all manufacturers. They comprise a mix of stations that are run by charging network companies such as SemaCharge,

[16] *See*: AAA Research: 25% of Americans say They'd Buy an EV for their Next Auto Purchase, AAA, available at https://info.oregon.aaa.com/aaa-research-25-of-americans-say-theyd-buy-an-ev-for-their-next-auto-purchase/

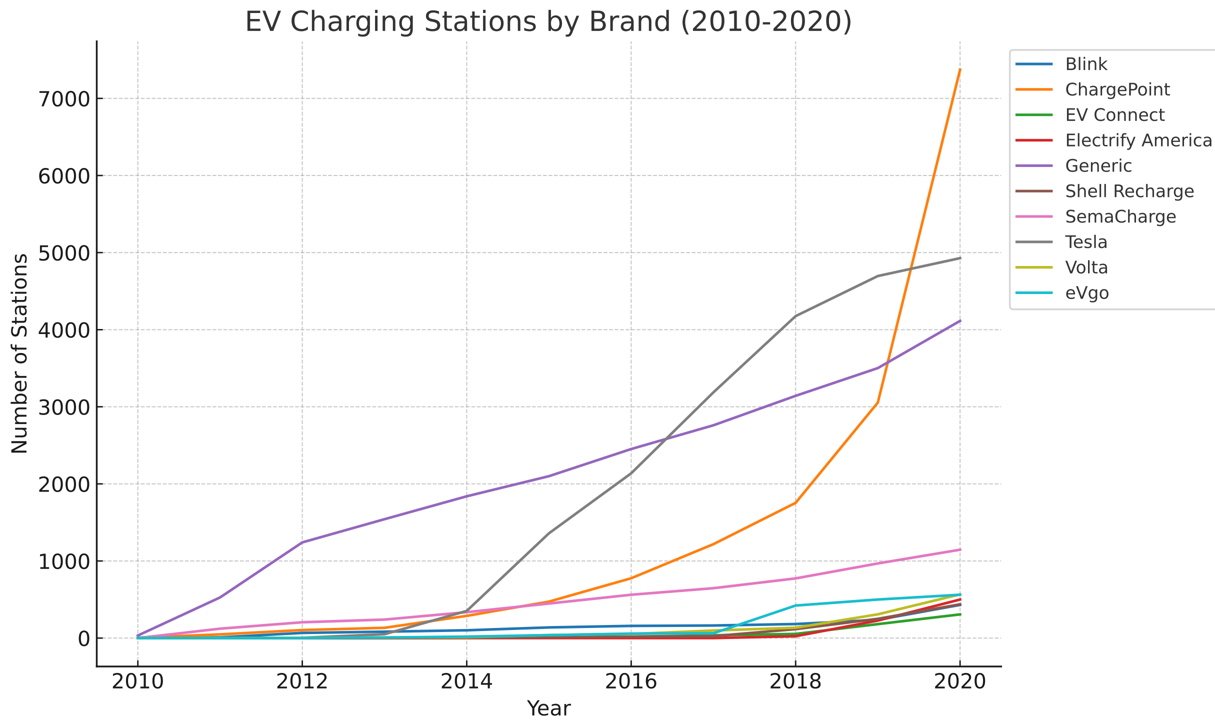


Figure 3.2: This figure reports total number of stations within the United States by brand between 2010-20.

eVgo, etc., independent charging locations such shopping centers, gas stations, etc. or charging stations installed by office spaces, government buildings and so on. Overall, the figure indicates that the public or the third-party charging stations network has grown exploding, having exploded in 2018-2019. On the other hand, Tesla's network grew sluggishly initially, exploded and as the end of decade, approached seems to have reach some saturation point.

Figure 3.2 provides the details of the evolution of charging stations by brand type, within the United States, within 2010-2020. Generic charging stations, those that are provided by government buildings, residential complexes, etc. have grown steadily during this period. As described in 3.1, Tesla's network grew sluggishly initially, exploded and as the end of decade, approached seems to have reach some saturation point. Of the other brands, ChargePoint seems to have exploded during the last few years of 2010-20. ChargePoint operates under a Hardware System Operator Model (SOM), which means that it focuses on EV hardware manufacturing and sales and is not vertically integrated, such as SemaCharge or eVgo, where the company owns the charging stations themselves. Given ChargePoint is a hardware SOM, its exploding from 2018 indicates that independent charging stations, which purchased charging hardware, went up. The other brands grew at sluggish growth and by 2020, reached a mass which is only a fraction of the total number of charging stations.

Subsidies and Rebates

In an attempt to promote the adoption of electric vehicles, the period 2010-2019 also witnessed various programs to subsidize purchase electric vehicles both at the federal and the state level. Section 30D of the Internal Revenue Code, also called the Federal EV Tax Credit, codifies tax credits of upto $7,500 for the purchase of new electric vehicles, "*There shall be allowed as a credit against the tax imposed by this chapter for the taxable year an amount equal to the sum of the credit amounts determined under subsection (b) with respect to each new clean vehicle placed in service by the taxpayer during the taxable year.*"[17] The amount of tax credit a new vehicle qualifies for is contingent upon its battery capacity, implying that larger credits are awarded to EVs with longer electric ranges. One of the important features of this law is the phase-out mechanism, which dictated once a manufacturer hit sales of 200,000 qualifying EVs within the United States, the full tax credit remained available until the end of the quarter when the limit was reached, following which it would be phased out. The rebate would be reduced by half for the next two quarters, halved again in the following two quarters, following which the tax rebate would cease to exist. Tesla became first to trigger the phase-out, reaching 200,000 sales in July 2018, followed by GM in March 2020. However, the Inflation Reduction Act (IRA) of 2022 reversed the phase-out of the Section 30D, allowing Tesla and GM to re-qualify for the tax credit.

Beyond, the federal Section 30D EV Tax Credit, many states within the United States have introduced incentive and sibsidy programs of their own to promote EV usage. The

[17] *See*: 26 U.S. Code 30D - Clean vehicle credit, Legal Information Institute, Cornell Law School, available at https://www.law.cornell.edu/uscode/text/26/30D

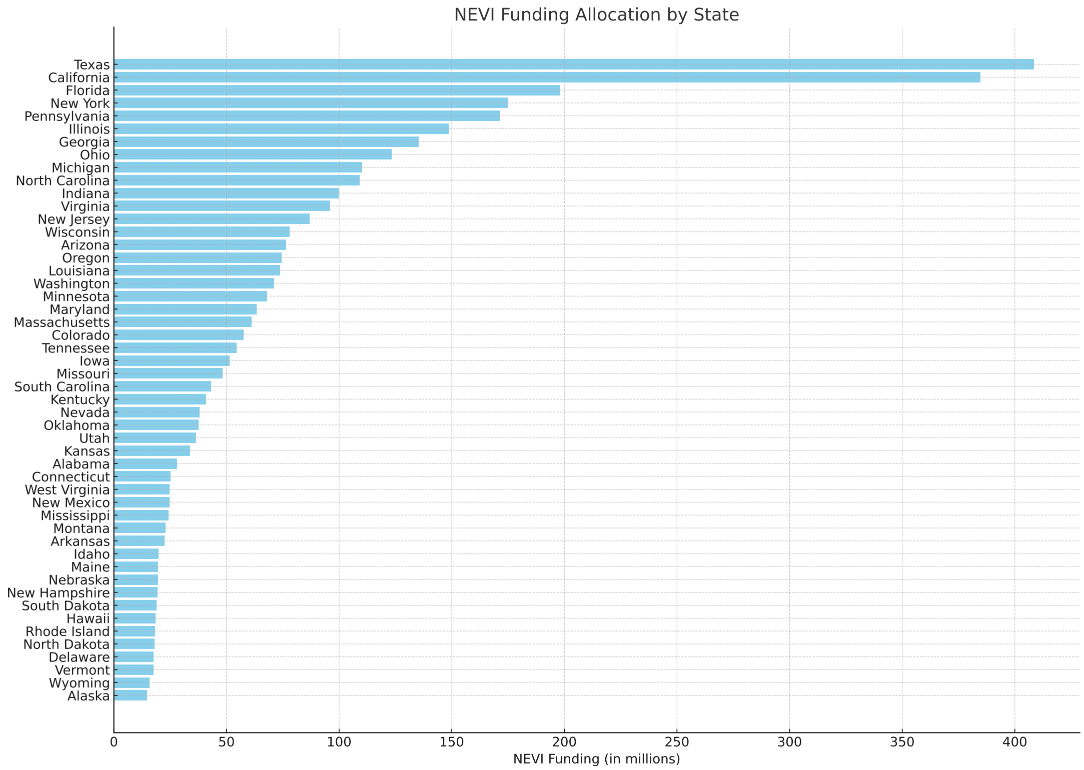


Figure 3.3: This figure reports funding allocation to each individual state according to National Electric Vehicle Infrastructure (NEVI).

"Clean Vehicle Rebate Project" (CVRP) from the state of California offers \$2,500 in rebates for the purchase of new Battery EVs. The "Drive Clean Rebate Program" in the state of New York offers rebates of up to \$2,000. Colorado offers a tax credit of up to \$5,000 for the purchase of an EV. Refer to Table 4.9 for a list of relevant subsidies at the state level.

National Electric Vehicle Infrastructure

The National Electric Vehicle Infrastructure (NEVI) Formula Program is a federal initiative in the United States designed to support the deployment of electric vehicle (EV) charging infrastructure across the country. Established under the Bipartisan Infrastructure Law, the program provides funding to help states build a national network of EV chargers. Each state receives its respective share of overall funding over five years, disbursed annually over time. States are required to submit plans detailing how they intend to use their funds for the installation and maintenance of EV chargers in areas that will maximize the impact on EV adoption and usage. Figure 3.3 presents the approved value in funds receivable for each state under NEVI.

Chapter 4

Data

In this chapter, I discuss the data used for estimation and analysis in this thesis. The research relies on household-level information about daily travel behavior and vehicle purchase decisions, along with demographic details such as household income, and location. I use microdata from the 2017 National Household Travel Survey (NHTS), a nationally representative survey of approximately 110,000 households across all U.S. states. This dataset provides detailed information on household income, travel requirements, and vehicle ownership, including the make and model of recently purchased new vehicles.

A key motivation for the research presented in this thesis is the limitation households face in relying on electric vehicles (EVs) due to range anxiety. Among other factors, range anxiety is influenced by daily travel requirements. All else being equal, households with individuals who travel more frequently or over longer distances are likely to experience a higher degree of range anxiety. Consequently, such households are less inclined to purchase electric vehicles. The NHTS records daily travel patterns for each individual in a sampled household. For a given household, I calculate the total distance traveled by each member on a given day, determine the median distance, and use it as the household's daily travel requirement.

Table 4.1 presents the summary statistics of households' daily travel requirements, mea-

Table 4.1: Summary Statistics of Daily Commute by State in miles

State	Obs	Median	Mean	Std. Dev.	State	Obs	Median	Mean	Std. Dev.
AK	186	33.10	56.80	62.57	MT	275	25.40	43.10	49.70
AL	269	48.90	68.29	63.31	NC	7540	43.87	63.37	59.74
AR	183	34.86	55.42	56.92	ND	244	23.88	49.43	60.71
AZ	2483	29.77	50.28	56.07	NE	237	33.60	57.48	64.31
CA	22193	36.38	55.78	57.48	NH	240	42.98	65.44	62.62
CO	399	40.61	60.55	61.62	NJ	498	37.85	55.87	53.59
CT	204	46.24	64.78	64.31	NM	216	29.78	45.71	49.38
DC	262	15.39	27.34	36.05	NV	188	30.98	44.71	42.66
DE	227	36.67	49.66	47.61	NY	14748	37.44	57.36	58.72
FL	1235	34.99	51.91	53.15	OH	881	40.00	57.28	54.26
GA	7474	41.55	58.48	55.47	OK	1071	41.81	58.20	53.63
HI	247	37.06	51.61	51.37	OR	333	32.86	53.59	59.39
IA	2367	30.94	48.29	52.59	PA	928	35.67	57.15	60.64
ID	282	33.17	53.73	57.21	RI	211	37.34	56.98	53.37
IL	852	35.78	57.00	58.09	SC	5994	43.19	60.70	57.17
IN	419	39.32	57.34	56.65	SD	258	31.17	55.12	62.04
KS	238	35.56	56.42	59.22	TN	368	45.53	63.07	57.35
KY	265	41.22	61.08	61.06	TX	21031	43.25	60.49	56.83
LA	214	36.19	54.59	53.22	UT	277	41.13	63.51	62.89
MA	450	34.33	50.50	50.60	VA	615	42.17	60.67	57.87
MD	1246	42.03	65.16	63.70	VT	334	39.46	59.36	59.81
ME	265	37.84	56.50	58.88	WA	539	39.27	57.32	58.49
MI	692	41.04	62.55	62.47	WI	10193	40.98	60.50	59.94
MN	529	41.61	61.81	60.04	WV	199	39.98	58.29	53.49
MO	402	45.45	62.62	59.63	WY	209	25.10	47.37	56.13
MS	173	54.17	77.21	69.22					

sured in miles, for each state. Based on the data, households in Mississippi (MS) have the highest median travel requirements, whereas households in the District of Columbia (DC) have the lowest. Table 4.2 presents the summary statistics of households' income, measured in \$, for each state. Based on the data, households in District of Columbia (DC) have the highest median income, whereas households in the West Virginia (WV) have the lowest.

Additionally, I use information on vehicles available for purchase from 2010-2019. From *thecarconnection.com*, I compile the set of make and model that were available for purchase from 2010 till 2019, including data on Manufacturer Suggested Retail Prices (MSRPs). From the same source, I also compile information on vehicle characteristics, such as horsepower,

Table 4.2: Summary Statistics of Household Income by State

State	Obs	Median	Mean	Std. Dev.	State	Obs	Median	Mean	Std. Dev.
AK	178	87,500	91,531	62,706	MT	269	62,500	62,900	49,225
AL	263	62,500	64,173	52,658	NC	7,273	62,500	66,407	54,525
AR	174	42,500	59,066	48,991	ND	238	62,500	69,664	53,217
AZ	2,397	62,500	65,360	53,015	NE	235	62,500	76,564	55,968
CA	21,569	62,500	88,856	67,557	NH	227	62,500	86,619	64,552
CO	391	62,500	85,115	65,051	NJ	479	87,500	99,828	71,480
CT	189	87,500	96,243	72,231	NM	213	62,500	72,101	58,328
DC	252	112,500	122,560	78,323	NV	181	62,500	70,925	51,422
DE	216	62,500	81,146	57,673	NY	14,256	62,500	79,190	61,105
FL	1,192	62,500	75,692	60,134	OH	862	62,500	73,619	58,279
GA	7,227	62,500	70,560	57,452	OK	1,032	62,500	70,153	52,744
HI	244	87,500	93,719	66,400	OR	320	62,500	75,297	53,196
IA	2,304	62,500	75,142	56,791	PA	894	62,500	74,765	58,713
ID	273	42,500	62,253	49,703	RI	201	62,500	84,826	65,789
IL	822	62,500	86,606	65,313	SC	5,782	62,500	66,552	53,949
IN	407	62,500	64,613	47,131	SD	255	62,500	67,578	48,464
KS	231	42,500	70,639	56,630	TN	350	62,500	70,557	55,650
KY	258	42,500	61,076	50,399	TX	20,458	62,500	83,762	64,809
LA	204	62,500	62,721	48,147	UT	269	62,500	81,422	56,196
MA	436	62,500	89,885	68,713	VA	604	87,500	91,714	65,021
MD	1,202	62,500	85,258	61,487	VT	324	62,500	78,202	58,011
ME	259	62,500	66,680	54,223	WA	520	62,500	90,361	65,457
MI	671	62,500	74,482	60,172	WI	9,906	62,500	71,461	52,879
MN	502	62,500	87,316	62,968	WV	194	42,500	55,825	49,939
MO	384	62,500	73,607	57,635	WY	201	62,500	73,694	50,896
MS	168	52,500	57,932	44,571					

weight, capacity, capacity and floor span. Data on fuel economy for each make-model-year are obtained from the Alternative Fuels Data Center (AFDC). Fuel economy is defined differently for gasoline vehicles and electric vehicles (EVs). For gasoline vehicles, it is measured in miles per gallon (MPG). For EVs, the Alternate Fuel Economy metric measures the distance a vehicle can travel (in miles) using an amount of energy equivalent to the energy contained in one gallon of gasoline. The U.S. Environmental Protection Agency (EPA) calculates this based on the energy content of gasoline, which is equivalent to 33.7 kWh (kilowatt-hours) of electricity. Table 4.3 provides summary statistics for the key variables associated with vehicles, including prices and characteristics. Fuel economy for a given vehicle is a key

Table 4.3: Descriptive Statistics for Vehicles

Variable	Obs	Mean	Std. Dev.
MSRP ($)	2,345	36,281.21	18,477.83
HorsePower	2,345	242.63	92.27
Torque	2,345	246.57	91.73
Fuel Economy (miles/gallon)	2,241	24.10	5.31
Battery Range (miles)	104	129.8	73.3
Alternate Fuel Economy	104	110.3	16.5
Base Curb Weight (lbs)	2,345	3,604.73	604.44
Floor Span (ft^2)	2,345	19.55	3.11
Passenger Capacity	2,326	4.96	1.37

characteristic in a household's utility from it. To generalize the comparison across EVs and non-EVs given fuel economy is defined differently for them, I evaluate miles per $.

Fuel economy for a given vehicle is a key characteristic in a household's utility from it. To generalize the comparison across EVs and non-EVs given fuel economy is defined differently for them, I evaluate miles per $. Evaluating fuel economy in unit $ requires information on gas prices as well electricity prices, available from Energy Information Administration (EIA). Table 4.4 provides summary statistics for electricity prices for the purposes of transportation for all US states from 2010-2020.[1] Data indicates that during the period of focus in this study, Rhode Island (RI) had the highest electricity prices for transportation, whereas Georgia (GA) had the cheapest.

The EPA provide data on gas prices for the following states - California (CA), Colorado (CO), Florida (FL), Massachusetts (MA), Minnesota (MN), New York (NY), Washington (WA), Ohio (OH) and Texas (TX). For the other states, it does not report gas prices at the state level but at an aggregate level referred to as Petroleum Administration for Defense Districts (PADDs). The United States is divided into five PADDs. The Petroleum Administration for Defense District 1 (PADD 1), also known as the East Coast region, is divided into three sub-regions to reflect its diverse market characteristics. PADD 1A (New England) in-

[1]For years in which there are no charging stations having already been set up in a state, there is no information on electricity prices for transportation available. For those years, I use the residential electricity prices as an alternate for respective states, also available from Energy Information Administration (EIA).

Table 4.4: Summary Statistics for Transportation Prices by State

State	Obs	Median	Mean	Std. Dev.	State	Obs	Median	Mean	Std. Dev.
AK	11	16.051	15.771	1.843	AL	11	9.967	10.076	0.449
AR	11	11.350	11.533	0.744	AZ	11	9.380	9.334	0.466
CA	11	8.680	8.737	0.782	CO	11	9.770	9.650	0.692
CT	11	11.530	11.791	1.461	DC	11	9.520	9.504	0.627
DE	11	9.323	9.320	0.543	FL	11	8.580	8.537	0.407
GA	11	5.850	6.411	1.195	HI	11	26.901	27.386	3.333
IA	11	8.209	8.204	0.739	ID	11	7.133	6.856	0.510
IL	11	6.720	6.538	0.458	IN	11	9.920	10.087	0.568
KS	11	9.323	9.085	0.732	KY	11	8.688	8.550	0.710
LA	11	9.080	9.048	0.498	MA	11	6.240	7.087	2.218
MD	11	8.290	8.246	0.740	ME	11	11.477	11.324	0.370
MI	11	10.650	10.294	1.366	MN	11	9.500	9.258	0.718
MO	11	7.840	7.725	0.754	MS	11	9.360	9.254	0.491
MT	11	9.305	8.998	0.580	NC	11	7.880	7.819	0.437
ND	11	8.127	7.891	0.626	NE	11	8.034	7.884	0.374
NH	11	13.280	13.459	0.786	NJ	11	9.770	9.820	0.995
NM	11	9.010	8.977	0.517	NV	11	8.580	8.665	0.456
NY	11	12.950	13.008	0.793	OH	11	7.330	7.421	0.770
OK	11	7.151	7.158	0.245	OR	11	9.140	8.793	0.768
PA	11	7.810	7.874	0.516	RI	11	17.010	16.009	3.733
SC	11	9.397	9.211	0.491	SD	11	8.430	8.212	0.753
TN	11	9.719	10.211	1.123	TX	11	8.080	8.024	1.965
UT	11	10.260	10.065	0.649	VA	11	8.240	8.196	0.299
VT	11	13.400	13.577	0.773	WA	11	8.540	8.686	0.750
WI	11	13.850	12.204	2.468	WV	11	8.600	8.414	0.424
WY	11	8.393	8.193	0.750					

cludes Connecticut (CT), Maine (ME), Massachusetts (MA), New Hampshire (NH), Rhode Island (RI), and Vermont (VT). PADD 1B (Central Atlantic) consists of Delaware (DE), the District of Columbia (DC), Maryland (MD), New Jersey (NJ), New York (NY), and Pennsylvania (PA). Lastly, PADD 1C (Lower Atlantic) encompasses Florida (FL), Georgia (GA), North Carolina (NC), South Carolina (SC), Virginia (VA), and West Virginia (WV). Meanwhile, PADD 2 (Midwest) covers a large central region, including Illinois (IL), Indiana (IN), Iowa (IA), Kansas (KS), Kentucky (KY), Michigan (MI), Minnesota (MN), Missouri (MO), Nebraska (NE), North Dakota (ND), Ohio (OH), South Dakota (SD), and Wisconsin (WI); PADD 3 (Gulf Coast) includes New Mexixo (NM), Arkansas (AS), Louisiana (LA),

Table 4.5: Summary Statistics for Gas Prices by State

State	Obs	Median	Mean	Std. Dev.	State	Obs	Median	Mean	Std. Dev.
AK	11	3.018	3.055	0.492	AL	11	2.446	2.609	0.596
AR	11	2.446	2.609	0.596	AZ	11	3.018	3.055	0.492
CA	11	3.483	3.421	0.429	CO	11	2.637	2.762	0.545
CT	11	2.742	2.878	0.611	DC	11	2.790	2.898	0.559
DE	11	2.790	2.898	0.559	FL	11	2.601	2.760	0.581
GA	11	2.563	2.730	0.588	HI	11	3.018	3.055	0.492
IA	11	2.596	2.763	0.592	ID	11	2.767	2.824	0.515
IL	11	2.596	2.763	0.592	IN	11	2.596	2.763	0.592
KS	11	2.596	2.763	0.592	KY	11	2.596	2.763	0.592
LA	11	2.446	2.609	0.596	MA	11	2.731	2.834	0.587
MD	11	2.790	2.898	0.559	ME	11	2.742	2.878	0.611
MI	11	2.596	2.763	0.592	MN	11	2.605	2.750	0.584
MO	11	2.596	2.763	0.592	MS	11	2.446	2.609	0.596
MT	11	2.767	2.824	0.515	NC	11	2.563	2.730	0.588
ND	11	2.596	2.763	0.592	NE	11	2.596	2.763	0.592
NH	11	2.742	2.878	0.611	NJ	11	2.790	2.898	0.559
NM	11	2.446	2.609	0.596	NV	11	3.018	3.055	0.492
NY	11	2.809	2.987	0.628	OH	11	2.533	2.748	0.593
OK	11	2.596	2.763	0.592	OR	11	3.018	3.055	0.492
PA	11	2.790	2.898	0.559	RI	11	2.742	2.878	0.611
SC	11	2.563	2.730	0.588	SD	11	2.596	2.763	0.592
TN	11	2.596	2.763	0.592	TX	11	2.441	2.611	0.604
UT	11	2.767	2.824	0.515	VA	11	2.563	2.730	0.588
VT	11	2.742	2.878	0.611	WA	11	3.113	3.160	0.473
WI	11	2.596	2.763	0.592	WV	11	2.563	2.730	0.588
WY	11	2.767	2.824	0.515					

Mississippi (MS), Texas (TX) and Alabama (AL); PADD 4 (Rocky Mountain) with Idaho (ID), Montana (MT), Wyoming (WY), Colorado (CO) and Utah (UT); and PADD 5 (West Coast), featuring Arizona (AZ), Nevada (NV), Oregon (OR), California (CA), Washington (WA), and Alaska (AK).

One of the important premises of the research presented in this thesis is predicated on the range anxiety drivers of electric vehicles potentially face on account of lack of charging stations, therefore, making data on availability of charging stations key to take into account. I collect data on availability of charging stations from Alternate Fuels Data Center (AFDC). The dataset contains information on availability of charging stations, including their respec-

Table 4.6: Summary Statistics for Public Charging Stations available annually by State

State	Obs	Median	Mean	Std. Dev.	State	Obs	Median	Mean	Std. Dev.
AK	11	0	3.73	7.76	AL	11	21	26.82	21.44
AR	11	0	6.09	11.38	AZ	11	35	60.27	66.28
CA	11	550	875.73	1132.96	CO	11	95	145.64	165.57
CT	11	119	101.09	63.71	DC	11	10	9.00	8.38
DE	11	10	11.00	11.01	FL	11	157	235.27	227.43
GA	11	90	141.73	141.33	HI	11	104	99.36	61.95
IA	11	5	18.55	28.33	ID	11	8	13.45	15.14
IL	11	95	121.18	110.56	IN	11	35	42.82	34.55
KS	11	22	20.82	23.56	KY	11	16	27.27	25.54
LA	11	6	11.91	15.25	MA	11	56	116.00	173.48
MD	11	133	190.45	166.26	ME	11	34	41.36	36.86
MI	11	43	78.45	78.81	MN	11	51	61.55	61.34
MO	11	43	99.27	108.02	MS	11	0	3.36	7.24
MT	11	1	5.55	8.57	NC	11	127	149.00	116.78
ND	11	0	2.00	6.63	NE	11	0	9.00	11.52
NH	11	16	21.18	17.41	NJ	11	42	65.09	63.53
NM	11	5	9.73	15.12	NV	11	19	26.73	31.98
NY	11	78	172.18	255.86	OH	11	66	103.09	104.35
OK	11	10	29.91	50.61	OR	11	85	130.73	114.39
PA	11	83	112.18	114.29	RI	11	8	16.45	19.85
SC	11	75	76.00	42.04	SD	11	0	1.09	2.47
TN	11	64	79.00	61.68	TX	11	111	180.27	200.52
UT	11	23	48.82	73.55	VA	11	100	128.18	106.30
VT	11	16	32.64	38.92	WA	11	145	206.55	183.51
WI	11	42	43.91	36.85	WV	11	8	12.18	9.84
WY	11	7	9.00	9.18					

tive locations and data since which they have been operative. From this data, I compute for each US state the number of charging stations available each year, within the duration this study focuses on.

To account for Tesla's unique differentiation to additionally provide charging station exclusive to its users, I account for public charging station available to all electric vehicles separately from Tesla charging station exclusively accessible to its users. Table 4.6 provides the summary statistics for public charging stations available annually in each state. These charging stations are accessible to all vehicle irrespective of make. Data indicates that during the period of focus in this study, South Dakota (SD) had the least number of public charging

Table 4.7: Summary Statistics for Tesla Charging Stations by State

State	Obs	Median	Mean	Std. Dev.	State	Obs	Median	Mean	Std. Dev.
AK	11	0	0.18	0.40	AL	11	8	14.91	17.19
AR	11	0	7.45	10.62	AZ	11	42	38.82	37.36
CA	11	320	362.91	365.15	CO	11	40	39.27	39.23
CT	11	18	19.00	19.53	DC	11	1	0.91	0.54
DE	11	1	2.91	3.70	FL	11	85	139.82	155.57
GA	11	33	58.64	67.54	HI	11	1	2.91	3.30
IA	11	5	8.91	10.10	ID	11	10	9.73	9.74
IL	11	17	36.00	42.57	IN	11	13	17.36	18.30
KS	11	9	7.91	8.13	KY	11	5	13.00	15.71
LA	11	7	9.00	9.24	MA	11	29	29.00	29.04
MD	11	14	24.18	27.61	ME	11	24	25.45	25.71
MI	11	13	22.27	24.94	MN	11	11	18.82	23.44
MO	11	18	24.00	26.39	MS	11	0	9.27	11.97
MT	11	11	8.91	8.55	NC	11	31	36.36	39.52
ND	11	0	0.36	1.21	NE	11	0	3.09	3.94
NH	11	14	12.18	12.15	NJ	11	20	27.73	30.99
NM	11	15	11.73	10.83	NV	11	31	35.09	34.99
NY	11	86	188.91	217.54	OH	11	26	39.18	43.79
OK	11	4	8.27	10.31	OR	11	42	48.18	48.34
PA	11	28	44.45	49.13	RI	11	1	1.91	2.12
SC	11	14	20.45	22.67	SD	11	3	4.91	5.41
TN	11	8	22.36	26.33	TX	11	56	114.00	127.58
UT	11	23	24.00	24.91	VA	11	39	63.73	71.92
VT	11	9	12.45	14.00	WA	11	45	53.27	54.63
WI	11	30	28.09	24.97	WV	11	3	11.64	14.45
WY	11	11	10.18	9.95					

stations, whereas California (CA) had the most. Table 4.7 provides the summary statistics for Tesla charging stations available annually in each state. These charging stations are available exclusively for Tesla users. Data indicates that during the period of focus in this study, Alaska (AK) had the least number of public charging stations, whereas California (CA) had the most.

Electric Vehicles are subject to a range of subsidies, both at the federal and the state level, institutionalized to expedite the adoption of them. At the federal level, the primary incentive is the federal tax credit, Internal Revenue Code Section 30D, which can provide up to $7,500 for the purchase of a new EV. This credit is based on the size of the vehicle's

Table 4.8: Federal Electric Vehicle Credit under Internal Revenue Code Section 30D

Criteria	Details
Battery Capacity	$2,917 for at least 5 kWh
Additional Capacity	Plus $417 for each kWh over 5 kWh
Maximum Credit	Up to $7,500
Vehicle Weight	Gross vehicle weight rating of less than 14,000 pounds
Manufacturer Limit	Made by a manufacturer that hasn't sold more than 200,000 EVs in the U.S.

battery and phases out for manufacturers after they have sold 200,000 qualifying vehicles.[2] Table 4.8 lists the relevant details of the Internal Revenue Code Section 30D that determine the federal subsidy subject to respecive electric vehicles which I take into account in the analysis presented in this thesis.

At the state level, incentives vary widely by location but often include additional rebates, tax credits, or exemptions from state sales taxes. Some states, like California, offer significant rebates through programs such as the Clean Vehicle Rebate Project (CVRP), which can provide up to $4,500 depending on the vehicle and the applicant's income level.[3] Figure 4.9 provides the list of the states that had state level rebates available between 2010-20.

Table 4.9: Summary of State-Level EV Rebates (2010-2020)

State	Year	Adjustment Summary
MA	2014+	+$2,500 for BEVs/PlugIns under $50k
WA	2015+	+6.5% MSRP for BEVs/PlugIns under $42.5k
DE, NY	2016+	+$1,500 (DE), +$2,000 (NY) for BEVs/PlugIns
CO	2017+	+$5,000 for BEVs/PlugIns
TX	2017+	+$3,000 for BEVs/PlugIns under $63k
ME	2018+	Varied by income: Up to +$3,500 for BEVs; Up to +$2,000 for PlugIns
CA	2019+	+$5,000 for BEVs/PlugIns
OR	2020+	+$5,000 for BEVs/PlugIns

[2] By the end of 2020, only GM and Tesla met the 200000 threshold. Threshold limit is no longer applicable since 2023.

[3] Adjustments depend on vehicle type, MSRP, and household income. BEV = Battery Electric Vehicle, PlugIn = Plug-in Hybrid

Chapter 5

Model

In this chapter, I provide the description of the model I rely upon to estimate parameters that rationalize household as well as firm behavior. The model comprises of households choosing whether or not they wish to be in the market to purchase a new vehicle in a given year, and conditional on choosing to be in the market to purchase a new vehicle in a given year, choosing from the set of all vehicles (make-model) available in that given year, the vehicle that maximizes their respective utility.

In addition to providing a detailed description of household behavior characterizing demand, the chapter explains the market structure as well as the competition among firms. The model consists of a forward-looking game played among auto manufacturers (i.e., firms), where they compete not only in prices but also in the entry of electric vehicles (EVs). Firms maximize their future expected lifetime profits by playing a Bertrand Nash game in setting prices for all the vehicles available to be sold in a given year, as well as by deciding to expand their respective product offerings by introducing a new EV model or not. The model takes into account the differentiation Tesla provides by the virtue of providing charging stations exclusive to its users. For a given year, in addition to choosing Bertrand Nash prices for a given year and whether or not to introduce a model, starting next year, Tesla uniquely chooses availability of charging station next year, modeled as a continuous decision.

5.1 Demand

I apply a nested approach to rationalize demand. Households residing in region d at time t, conditional on the state variables that are relevant to them, as well as the set of automobiles they can purchase from, first decide whether or not they wish to be in the market to purchase a new automobile. If a household does decide to be in the market for the purchase of an automobile, they receive K *utils* on the outset or the outside margin. If the household decides not to purchase anything, which is the the outside option, it receives 0 *utils*. Having received K, each household chooses the vehicle that maximizes its respective utility from set of all vehicles available. The utility that a household i receives, residing at region d, from the purchase of vehicle j is defined as follows:

$$\begin{aligned} U_{ijdt} &= \mathbf{X}_j\beta + \alpha\frac{(p_{jt} - s_{jt} - s_{jdt})}{Y_i} + \gamma R_{ijdt} + \xi_{jt} + \varepsilon_{ijt} \\ &= V_{ijdt} + \varepsilon_{ijt} \end{aligned} \tag{5.1}$$

For a vehicle $j \in \mathcal{J}_t$ included in the set of all vehicles (make-models) available in a given year t, the utility household i receives residing in region d, is a function of vehicle characteristics $\mathbf{X}_j$, price of the vehicle p_{jt}, federal subsidy available s_{jt}, state subsidy available s_{jdt}, its income Y_i, and most importantly range-anxiety R_{ijdt}. For a vehicle j, the set of exogenous characteristics $\mathbf{X}_j$ includes features such as Horsepower/Weight, Mileage for unit \$, Floor span and Passenger capacity. It is important to highlight that in this model, consumers are in the market for all automobiles, i.e. once on the inside, they can potentially choose both an EV as well as a non-EV. However, EVs do qualify for a menu of subsidy schedule depending on the period the household is making its decision in as well as its location.

5.1.1 Range Anxiety

Anecdotal evidence suggests limited availability of charging stations to be one of the biggest bottlenecks to greater EV adoption. For the scope of technological progress gone into the evolution of EVs, from the point of view of a household, EVs might potentially be an inferior good on account of Range Anxiety. In my description of the automobile market, households potentially purchase from the set of all vehicles, not exclusively EVs or non-EVs. Given Range Anxiety do not apply to the non-EVs, EVs are almost vertically differentiated from non-EVs.

In my model, utility from EVs suffer from Range Anxiety, whereas utility from non-EVs don't. Range-Anxiety is defined as:

$$R_{ijdt} = \frac{\text{Daily Travel Requirement}_i/\text{Charging Stations}_{jdt}}{\text{Battery Range}_j} \tag{5.2}$$

For a given EV j, for a household i that resides in region d at time t, Range Anxiety depends on - i) how many miles does the household i travel on a given day ii) the range the vehicle j can cover on a full charge measured in miles and iii) the relevant number of charging stations for vehicle j in region d at time t. For a given vehicle j, for two identical households with similar travel needs, range-anxiety will differ on account of their respective states of residence with differing availability of charging stations.

For a given household i, Range-Anxiety will differ within the class of EVs depending on whether the vehicle is a Tesla or not. Tesla users have access to additional charging stations beyond the publicly available ones, provided by Tesla. In my model, I assume every non-Tesla EV has access to all publicly available charging stations within a given state. Therefore, for a given household i, the Range-Anxiety from all non-Tesla EVs is the same. However, due to the additional stations exclusively available to Tesla users, the extent of Range-Anxiety for Tesla EVs is alleviated based on the size of this additional network.

5.1.2 Outside Margin and Preference Effect

If a household does decide to be in the market for the purchase of an automobile, they receive K *utils* on the outset or the outside margin. At the outside margin, the decision for households is modeled as discrete, with households choosing to go to the market of new automobiles if and only if

$$\mathbf{E}\Big[(max_{j\epsilon \mathbf{J}_t} \quad U_{ijdt})\Big] + K + \mu_1 > \mu_0 \tag{5.3}$$

where μ_0 and μ_1 are payoff shocks that follow an extreme value distribution. J_t is the set of of all make-models available to purchase from at a given year t and U_{ijdt}, defined as per 5.1 is the utility household i receives from vehicle j, residing at region d at time t. From XXrefXX, $\mathbf{E}\Big[(max_{j\epsilon \mathbf{J}_t} U_{ijdt})\Big] = ln\Big(\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})\Big)$, defined as the log sum of the inside options. Given the distribution of the payoff shocks, the probability with which a given household chooses to go to the inside or the market for new automobiles is defined as :

$$Pr(\text{i buys any vehicle}|d, \mathbf{J}_t) = \frac{exp\Bigg(ln\Big(\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})\Big) + K\Bigg)}{1 + exp\Bigg(ln\Big(\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})\Big) + K\Bigg)} \tag{5.4}$$

Combining the probability of choosing to go to the market for new automobiles, i.e. to go to the inside and the probability of choosing a vehicle conditional on being on the inside, defined as a typical logit share, for HH i living in d at t, the unconditional probability that it purchases a vehicle $j \in \mathbf{J}_t$ is given as :

$$s_{ijdt} = Pr(\text{i buys j}|t) = \underbrace{\frac{exp(ln(\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K)}{1 + exp(ln(\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K)}}_{\text{Probability HH } i \text{ goes to the inside}} \times \underbrace{\frac{exp(V_{ijdt})}{\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})}}_{\text{Probability } i \text{ buys j once inside}} \tag{5.5}$$

To form the aggregate demand for vehicle j at time t, I integrate the household level demand, s_{ijdt}, across the distribution of households nationally, $d\mathcal{G}(\mathcal{I})$.

$$S_{jt} = \int s_{ijdt} d\mathcal{G}(\mathcal{I}) \tag{5.6}$$

K, which is received before the exact purchase of a vehicle is made, is intended to capture the 'preference effect' or 'opportunity cost' for households simply on account of choosing to purchase any vehicle. One can imagine K to capture the operative cost or the gross benefit simply by the virtue of having a vehicle. K could alternatively be specified within the utility specification 5.1 itself. However given it's equal for all options, it cannot be estimated on the *inside*. For the analysis that is presented to rationalize competition, I shall assume K to be held constant.

5.2 Supply

To analyze the behavior of agents on the supply side, I design a forward-looking game played among auto manufacturers (i.e., firms). The auto manufacturers are the agents in this setting, where they compete not only in prices but also in the entry of electric vehicles (EVs). In addition to maximizing current variable profits by choosing Bertrand Nash prices, firms maximize lifetime profits deciding whether or to expand their respective product offerings by introducing a new EV model. Each period, a given firm makes a draw of vehicle characteristics and, based on its expectations of competitors' behaviors, decides whether to "package" these characteristics into a new EV model or not, with the sales of the new EV beginning in the next period.

Introducing a new model, an EV in this case, allows firm a greater degree of differentiation in product offerings but at the same time, involves considerations of cannibalization into the sales of its existing offerings, in addition to the sunk cost incurred in building the new product. In the dynamic setup as modelled in this paper, firms compare the expected lifetime profitability from having introduced a new EV or not, and optimize accordingly. Beyond considerations of the sunk costs of developing a new EV model and potential cannibalization of sales from existing offerings, the size of the available charging network is also a crucial factor in the decision to introduce an EV model. Given the distribution of households' daily travel requirements and the characteristics drawn for the potential new EV, firms might be deterred from introducing the model due to the lack of a sufficiently large network.

Between 2011 and 2020, the period of study in this paper, Tesla dominated EV sales within the United States, peaking in 2019 with 82.5 % of the EV market share in Q3 of 2019.[1]. One explanation for Tesla's dominance in the EV sub-segment is the exclusive charging network it provides to its users. Since Tesla does not offer non-EV vehicles, addressing range anxiety has been a top priority and from its inception, Tesla has gradually expanded its network to support the sales of its product. To capture this unalienable feature of the US EV landscape, in this model, I allow Tesla to offer charging stations exclusively to its users, to incrementally solve for Range Anxiety compared to all non-Tesla offerings. In my model, each period, Tesla not only chooses the prices of existing goods and whether to introduce a new EV model or not, but also decides availability of charging station in each US state.

Any government intervention to build public charging stations helps address range anxiety for all vehicles, both Tesla and non-Tesla. Given the complementarity between the size of the charging network and the utility of owning an EV, building more stations encourages greater substitution from non-EVs to EVs among consumers for the existing set of available vehicles. As range anxiety is progressively reduced, firms have stronger incentives to introduce new models. However, public provision of charging stations dampens Tesla's market power given a key aspect of Tesla's differentiation from other EV manufacturers is its exclusive charging network. When the government provides public stations that are accessible to everyone, the value of Tesla's exclusive network diminishes, reducing Tesla's incentive to build these stations. This loss of market power also impacts Tesla's decision to introduce new EVs given they lose their differentiation compared to other EVs in terms of range anxiety.

[1] *See* "Tesla's US EV market share dips below 50% in Q2 as Ford, Kia, BMW see growth", Yahoo News, July 11, 2024

Although concerns about cannibalization of existing products are less significant for Tesla compared to other firms, the reduction in Tesla's relative superiority in addressing range anxiety diminishes its incentive to introduce new EV models.

5.2.1 Competition Structure

The model comprises of $\mathcal{O}$ ($o = 1, 2....\mathcal{O}$) firms playing a forward-looking dynamic oligopoly game. Every period t, a given firm o, conditional on the publicly observed state variables, $\mathcal{M}_t$, chooses action a_{ot} that maximizes its expected lifetime profits. Firms choose actions taking into account not only profits which are received *today*, but also expected profits received in the future, on account of some of those actions potentially changing next period's market structure. The timing of the game is structured as follows:

1. At the start of the period t, each firm observes the state variables, $\mathcal{M}_t$.

2. Given the the publicly observed state variables, $\mathcal{M}_t$, each firm chooses its action a_{ot}. a_{ot} refers to the following three or two decisions, depending on whether the firm is Tesla or not:

   (a) the set of Bertrand-Nash prices, $\{p_j\}_{J_{ot}}$ for each of its product $j \in J_{ot}$, where J_{ot} is the set of vehicles it offers at t.

   (b) the decision to introduce an EV or not, a^e_{ot}, for a set of drawn EV characteristics, $\{\mathcal{X}_{oj}\}$, starting next year.

   (c) (For Tesla only) the decision regarding next year's availability of exclusive charging stations, $\{h_{dt}\}_d$, each US state d. I elaborate upon the modeling details for this decision in one of the following subsections.

3. Each firm's decision to introduce an EV next year, $\{a^e_{ot}\}_{\mathcal{O}}$ and Tesla's decisions regarding next year's availability of stations, $\{h_{dt}\}_d$ are subject to modify next year state variables, $\mathcal{M}_{t+1}$.

- $\mathcal{M}_{t+1}$ is also subject to changes in availability of third-party stations, i.e. non-Tesla or public. I assume availability of third-party stations follow an endogenously pre-determined policy function, modeled as a linear combination of polynomials of selected state variables.[2]

- Other changes to $\mathcal{M}_{t+1}$, including changes in availability of non-EV models, vehicle characteristics excluding range-anxiety, gas prices, electricity prices and incentives subsidizing EV purchase, are modelled exogenously.

4. At the start of period $t+1$, firms observe $\mathcal{M}_{t+1}$ and the process repeats.

5.2.2 Model Introduction

A firm o that makes a draw of characteristics $\{\mathcal{X}_{oj}\}$, chooses as to whether they wish to introduce a new EV model packaged with those characteristics or not, i.e. a discrete binary decision. If a firm chooses to do so, it has to pay a sunk cost τ. In this context, sunk cost refers to the irreversible expenses incurred in developing a new electric vehicle, such as research and development expenses, production setup, and marketing efforts. To allow for uncertainty to payoffs associated with the decision of introducing a new EV or not, on account of large scale cost uncertainty in changing production lines, inventory management, hiring new labor, etc., I assume that there is payoff shock conditional on the decision made.

Assumption A.1: Firms observe privately an iid payoff shock $\nu_{ot}(a^e_{ot})$, distributed Type 1 extreme value before deciding upon model introduction

In the setting of the model, a given firm o makes a public random draw of characteristics, $\{\mathcal{X}_{oj}\}$ which includes Horsepower/Weight, Mileage, Floor Span, Passenger Doors and Battery Range. A given draw of $\{\mathcal{X}_{oj}\}$ refer to the characteristics a new EV model would have if firm o would choose to introduce one. I assume all firms to make their respective draws independently, from a convex hull of the characteristics, $Conv()_t$, defined for period t.

[2]For the purposes of estimation, I assume *perfect foresight* on firms' behalf regarding the availability of third-party stations. By assumption, this policy function predicts the supply of 3rd party stations next period conditional on state as observed. For estimation purposes, that would be the data as observed.

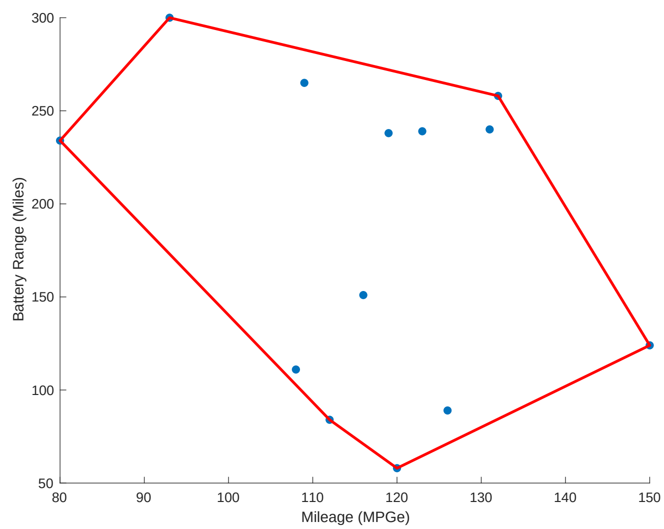


Figure 5.1: The convex hull is inferred from the data observed in the next period, representing the feasible set of characteristics for new EV models. This 2-D representation illustrates the convex hull in terms of two key attributes: Battery Range and Mileage.

$Conv()_t$ is intended to capture the characteristic space that firms can potentially draw from given the state of technology at period.

For empirical purposes, inferring what the true $Conv()_t$ for given time t is going to be a challenge. I propose using data as observed to capture the $Conv()_t$. $Conv()_t$ is defined as the convex hull of characteristics as observed in data for the set of all EVs, that were available in $t+1$. Figure 5.1 depicts the convex hull for 2018 of a representation using only two key attributes: Battery range and Mileage, whereas Figure 5.2 depicts the convex hull for 2018 of a representation using three key attributes: Battery Range, Mileage and Floor Span.[3] The convex hull is inferred from the data observed in the next period, representing the feasible set of characteristics for new EV models. It encloses the set of possible combinations of these attributes, reflecting the boundary within which firms can introduce new EV models

[3]I assume battery technology to change over time exogenously. Battery technology has applications extending well beyond the automotive sector, including in industries such as robotics, grid-scale energy storage, aerospace, and consumer electronics. Consequently, innovation and improvements in battery technology are driven by a wide range of global research efforts and industrial demands, not solely by incentives within the automobile industry.

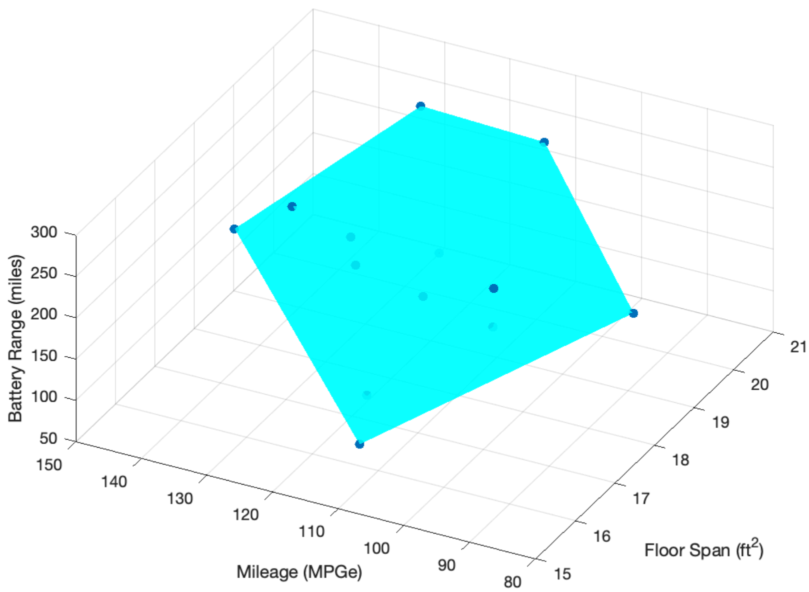


Figure 5.2: The convex hull is inferred from the data observed in the next period, representing the feasible set of characteristics for new EV models. This 3-D representation illustrates the convex hull in terms of three key attributes: Battery Range, Mileage and Floor Span.

based on the observed characteristics. Information from next period informs us to trace the technological today, however, admittedly, this approach suffers from an issue of selection on account of only observed data points defining the boundary of this convex hull, potentially ignoring many other draws of $\{\mathcal{X}_{oj}\}$ made, but not realized in a new EV model.

5.2.3 Station Build-out by Tesla

According to the model presented, Range Anxiety is a significant factor impacting consumers' evaluation of an EV. Gas vehicles do not suffer from range anxiety which explains why EVs have had a sluggish growth rate of adoption, despite being available for more than 10 years and plethora of subsidies available both at the central as well as state levels. Concurrently, Tesla has outperformed other manufacturers in EV sales, arguably on account of differentiating itself from other firms on account the additional availability of charging network it exclusively provides to its users.

In the model as presented in this paper, I allow Tesla to choose the availability of charging stations exclusive to its users. At period t, Tesla chooses for each US state or region d, $h_{dt} \in [0, 1)$ defined as:

$$h_{dt} = \frac{T_{d,t+1}}{H_{d,t+1} + T_{d,t+1}} \times \frac{1}{A_d} \tag{5.7}$$

where $T_{d,t+1}$ is the number of Tesla stations to be operated in region d next period, t+1, $H_{d,t+1}$ is the number of third-party public stations operated in region d next period, t+1 and A_d is area (sq. miles) of region d.

I model Tesla's decision regarding station provision as a continuous rather than a discrete one for the sake of computational feasibility. Rationalizing a setup where Tesla, for each region, chooses discretely, such as 1, 5, or 20 stations, would require solving the system for each possible choice and then selecting the optimal number. Such solution concepts suffer from the *curse of dimensionality* and are prohibitively expensive from a computational perspective. Tesla makes the simultaneous decision regarding entry of a new EV model and station build-out. By modeling Tesla's station build-out decision in a continuous space, conditional on the entry decision, a unique station solution is ensured.

In this model, Tesla's station build-out decisions are reversible, unlike the model entry decision. Tesla chooses upon the number of its operational stations in relation to the area of the region and the availability of public third-party stations. I assume that for each station Tesla maintains, it has to pay $\tilde{\tau}$ in annual fixed cost. If $\tilde{\tau}$ is the annual fixed cost of maintaining a charging station in d, cost of h_{dt} is:

$$f_d(h_{dt}) = \frac{\tilde{\tau} h_{dt} A_d}{1 - h_{dt} A_d} H_{d,t+1} \tag{5.8}$$

For a region d at time t, for Tesla to choose h_{dt}, implies $\frac{h_{dt} A_d}{1 - h_{dt} A_d} H_{d,t+1}$ Tesla stations to be built, resulting in $\frac{\tilde{\tau} h_{dt} A_d}{1-h_{dt} A_d} H_{d,t+1}$ in fixed costs.

This model treats Tesla providing exclusive stations for its users as a feature. However, Tesla building a network of charging stations could be a result of equilibrium behavior, i.e. it optimally chooses to a build a network exclusive to its users, subsequently deciding upon the state wise availability. The limitation I suffer from to identify this margin is that there is no variation in the data in the period as investigated in this thesis where Tesla does not have exclusive stations. In a pilot project recently, Tesla opened its network to other users and therefore, an interesting counterfactual would be study the impact of such a policy. However, this question is left to be explored in future work subject to access to pricing data from charging stations.

5.3 Equilibrium

Assumption A.2 : Firms use stationary Markov Perfect Nash (MPNE) strategies.

In this model, firms use stationary Markov Perfect Nash (MPNE) strategies by choosing actions that maximize their respective discounted lifetime profits. For the purposes of notation, I use Γ to denote the stationary Markov perfect strategies for all firms. By using a_{ot} to collectively refer to the actions a given firm o takes at time t, the Bellman optimal condition can be written down as

$$V_o^{\Gamma}(\mathcal{M}_{o,t}) = \max_{a_{ot} \in A_o(\mathcal{M}_{o,t})} [\pi_o(a_{ot}, \mathcal{M}_{o,t}) + \beta \int V_o^{\Gamma}(\mathcal{M}_{t+1}) d\mathcal{G}(\mathcal{M}_{t+1} | a_{ot}, \Gamma_{-o}, \mathcal{M}_{o,t})] \tag{5.9}$$

The Bellman condition for firm o, as represented in Equation in 5.9, characterizes the "value" of firm o's decision problem at a given point in time in terms of the value at future points in time.

$\pi_o(a_{ot}, \mathcal{M}_t)$ is the flow profits for period time t, firm o receives on account of their decisions a_{ot} and state $\mathcal{M}_t$. Flow profits not only include the contemporaneous profits from sales of products as offered by firm o, but also include the sunk cost of introducing an EV and in Tesla's fixed cost of operating stations as well. For firms other than Tesla, flow profits consists of:

$$\pi_o(a_{ot}, \mathcal{M}_{o,t}) = \underbrace{\sum_{j \in J_{ot}} S_{jt}(H_{others}, \mathcal{M}_{o,t}, \Theta, \mathbf{p})(p_{jt} - c_j)}_{\text{Profits from sales}} \quad - \quad \underbrace{\tau . a^e_{ot}}_{\text{Product sunk cost}} \quad + \quad \nu_{ot}(a^e_{ot}) \tag{5.10}$$

Tesla's flow profits, on account of the station decisions it makes as well, are defined differently as:

$$\begin{aligned} \pi_o(a_{ot}, \mathcal{M}_{o,t}) = \underbrace{\sum_{j \in J_{ot}} S_{jt}(H_{tesla}, \mathcal{M}_{o,t}, \Theta, \mathbf{p})(p_{jt} - c_j)}_{\text{Profits from sales}} \quad - \quad \underbrace{\sum_{d} f(h_{dt})}_{\text{Station cost}} \\ - \quad \underbrace{\tau . a^e_{ot}}_{\text{Product sunk cost}} \quad + \quad \nu_{ot}(a^e_{ot}) \end{aligned} \tag{5.11}$$

Equations 5.10 and 5.11 highlight the asymmetry of the optimization problem as faced by Tesla versus the other firms. On account of Tesla users availing a differentially sized network of charging stations, as opposed to their non-Tesla counterparts, H_{tesla} v/s H_{others}, the demand of Tesla vehicles is defined differently. Additionally, Tesla being the sole firm maintaining exclusive charging stations for its users, it has to account for the associated maintenance costs, which does not enter the optimization problem for the other firms. The Bellman equation as represented in Equation 5.9 is a convenient and tractable representation of an infinite sequence of the flow payoffs conditional on all firms following the MPNE. Given the asymmetry as highlight in equations 5.10 and 5.11, it is reasonable to expect Tesla to behave differently compared to the rest of the firms, for a policy shock.

5.3.1 Optimal Prices

Assumption A.3 : There are no switching costs to setting new prices every period

In this model, firms can set new prices every period, without paying any additional costs, for each of the products offered by them in the market. What this implies is that the price chosen for a given product at a given period, does not have bearing on the decisions taken in the next period. When firms can set an altogether new set of prices without paying any switching costs, information of current prices do not need to be taken over to the next period, and therefore does not qualify as a state variables and does not enter the transition matrix. Since prices do not enter the transition matrix, in equation 5.9, optimizing with respect to them, implies that the discounted terms drop out, making the Bertrand Nash prices typical of a static problem. One can imagine other settings, where firms commit to long term prices, or changing prices involve a menu cost, where it would become appropriate to account for prices within the set of state variables. However, in the current setting of the automotive market, it is appropriate to assume firms can costly change their respective retail prices every period without any expense. Conditional to the state variables observed at a given time, the simplification of the Bellman equation in Equation 5.9 is akin to choosing prices to maximize flow profits as represented in Equation 5.10 and 5.11. Price set at time t do not enter the state transition matrix within the discounted term in Equation 5.9, and therefore the pricing problem in this dynamic setting is akin to that of a static problem.

The equilibrium price of each product $j \in J_{ot}$ offered by a firm o, is determined as:

$$S_{jt}(H_o, \mathcal{M}_{o,t}, \Theta, \mathbf{p}) + \sum_{j' \in J_{ot}} (p_{j't} - c'_j) \frac{\partial}{\partial p_{jt}} S_{j't}(H_o, \mathcal{M}_{o,t}, \Theta, \mathbf{p}) = 0 \tag{5.12}$$

The second term of the above equation includes not only accounting for own-price derivative, $\frac{\partial}{\partial p_{jt}} S_{jt}$, but cross-price derivative, $\frac{\partial}{\partial p_{jt}} S_{j't}$, as well. To see the formulation of $\frac{\partial}{\partial p_{jt}} S_{jt}$ and $\frac{\partial}{\partial p_{jt}} S_{j't}$, please refer to Section A.1 and Section A.2, respectively.

5.3.2 Optimal Model Introduction

In this model, each firm makes a characteristic draw and decides whether or not to introduce a new EV, packaged with the characteristic draw they made. If a firm chooses to introduce a new EV, it pays a sunk cost τ, and if it chooses not to introduce the EV, it does not have to pay the sunk cost. When firms make this decision, they also form expectations about the behavior of other firms, who face the identical problem. The decision of whether or not to introduce the new EV has implications for the state in the next period, which could potentially witness other new EVs introduced by other firms.

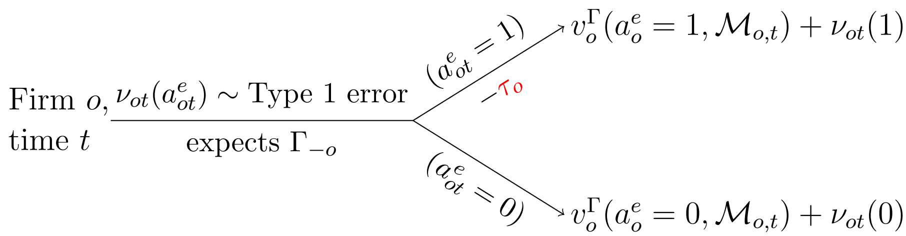


Figure 5.3: Decision tree for a typical firm at time t

The Bellman equation in Equation 5.9 defines a firm's expected lifetime value in a particular state when it chooses an optimal strategy, given other firms are using strategies as defined in the MPNE Γ. Given Γ_{-o} or expectations of behavior by other firms, each firm chooses optimally, i.e. makes decisions to maximize lifetime payoffs, and it is this payoff that defines the Bellman Value Function and the decision a component of the MPNE Γ. The decision to introduce an EV or not is a discrete decision and for a typical firm, given state as observed $\mathcal{M}_{o,t}$, expecting others to behave following the MPNE, Γ_{-0}, firms choose the path that provides a higher payoff, illustrated in Figure 5.3. Given our assumption **A.2** in Sec 5.2.2, with respect to payoff shocks allows us to map the optimal decision regarding model introduction in the space of choice probabilities as

$$P^{\Gamma_o}(a^e_{ot}, \mathcal{M}_{o,t}) = \frac{exp(v^\Gamma_o(a^e_o = 1, \mathcal{M}_{o,t}))}{exp(v^\Gamma_o(a^e_o = 1, \mathcal{M}_{o,t})) + exp(v^\Gamma_o(a^e_o = 0, \mathcal{M}_{o,t}))} \tag{5.13}$$

where $exp(v_o^\Gamma(a_o^e = 1, \mathcal{M}_{o,t}))$ or $exp(v_o^\Gamma(a_o^e = 0, \mathcal{M}_{o,t}))$ refer to choice-specific value function. For a firm o at time t, choice-specific value function omit the payoff shock related to the choice, and captures the expected lifetime value from the choice at time t, i.e. $a_o^e = 1$ or $a_o^e = 0$, assuming others to follow the MPNE Γ both in the current and subsequent periods and itself to follow the MPNE Γ in subsequent periods.

In this model, Tesla faces a problem unlike the other typical firms. One of the crucial details regarding the EV landscape within the United States is Tesla providing an additional network of stations, exclusive to its users, in attempt to alleviate range anxiety. To capture this important element of the EV landscape, in this model Tesla chooses every period t the optimal availability of charging stations in each US state d next period t+1, in addition to the decision of introducing a new EV model starting next period. Figure 5.4 illustrates the problem that Tesla faces each period.

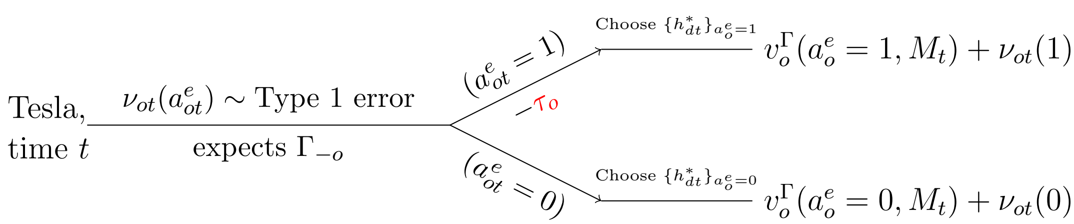


Figure 5.4: Decision tree for Tesla at time t

In Section 5.2.3, I provide the modeling details to account for Tesla's decision to maintain charging stations in each US state next period. The availability of the station decision is modeled as a continuous variable, h_{dt} with a cost function $f(h_{dt})$ that is also continuous in h_{dt} within a given range. With the modeling details as specified, given Tesla's expectations of other firms capture in Γ_{-o}, Tesla solves for its optimal availability of stations, conditional on its decision to introduce a new EV or not. For each state d, Tesla solves for the following

$$-\frac{\partial}{\partial h_{dt}} f(h_{dt}) + \beta \frac{\partial}{\partial h_{dt}} \int V_o^\Gamma(\mathcal{M}_{t+1}) d\mathcal{G}(\mathcal{M}_{t+1} | a_{ot}^e, \Gamma_{-o}, \mathcal{M}_t) = 0 \qquad (5.14)$$

with the h_{dt} optimally chosen impacting the state observed period, $\mathcal{M}_{t+1}$. For its decision to introduce a new EV or not, Tesla solves for its candidate station decisions, $\{h^*_{dt}\}_{a^e_o=1}$ and $\{h^*_{dt}\}_{a^e_o=0}$, respectively, and nests those decisions directly into its evaluation of choice-specific value functions, and maps into the space of choice-probability as

$$P^{\Gamma_o}(a^e_{ot}, \mathcal{M}_{o,t}) = \frac{exp(v^\Gamma_o(a^e_o = 1, \{h^*_{dt}\}_{a^e_o=1}, \mathcal{M}_{o,t}))}{exp(v^\Gamma_o(a^e_o = 1, \{h^*_{dt}\}_{a^e_o=1}, \mathcal{M}_{o,t})) + exp(v^\Gamma_o(a^e_o = 0, \{h^*_{dt}\}_{a^e_o=0}, \mathcal{M}_{o,t}))} \tag{5.15}$$

In this model, households are assumed to be myopic agents who do not internalize expectations about future periods when making their current choices. Arguably, one could model households as forward-looking, forming expectations about the future availability of EV models or charging stations, which would in turn influence their choices today. However, allowing both the demand and the supply side to be forward-looking would introduce the possibility of multiple equilibria in the model, which would require an equilibrium selection mechanism for estimation. The focus of this thesis is to analyze firm behavior, and therefore the priority is placed upon the forward-looking decision-making on the supply side. This modeling choice reflects the central research objective of understanding firm incentives and strategic behavior in the development of the electric vehicle ecosystem, while retaining robustness in estimation by avoiding equilibrium multiplicity.

Chapter 6

Identification and Estimation Strategy

In this chapter, I provide the details of the estimation strategy I apply to estimate the parameters that characterize the model I presented in Chapter 5. The chapter presents the discussion on estimation, separately for each component of the model as elicited in 5. A separate discussion on identification is presented in Chapter **??**.

6.1 Estimation of Coefficients Characterizing Demand

To estimate the coefficients characterizing the utility specification as represented in Equation 5.1, I follow the Conditional Logit model as elicited in McFadden (1974). As described in Chapter 4, I use micro-data from National Highway Transportation Survey (NHTS) that records purchases of vehicles at the household level. In addition, the data also provides information on housholds' incomes as well as their respective travel need, which is crucial to context being investigated in this thesis.

Within a conditional logit framework, each household has access to all possible vehicles available in a given year, and the vehicle it chooses to purchase maximizes its utility relative to all available options. In equation 5.1, the utility is also dependent on an idiosyncratic error term, ε_{ijt}, which follows a Type 1 extreme value distribution. The assumption of distribution of this idiosyncratic term allows us to map demand at the level of the household in the choice probability space. The condition logit framework estimates the the coefficients that characterize the utility specification by maximizing the likelihood or probability of the realized outcome as observed in data. While other logistic regression frameworks also rely on maximizing the likelihood of observed choices, within this setting, the likelihoods of options across the choice set is specific to the households, therefore making conditional logit, most appropriate. For a detailed discussion on conditional logistic regression, see Hosmer Jr et al. (2013) and Chamberlain (1980).

Beyond the coefficients that characterize the utility specification, the remaining parameter that characterize the demand system is K. To recap the discussions presented in 5 Section 5.1.2, a household that decides to be in the market for the purchase of an automobile, receives K *utils* on the outside margin. At the outside margin, the decision for households is modeled as discrete, with households choosing to go to the market of new automobiles if and only if

$$ln\Big(\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})\Big) + K + \mu_1 > \mu_0 \tag{6.1}$$

where $ln\Big(\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})\Big)$ is the expected utility from households maximizing their utility from purchase of vehicle at the inside margin, and μ_0 and μ_1 are payoff shocks that follow an extreme value distribution. Given the distributional assumptions regarding the payoff shocks, the probability with which a given household chooses to go to the inside margin, i.e. the market for new automobiles is defined as :

$$Pr(\text{i buys any vehicle}|d, \mathbf{J}_t) = \frac{exp\Big(ln\Big(\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})\Big) + K\Big)}{1 + exp\Big(ln\Big(\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})\Big) + K\Big)} \tag{6.2}$$

Similarly, the probability with which a given household does not choose to go to the inside margin is defined as :

$$Pr(\text{i buys any vehicle}|d, \mathbf{J}_t) = \frac{1}{1 + exp\Big(ln\Big(\sum_{j'\epsilon\mathbf{J}_t} exp(V_{ij'dt})\Big) + K\Big)} \tag{6.3}$$

To estimate K, I use the micro-data from the National Highway Transportation Survey (NHTS), now also focusing on households that did not report purchasing any vehicle. Households that are covered in the survey but do not report purchasing a new vehicle are considered to be choosing the outside option, whereas covered households that do report purchasing a new vehicle are considered to be going to the inside option. Using information on location, income, and travel details of households, I can construct the log-sum of the available choice set on the inside-option for both the set of households. Given the Equations 6.2 and 6.3, I estimate K by maximizing the realized likelihood of behavior as observed in the data at the outside margin, i.e. whether they went into the market for new vehicles or not.

As an alternative to the approach I present, K could be defined within the utility specification itself. However, given the conditional logit setting, K cannot be estimated on the inside. Estimation of the utility specification is confined to moment conditions that are restricted to sub-samples of households that make the purchase of any new vehicle. Since K is same across all vehicles, by definition, it cannot be directly identified. If outside option where to be constructed within the choice set in parallel to product options available, K could potentially be identified. However, in such settings, Andersen (1970) and Chamberlain (1980) show the maximum likelihood estimate of K or *fixed effect* would be inconsistent.

6.2 Estimation of Marginal Costs

In Section 5.3.1, I discuss the price-setting strategy firms follow in the model presented. In this model, firms can set new prices every period, without paying any additional costs, for each of the products offered by them in the market. What this implies is that the price chosen for a given product at a given period, does not have bearing on the decisions taken in the next period. When firms can set an altogether new set of prices without paying any switching costs (**Assumption A.3)**, information of current prices do not need to be taken over to the next period, and therefore does not qualify as a state variables and does not enter the transition matrix. Since prices do not enter the transition matrix, in equation 5.9, optimizing with respect to them, implies that the discounted terms drop out, making the Bertrand Nash prices typical of a static problem. The equilibrium price of each product $j \in J_{ot}$ offered by a firm o, is determined as:

$$S_{jt}(H_o, \mathcal{M}_{o,t}, \Theta, \mathbf{p}) + \sum_{j' \in J_{ot}} (p_{j't} - c_j') \frac{\partial}{\partial p_{jt}} S_{j't}(H_o, \mathcal{M}_{o,t}, \Theta, \mathbf{p}) = 0 \tag{6.4}$$

The second term of the above equation includes not only accounting for own-price derivative, $\frac{\partial}{\partial p_{jt}} S_{jt}$, but cross-price derivative, $\frac{\partial}{\partial p_{jt}} S_{j't}$, as well. To see the formulation of $\frac{\partial}{\partial p_{jt}} S_{jt}$ and $\frac{\partial}{\partial p_{jt}} S_{j't}$, please refer to Section A.1 and Section A.2, respectively. The first order condition in Equation 6.4 above could alternatively be written in matrix form as:

$$\mathbf{S}_o + \Delta_o(\mathbf{p}_0 - \mathbf{c}_0) = 0 \tag{6.5}$$

$\mathbf{S}_o$ is $|J_{ot}| \times 1$ matrix, with each row representing the demand for every vehicle included in the product portfolio J_{ot} for firm o at time t. $\mathbf{p}_0$ and $\mathbf{c}_0$ are also $|J_{ot}| \times 1$ matrices, with each row representing the price and the marginal cost for every vehicle included in the product portfolio J_{ot}, respectively, for firm o at time t. Δ_o is a $|J_{ot}| \times |J_{ot}|$ matrix, with the diagonal elements representing the own-price derivatives and the non diagonal elements representing cross-price derivatives, for the set of products J_{ot} for firm o at time t. Given demand is estimated for each product, the first order in Equation 6.5 can be manipulated to estimate the marginal costs directly is a systems of equation as:

$$\mathbf{c}_0 = \mathbf{p}_0 + \Delta_o^{-1}\mathbf{S}_o \tag{6.6}$$

6.3 Solution Concept

In order to solve dynamic games, it is necessary to infer value functions, rationalizing behavior as observed in data. A typical way to solve for forward-looking game theoretical models involves forward simulation (Rust (1987); Bajari et al. (2007)), rationalizing every observed data-point by calculating potential continuation values. This can become computationally expensive as number of agents, actions, periods, state variables grow. To address the computational challenge of a large state space with sizeable number of players, I follow Sweeting (2013) to apply parametric approximation to the value function to solve and estimate the dynamic oligopolistic model presented in this paper. Instead of solving for value function at each state realization, I assume that the value function can be approximated by a linear combination of the polynomials of the state variables that characterize the model

$$V_o^{\Gamma}(\mathcal{M}_{o,t}) \approx \sum_{k=1}^{K} \lambda_k \phi_k(\mathcal{M}_{o,t}) \tag{6.7}$$

For a set of N states, solving the value function now requires finding K coefficients rather than N values, as would be the case using forward simulation. Given the distributional assumption on payoff shocks associated with model entry decision (**Assumption A.1**), I can map the Markov Perfect Nash Equilibrium Γ into choice probability space, as shown in Equations 5.13 and 5.15. For a detailed discussion of mapping the MPNE into the space of conditional choice probabilities, refer to Chapter 5 Section 5.3.2. At the set of equilibrium strategies mapped into choice probability space, Equation 6.7 can be rewritten as:

$$V_o^{P^*}(\mathcal{M}_{o,t}) \approx \sum_{k=1}^{K} \lambda_k \phi_k(\mathcal{M}_{o,t}) \tag{6.8}$$

At the equilibrium strategies P^* comprising the MPNE, the Bellman as in Equation 6.8 if stacked for the N states in matrix form should give us

$$\Phi\lambda = \tilde{\pi}(P^*) + \beta(E_{P^*}\Phi)\lambda \tag{6.9}$$

Each row of the matrix Φ corresponds to a state specific to each firm whereas each column corresponds to the k^{th} polynomial, with an element being $\phi_k(\mathcal{M}_{o,t})$. $E_{P^*}\Phi$ is defined similarly as Φ with the exception that the polynomial approximation is weighted conditional on the state transition matrix, with each element defined as $\int \phi_{ko}\big(\mathcal{M}_{o,t+1}\big) g\big(\mathcal{M}_{o,t+1}|P^*, \mathcal{M}_{o,t}\big) d\mathcal{M}_{o,t+1}$. As along as the model is over-identified, i.e. the number of states the model is solved over is at least as large as the number of polynomials the model is approximated over, the set of λ_k parameters can be identified using typical OLS inversion. For the over-identified case $(N > K)$, the set of coefficients characterizing the linear combination of polynomials, $\hat{\lambda^P}$ can be found using an Ordinary Least Squares (OLS) estimator for any candidate choice of choice probabilities.

$$\hat{\lambda^P} = \Big(\big(\Phi - \beta E_P \Phi\big)'(\big(\Phi - \beta E_P \Phi\big)\Big)^{-1} \big(\Phi - \beta E_P \Phi\big)' \tilde{\pi}(P) \tag{6.10}$$

The OLS estimator as defined in Equation 6.10 can be applied to any candidate P. However, the Bellman condition is representative of the true equilibrium P^* in choice probability space, which we don't know and need to solve for. It is standard to use policy iteration to solve for dynamic models (Judd (1998); Rust (1987)). Policy iteration involves repeatedly iterating over one, *policy valuation*, which involves calculating the value function V^{P_i} for a candidate set of choices probabilities P_i and two, *policy improvement*, which involves using the calculated V_i^P to update the computed set of choices probabilities P_i. This two-step procedure is iterated until convergence in choice probabilities in reached, and set of choice probabilities at which the procedure converges to is representative of the equilibrium.

6.3.1 Parametric Policy Iteration

In this section, I sketch the outline of the method I use to solve for the value function using parametric policy iteration procedure (Benitez-Silva et al. (2000)). The parametric policy iteration procedure I implement consists of the following steps:

1. Select N states to fit the model over. This includes the observed states as well as their duplicates, obtained by perturbing state variables which vary over time.

2. Calculate Φ or the polynomials for each of these N states. The polynomials of state variables that I use to fit the model over are Chebyshev polynomials of the first and second degree.

3. Estimate Initial Policy

   - **For Model Entry**, I use a reduced form parametric multinomial logit model with linear & interaction terms of variables included within state.

   - **For Tesla's Station Decision**, Station decisions are conditional on decision to enter from Tesla. I use OLS with linear & interaction term of variables included within state.

4. Given estimates of policy for iteration i, I estimate $G(\mathcal{M}'_{o,t}|P^i, \mathcal{M}_{o,t})$. I would highlight that the marginal distribution of Tesla's station decisions is conditionally degenerate. Given model assumptions regarding the continuous nature of station decision and well behaved cost function of station maintenance, Tesla's station decisions are conditionally unique to decision of Tesla to introduce a new EV model or not. For a more detailed discussion, refer to Chapter 5 Section 5.3.2.

5. With the candidate P^i (i stands for iteration),

   - Calculate $\tilde{\pi}(P^i)$. This is the expected flow profit
   - Calculate $E_{P^i}\Phi$. This is the matrix comprising the polynomial terms for each firm, weighted with respect to the state transition matrix
   - Create the matrices $(\Phi - \beta E_{P^i}\Phi)$
   - Use the OLS operator shown above in Equation 6.10 to estimate $\widehat{\lambda^{P^i}}$

6. From $\widehat{\lambda^{P^i}}$, calculate the choice-specific value function for each choice for each firm

$$v(a_o^e|\mathcal{M}_{o,t}, P_o^i) = \pi(a_o^e, \mathcal{M}_{o,t}) + \beta\{E_{P^i}\Phi\}\widehat{\lambda^{P^i}}$$

   Choice-specific value functions represents the expected payoff firm o receives from choosing to enter with a new EV or not, conditional on other firms following the MPNE as well as itself following the MPNE in the subsequent periods. For a firm o at time t, choice-specific value function omit the payoff shock related to the choice, and captures the expected lifetime value from the choice at time t, i.e. $a_o^e = 1$ or $a_o^e = 0$, assuming others to follow equilibrium behavior both in the current and subsequent periods and itself to follow the equilibrium behavior in subsequent periods. For a more detailed discussion, refer to Chapter 5 Section 5.3.2.

7. Update policy:

   - **For Model Entry**, update conditional choice probabilities for every firm and state

$$P_o^{'}(M) = \frac{e^{v(1|\mathcal{M}_{o,t}, P^i)}}{e^{v(1|\mathcal{M}_{o,t}, P^i)} + e^{v(0|\mathcal{M}_{o,t}, P^i)}}$$

   - **For Tesla's Station Decision**, in every region d, solve for the system of equations conditional on either $a^e_{Tesla} = 0$ or 1:

$$-f'(h_d) + \beta \frac{\partial}{\partial h_d} v(a^e_o | \mathcal{M}_{o,t}, P^i_o) = 0$$

8. If the maximum absolute difference between $P^{'}_o$ & P^i_o is below a certain threshold, the iterative procedure is terminated and the $\widehat{\lambda^{Pi}}$ is saved as λ^*. In other words, if $||P^{'}_o - P^i_o|| < \mu$ for all firms and states ($\mu = 1e - 4$), the procedure is terminated. Otherwise, I update the conditional choice probabilities for the subsequent iteration as $P^{i+1}_o(M) = \psi P^i_o(M) + (1 - \psi) P^{'}_o(M)$ with $\psi = 0.1$ and the procedure repeats from Step 4.

The parametric policy iteration involves repeatedly solving for a set of choice probabilities for every selected state that the model is solved over, and subsequently recovering a set of coefficients $\widehat{\lambda_o}$ that attempts to approximate the value function at those choice probabilities. The model is solved when choice probabilities converge across iteration and those probabilities comprise the MPNE strategies that the firms follow. $\widehat{\lambda_o}$ solved for choice probabilities that shows convergences solves the value function approximation at equilibrium. They are the true parameters for our polynomials, whose linear combination approximate the value function; i.e. $\widehat{\lambda_o}(P^*) = \lambda^*_o$.

6.4 Estimation of Dynamic Parameters

There are two key parameters that characterize the forward looking oligopolistic nature of the model as presented in this thesis - sunk cost of EV entry and fixed cost for maintaining a Tesla station. Firms if they choose to introduce a new EV next period have to pay a sunk cost in the current period. In a way, firms compare the sunk cost of model entry in EV with the differential in lifetime profits from either introducing the EV as drawn or not and decide accordingly. Additionally, Tesla's unique product positioning involves providing stations exclusive to its users. Depending on its decision on how many station Tesla wishes to maintain next period, Tesla has to pay a fixed cost in the current period. Both the product decision as well as the station decisions is contingent upon an inter-temporal trade-off between payoffs and costs, making the sunk cost of EV entry and fixed cost of maintaining a Tesla station the two key dynamic parameters that need to be estimated to fully characterize the model as presented in this thesis.

The value function iteration method, as I explain in Section 6.4, allows us to solve for the value function as linear combination of polynomials of various state variables. Updating choice probabilities and simultaneously solving for the coefficients characterizing the polynomials approximating the value function requires one to assume respective values for the dynamic parameters. Step 5 of the parametric policy iteration requires us to solve for the expected flow profits, $\tilde{\pi}(P^i)$ which requires on to assume values for the sunk cost of introducing EV model as well as the fixed cost for maintaining a Tesla Station. Given the linear combination of polynomials are endogenous to the choice of these dynamic parameters, we cannot analytically solve for them, as is typical in Generalize Method of Moments (GMM) or Maximum Likelihood Estimation (MLE) settings.

I proceed to computationally estimate for the dynamic parameters that characterize this model using Grid Search over potential parameter values. For a given tuple of candidate dynamic parameters, I solve for the dynamic model, by recovering for the set of coefficients that approximate the value function that show convergence in beliefs, and estimate the respective choice probabilities for each firm at each period and calculate the log-likelihood of behavior as observed in the data. The Grid Search method involves repeatedly solving for the model at different value of dynamic parameters and looking for the parameters that maximize the likelihood of behavior as observed in data. The Grid Search I implement to solve for the dynamic parameters involves solving for the model for sunk cost of EV entry between 500 million USD and 10 billion USD in increments of 100 million USD, and fixed cost of maintaining a Tesla stations between 10,000 USD and 500,000 USD in increments of

10,000 USD. The pair for the candidate sunk cost of EV entry and candidate fixed cost of maintaining Tesla station that maximized the likelihood of behavior as recorded in data are estimated dynamic parameters, θ^* that characterize the model.

To estimate the standard error for the dynamic parameters the maximize the likelihood of data as observed, I analytically solve for the variance-covariance matrix of θ^*, which is calculated as the inverse of the Information matrix, which is in turn is the negative of the expected value of the Hessian matrix of the log-likelihood function with respect to θ^*.

$$\begin{aligned} var(\theta^*) &= [I(\theta^*)]^{-1} \\ &= (-\mathbf{E}[H(\theta^*)])^{-1} \\ &= \left(-\mathbf{E}\left[\frac{\partial^2 \ln L}{\partial\theta^* \partial\theta^{*\prime}}\right]\right)^{-1} \end{aligned} \tag{6.11}$$

A detailed account of how this Hessian matrix is analytically derived for the set of parameters $\theta^* = (\tau, \tilde{\tau})$ that maximizes observed likelihood is provided in Appendix C.

Chapter 7

Results

In this chapter, I provide the results from estimation of parameters that characterize the model I presented in Chapter 5. The chapter presents the results, separately for each component of the model. For the discussion on estimation and identification, refer to Chapter 6.

7.1 Estimation of Demand parameters

Following McFadden (1974), I follow the Conditional Logit model to estimate the coefficients that characterize the utility specification as represented in Equation 5.1. Using micro-data that records purchase of new vehicles at the household level, the approach estimates the demand parameter by maximizing likelihood estimates at the household level, rationalizing the data as observed. From the estimates as presented in Table 7.1, it is evident that a household's valuation of a vehicle from the set of vehicles available to them, depends on their respective Range Anxiety from it. The estimates imply that as Range Anxiety goes up, the utility from the respective vehicle goes down. Given gas vehicles or Hybrid vehicles do not suffer from Range Anxiety, an EV, say with the same set of characteristics as well as price as a non-EV, would be valuated less on account of Range Anxiety, and therefore resulting in lower sales. As the available size of the charging network increases, given the

Table 7.1: Estimation of Utility Specification

	(1)	(2)
Horsepower/Weight	6.744***	4.775**
	(1.700)	(2.258)
Miles per $	0.0284***	0.0295***
	(0.00370)	(0.00378)
Area spanned	0.888***	0.923***
	(0.0345)	(0.0435)
PassengerDoors=3	-0.529**	-0.525**
	(0.211)	(0.211)
PassengerDoors=4	0.698***	0.698***
	(0.0537)	(0.0537)
PassengerDoors=5	0.186	0.0735
	(0.362)	(0.371)
Price/Income	-4.421***	-4.267***
	(0.245)	(0.269)
Range anxiety	-407.2***	-406.9***
	(102.5)	(102.4)
First-stage residuals		-0.154
		(0.115)
IVs included	No	Yes

Note: This table presents the estimation results of parameters that characterize the utility a household receives from the purchase of a new vehicle. The estimates follow condition logit method relying on data at the household level that purchase the records the purchase of new vehicles as well as the respective household characteristics. From the set of households that purchase a vehicle, the results are estimated using 1,564,045 observation or household-vehicle pair. Column (2) presents the results using the Control function approach to account for the endogeneity of prices with respect to the unobservables. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

definition of Range Anxiety I present in Equation 5.2, Range Anxiety falls and some of the discrepancy between the evaluation of an EV and non-EV of similar characteristics is alleviated away, and therefore, potentially increasing the sales of the respective EV, and also potentially increasing the likelihood of introduction of newer EV models from various auto manufacturers.

Households, in this model, first decide whether or not they wish to be in the market to purchase a new automobile before deciding which vehicle to purchase, i.e. the vehicle

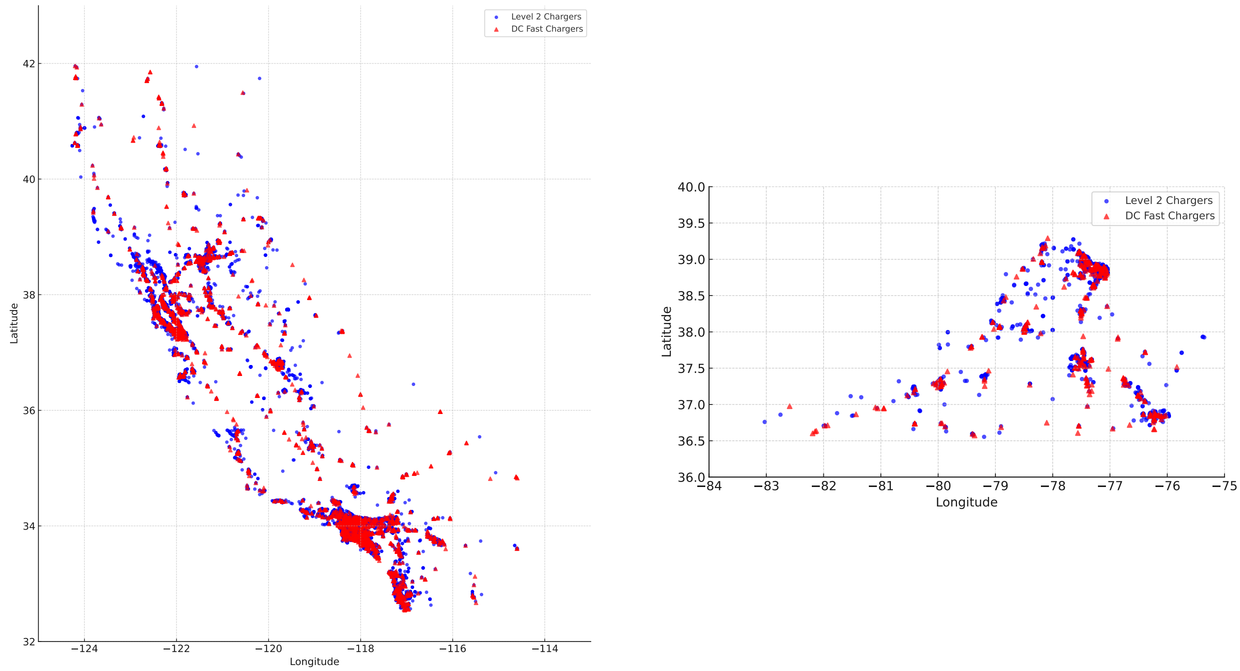
Table 7.2: Estimation of K

K	-11.86***
	(0.0152)

Note: This table presents the estimation results of K utils a household receives on the outside margin if it chooses to go into the market to purchase a new vehicle. The estimates follow maximizing log likelihood of utility maximization at the outside margin relying on data at the household level that purchasing behavior of the respective household characteristics. K is estimated using information on 113,634 households. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

that maximize their respective utilities. Beyond the coefficients that characterize the utility specification, the remaining parameter that characterize the demand system is K. To recap the discussions presented in 5 Section 5.1.2, a household that decides to be in the market for the purchase of an automobile, receives K *utils* on the outside margin. Given the Equations 6.2 and 6.3, I use micro-data at the household level using information on location, income, and travel details, I estimate K by maximizing the realized likelihood of behavior as observed in the data at the outside margin, i.e. whether they went into the market for new vehicles or not and report the estimate

One feature of the demand model specification is that I do not separately account for Level 2 and DC fast charging stations. The number of charging stations that enters households' formulation of range anxiety is defined as the sum of Level 2 and DC fast charging stations. This modeling choice is based on the underlying assumption that there is a strong geographic correlation of Level 2 and DC fast charging stations. In Figure **??**, I map the latitude and longitude of charging stations by type in California and Virginia, and find that DC fast charging stations are predominantly located in areas where Level 2 stations are also present. Specifically, 79% of DC fast stations in California are located within one kilometer of a Level 2 station, while Level 2 stations are somewhat more independently distributed across locations. Given that households primarily value access to any charging opportunity to mitigate range anxiety, aggregating Level 2 and DC fast charging stations into a unified



(a) California

(b) Virginia

Figure 7.1: Latitude and longitude representation of charging stations by their respective types in California (a) and Virginia (b).

measure is a natural modeling simplification. To highlight the limitations of the model, DC fast stations are perceived as substantially more valuable than Level 2 stations, then the estimated γ reflects an average sensitivity, weighted toward the effects of Level 2 stations given their greater abundance. Consequently, the model may understate the specific role of DC fast chargers in alleviating range anxiety.

Another limitation of the model is that it does not explicitly distinguish between households with different travel needs — for instance, households that typically drive shorter distances versus those that require longer range on a regular basis. In reality, households with lower travel demands may exhibit less sensitivity to charging station availability, while households with higher travel demands may place greater value on an expanded network. In the current framework, the parameter γ captures an average responsiveness across all households, effectively representing a weighted mean of the underlying heterogeneity in travel behavior. As a result, the estimated γ should be interpreted as an aggregation of the varying marginal utilities associated with station availability across different household types, rather than as a parameter specific to any single group. Exploring this is left to future work. What is also to be done later is re-estimating the entire model and assuming there is no range-anxiety, i.e. $\gamma = 0$ and evaluating how do the estimates differ.

7.2 Marginal Rate of Substitution

One of the key motivations for this thesis relies upon the fact that Tesla provides a network of charging stations exclusive to its own users. Given Tesla users can access both the Tesla as well as the public network accessible to all, the range anxiety they experience for a Tesla EV is less compared to a similar EV, in terms of other characteristics, manufactured by others. The exclusive network that Tesla users have access to is an important differentiator and potentially explains Tesla's success in terms of sales within the EV segment.

In Table 7.3, I provide the details of the marginal rate of substitution of a vehicle's price with respect to household's daily travel requirement in miles, calculating the statistics across the sample of households available from the micro-data. The marginal rate of substitution of a vehicle's price with respect to household's daily travel requirement in miles calculates by how much should the price of a vehicle fall if their traveling needs were to increase by a mile,such that the utility from an EV a household receives remains unchanged. Given the additional stations Tesla builds for its users, the statistics reflect that the marginal rate of substitution of a vehicle's price with respect to household's daily travel requirement is less than that for other manufacturers. As more stations are build across the time, the value falls for both Tesla EVs as well as others.

Interventions to build public charging stations help address range anxiety for all vehicles, including both Tesla as well non-Tesla EVs. Given the complementarity between the size of the charging network and the utility of owning an EV, building more stations encourages

Table 7.3: Marginal Rate of Substitution (Distance) by Year and Manufacturer

Year	Tesla	Others
2011	-	-3290.6
	-	(5363.18)
2012	-843.77	-2322.25
	(1431.57)	(4024.88)
2013	-759.28	-2041.38
	(1446.25)	(4224.15)
2014	-533.34	-1571.50
	(1072.54)	(3129.68)
2015	-267.17	-1539.27
	(565.19)	(3879.99)
2016	-197.14	-1270.66
	(427.48)	(3481.84)
2017	-158.57	-785.16
	(340.00)	(1785.45)
2018	-125.18	-532.56
	(337.91)	(1314.34)
2019	-99.49	-279.83
	(294.33)	(764.23)

Note: This table presents the estimates of mean and standard deviation of the marginal rate of substitution of price with respect to household's daily travel requirement in miles. In other words, the statistic represents for the utility from an EV a household receives to remain unchanged, how much compensation should the household receive if their traveling needs were to increase by a mile. The mean and the standard error are calculated across the sample of 107,671 households in the data. Given the available vehicles and the size of the charging network vary each year, the estimates are separately provided for each year. The estimates are provided separately for Tesla and all the other manufacturers, highlighting their differences.

greater substitution from non-EVs to EVs among consumers for the existing set of available vehicles. As range anxiety is progressively reduced, firms have stronger incentives to introduce new models. However, government provision of charging stations for all dampens Tesla's market power, reducing the value of each of its stations. A key aspect of Tesla's differentiation from other EV manufacturers is its exclusive charging network, which is only accessible to Tesla users. When the government provides public stations that are accessible to everyone, the value of Tesla's exclusive network diminishes.

Table 7.4: Marginal Rate of Substitution (Stations) by Year and Manufacturer

Year	Tesla	Others
2011	-	15936.54
	-	(198192.2)
2012	3286.73	9123.48
	(22281.24)	(61954.00)
2013	3200.76	10381.88
	(29531.62)	(135704.50)
2014	1795.12	5982.57
	(17724.91)	(54599.43)
2015	606.36	7696.40
	(4214.15)	(79588.93)
2016	351.20	7146.12
	(2835.37)	(123034.50)
2017	181.94	2703.68
	(1369.37)	(46374.62)
2018	161.12	1587.23
	(2689.49)	(33945.92)
2019	111.02	580.21
	(1626.28)	(8886.24)

Note: This table presents the estimates of mean and standard deviation of the marginal rate of substitution of price with respect to number of charging station available in a household's state of residence. In other words, the statistic represents for the utility from an EV a household receives to remain unchanged, how much additional payment could be received from the household if the number of charging stations were to increase by 1. The mean and the standard error are calculated across the sample of 107,671 households in the data. Given the available vehicles and the size of the charging network vary each year, the estimates are separately provided for each year. The estimates are provided separately for Tesla and all the other manufacturers, highlighting their differences.

In Table 7.4, I estimate the marginal rate of substitution of a vehicle's price with respect to number of charging station available in a household's state of residence, across the sample of households available from the micro-data. Marginal rate of substitution of a vehicle's price with respect to number of charging station available in a household's state of residence measures how much additional payment could be received from the household if the number of charging stations were to increase by 1, for the utility of a household from an EV to remain unchanged. Given available stations to Tesla users is more than stations available to non-Tesla users, non-Tesla users value stations more than Tesla users, across all years. As more stations are built over time, stations get more incrementally devalued for both Tesla as well as non-Tesla users.

7.3 Marginal Costs

In Section 5.3.1, I explain how firms, each period, choose the optimal prices for their respective products. According to the model presented, firms can set new prices every period, without paying any additional costs, for each of the products offered by them in the market. Within the context of the model of dynamic oligopoly which characterizes firms' behavior in this model, what this implies is that price chosen for a given product at a given period, does not have bearing on the decisions taken in the next period. The information of current prices do not need to be taken over to the next period, and therefore, the pricing sub-game in this model is akin to that of the Bertrand Nash pricing sub-game of a typical static problem.

In Section 6.2, I provide a detailed description of the estimation process for marginal costs. The marginal costs of vehicles produced by a firm in a given year can be estimated or recovered by inverting the firm's first-order condition characterizing the pricing sub-game: $\mathbf{c}_0 = \mathbf{p}_0 + \Delta_o^{-1}\mathbf{S}_o$ (Equations 6.4, 6.5, and 6.6). Here, $\mathbf{c}_0$ and $\mathbf{p}_0$ are $|J_{ot}| \times 1$ matrices, where each row represents the price and the marginal cost for every vehicle offered by firm o at time t. $\mathbf{S}_o$ is a $|J_{ot}| \times 1$ matrix, where each row represents the demand for every vehicle

Table 7.5: Estimates of Marginal Costs by Vehicle Type

Statistic	Battery EVs	Plug-in Hybrids	Gas Vehicles
Mean	23,647.57	30,691.40	17,442.02
Standard Deviation	14,248.30	23,689.61	19,002.44
Median (50%)	18,390.67	18,893.09	11,402.17
25th Percentile	13,445.28	11,498.74	3,423.79
75th Percentile	29,139.03	50,581.84	25,373.71
Observations	104	120	2,112

Note: This table presents summary statistics of estimates of marginal costs in $ of vehicles available to be sold from 2010-2019, including their mean, standard deviation, median, 25^{th} percentile and 75^{th} percentile. Between 2010-2019, there were 2336 vehicles available to be sold, including 2112 Gas vehicles, 120 Plug-In Hybrids and 104 Battery EVs.

offered by firm o at time t. Δ_o is a $|J_{ot}| \times |J_{ot}|$ matrix, with diagonal elements representing the own-price derivatives and off-diagonal elements representing the cross-price derivatives for the set of products J_{ot} of firm o at time t.

In Table 7.5, I provide the summary statistics for the estimated marginal costs of vehicles available for sale in the United States between 2010 and 2019. During this period, gas vehicles were, on average, the cheapest to produce, with an average marginal cost of $17,442. Battery EVs were more expensive to produce, as intuition suggests, given their reliance on a new mechanical and technological platform. The average marginal cost for Battery EVs during this period was $23,647.57. Plug-in hybrids, however, were significantly more expensive than both gas vehicles and Battery EVs. The average marginal cost for plug-in hybrids from 2010 to 2019 was $30,691.40. This aligns with expectations, as plug-in hybrids rely on a dual technological system that integrates both internal combustion as well batteries, leading to higher production costs. Li et al. (2019) estimates the mean of the marginal costs for both Battery EVs and plug-in hybrids combined up until 2015 to be $29,263. In contrast, I estimate the marginal costs for the same sub-sample, Battery EVs and plug-in hybrids combined up until 2015, to be $26,679.53.

I also estimate the markups of vehicles available for sale in the United States between 2010 and 2019, and the provide the summary statistics in Table 7.6. According to the estimates, the estimated markups on Battery EVs during 2010-2019 were lowest, averaging

Table 7.6: Descriptive Statistics of Markups by Vehicle Type

Statistic	Battery EVs	Plug-in Hybrids	Gas Vehicles
Mean	16,023.69	20,426.97	17,856.69
Standard Deviation	6,708.70	1,972.32	6,404.43
Median (50%)	17,591.35	20,740.65	20,082.20
25th Percentile	14,373.52	19,313.60	17,180.36
75th Percentile	20,487.21	21,861.99	22,066.51
Observations	104	120	2,112

Note: This table presents summary statistics of markup estimates for vehicles available for sale from 2010 to 2019, including the mean, standard deviation, median (50^{th} percentile), 25^{th} percentile, and 75^{th} percentile. During this period, 2,336 vehicles were available for sale, consisting of 2,112 gas vehicles, 120 plug-in hybrids, and 104 battery EVs.

at $16,023.69. Battery EVs to have the lowest markups can potentially be explained by range-anxiety with firms compensating consumers by reducing prices, hence, serving our intuition well. The markups for gas vehicles during this period were intermediate, averaging at $17,856.69. The markups for Plug-In Hybrids during 2010-2019 were highest, averaging at $20,426.97. Plug-In Hybrids do not suffer from Range Anxiety, given they also have internal combustion engines in addition to batteries. However, they are subject to various incentive schemes which provide direct subsidies to consumers. Not suffering from Range Anxiety and being subject to purchase subsidies serves our intuition well to explain plugin hybrids to have the highest markups among vehicles during this period. Li et al. (2019) estimates the mean of the markups for both Battery EVs and plug-in hybrids combined up until 2015 to be $13,872. In contrast, I estimate the markup for the same sub-sample, Battery EVs and plug-in hybrids combined up until 2015, to be $16,324.17.

7.4 Dynamic Parameters

In Section 6.4, I explain the estimation strategy I adopt to estimate the two key dynamic parameters characterizing the model. Firms, if they choose to introduce a new model of EV starting next period, have to incur a sunk cost associated with product entry in the current period. Tesla, in addition to deciding whether or not it wishes to introduce a new EV also

Table 7.7: Estimates of Model Sunk Cost and Station Fixed Cost

	Model Sunk Cost	**Station Fixed Cost**
Panel A: β = 0.95		
Estimate	43.4	0.0083
Standard Error	(0.1705)	8.8425e-05
Panel B: β = 0.98		
Estimate	87.2	0.0266
Standard Error	(0.1819)	2.5099e-04

Note: Estimates are normalized in 100 million. Standard errors are reported in parentheses. The estimates correspond to different discount factor assumptions.

have to decide how many stations it wishes to maintain next period and has to pay the fixed cost in the current period to maintain each of the stations. The product decision as well as Tesla's decision to maintain availability of stations exclusive to its users is characteristic of an inter-temporal trade-off comparing contemporary costs and expected discounted flow of payoffs from the future.

The solution algorithm I adopt to approximate the value function, as I elaborate in Section 6.3, is endogenous upon the choice of the values of these dynamic parameters which makes it difficult to analytically solve for these parameters as is typical in many settings such as Maximum Likelihood Estimation (MLE) or Generalized Method of Moments (GMM). I computationally solve for the dynamic parameters by implementing a grid search over potential parameter values and finding those that maximize observed likelihood. In the Grid Search method, for any candidate tuple of dynamic parameters, I solve for the value function reaching convergence in conditional choice probabilities and calculate the likelihood of data as observed. By iterating the procedure over other candidate parameter values, I look for the grid point at which the observed likelihood is maximized. For these parameter values that maximize the observed likelihood of observed data, I analytically solve for their standard errors by calculating the Hessian matrix of the log-likelihood function. For a detailed exposition, see Appendinx C.

In Table 7.7, I provide the estimation results of the dynamic parameters. Solving dynamic model require us to assume values of the discount term as given. The discount term which "weighs" payoffs from the future time periods has to be assumed at a given value on account of not being separately identifiable from the expected value function characterizing the future payoff stream. I solve for the dynamic parameters for two plausible values of the discount factor, i.e. for $\beta = 0.95$ and $\beta = 0.98$. At the $\beta = 0.95$, the sunk cost of introducing an EV model is estimated at \$4.34 billion and the fixed cost of maintaining a Tesla station is estimated at \$83,000. Alternatively, using $\beta = 0.98$, the sunk cost of introducing an EV model is estimated to be \$8.72 billion and the fixed cost of maintaining a Tesla station is estimated at \$266,000. The estimates for the sunk cost of product entry and fixed cost of maintaining a Tesla station is higher for $\beta = 0.98$ as opposed to $\beta = 0.95$. Given future profits as "weighed" more with a higher discount factor, for the same set of data as observed, it is intuitively appealing that set of costs that rationalizes the observed data is higher for the discount term that is greater in value.

Chapter 8

Counterfactual Experiments

In this chapter, I provide results from counterfactual experiments I conduct using the model parameters estimated. First, I simulate the entry game over multiple draws of EV characteristics across all firms and evaluate how the respective probabilities of entry in new EV models compare across the respective firms over the years.

8.1 Simulating Vehicle Draws

In this model, each period, each firm makes an independent random draw of vehicle characteristics specific to EVs and then decides whether to introduce a new EV packaged with the realized characteristics. As described in Section 5.2.2, a given firm o makes a public random draw of characteristics—including Mileage, Battery Range, Area Spanned, and Horsepower/Weight—that a new EV model would have if firm o chose to introduce one. If a firm chooses to introduce a new EV model with these characteristics, it incurs a sunk cost; otherwise, it pays nothing.

Each draw of vehicle characteristics for a given period is made from the convex hull of characteristics observed in the data from EVs in the next period. The convex hull is intended to capture the characteristic space that firms can potentially draw from, given the state of technology at a given period. I infer this space using characteristics observed from

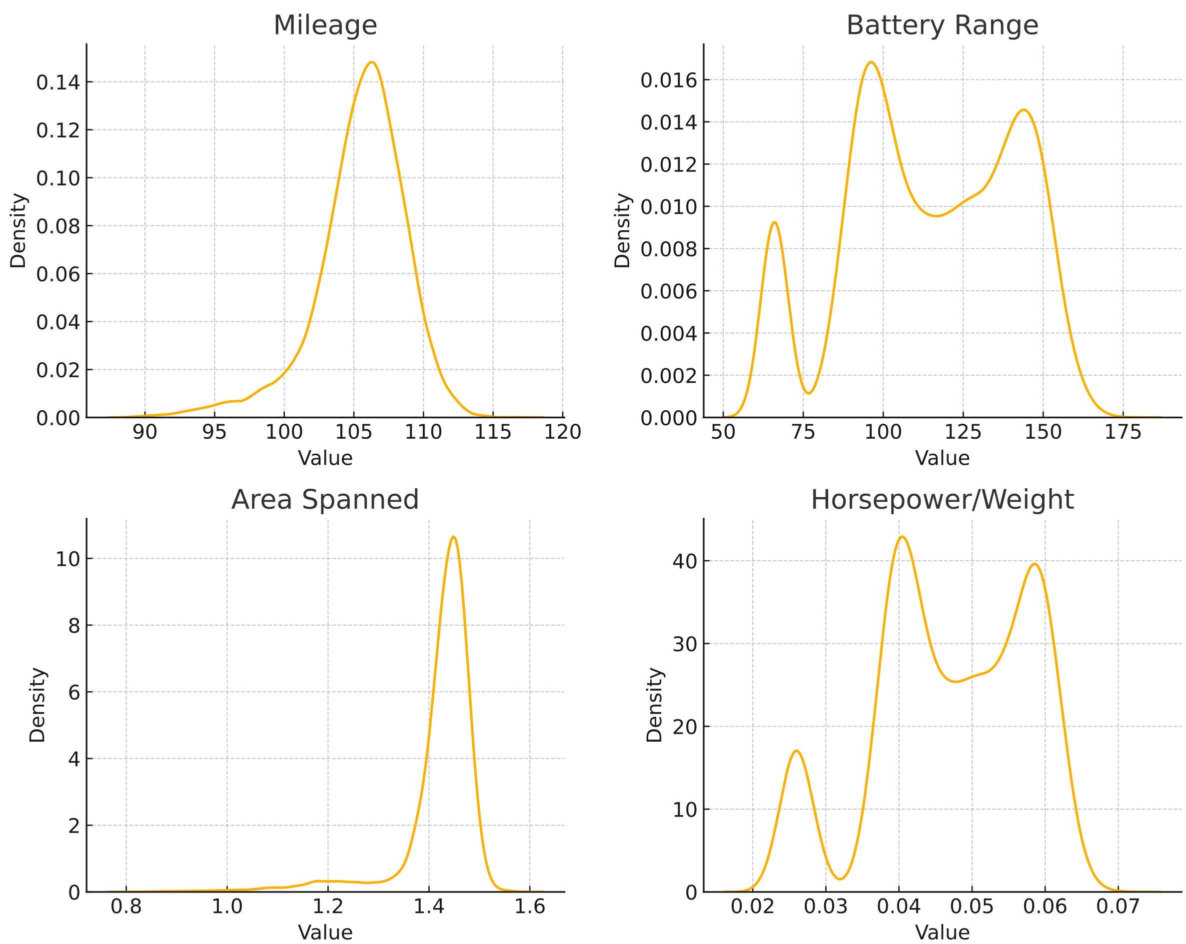


Figure 8.1: The figure plots the k-density plots of the various characteristics that are independently drawn. Each set of characteristics drawn represent an EV draw for given firm and year from their respective convex hull. 100 draws are iterated for each firm-year.

EVs in the next period. It encloses the set of possible combinations of these attributes, defining the boundary within which firms can introduce new EV models based on observed characteristics.

The decision to introduce an EV depends not only on market structure, such as the availability of charging stations, and competition, such as the number of competing products or the risk of cannibalization, but also on the quality of the characteristic draw itself. If the characteristic draw a firm makes has a lower realization of say battery range, it exasperates the issue of range anxiety and therefore, potentially inhibiting it from introducing a new model of EV with that realization. Alternatively, if a firm makes a really good draw, it

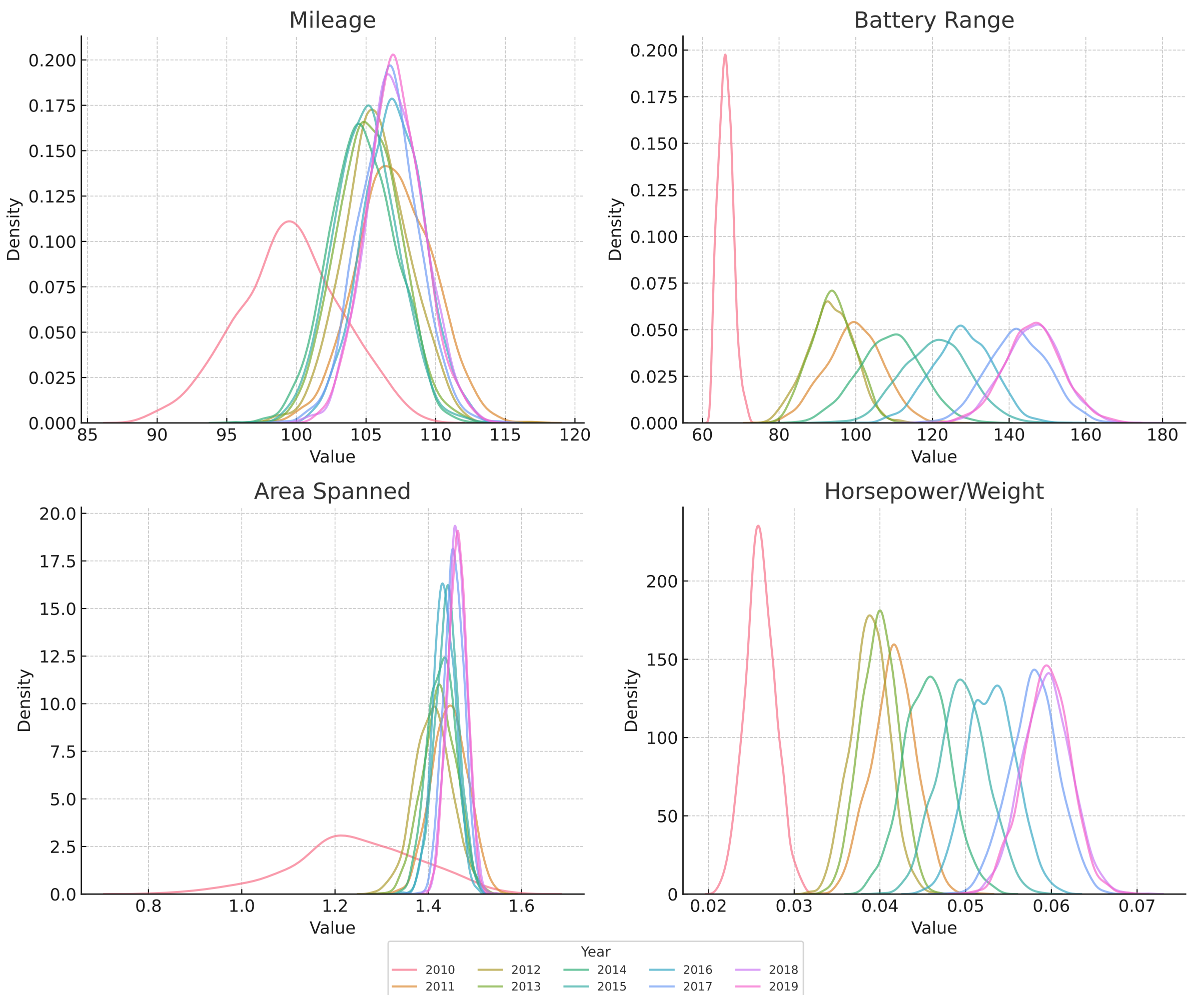


Figure 8.2: The figure plots the k-density plots of the various characteristics that are independently drawn by year. Each set of characteristics drawn represent an EV draw for given firm and year from their respective convex hull. 100 draws are iterated for each firm-year.

improves its chances of introducing the new EV model with that draw. To evaluate the relative likelihood with which firm introduces a new EV model across different time periods, it is informative to solve for the probability of model entry across a multiple draws of vehicle characteristics, which is what I proceed to conduct in this section.

In this counterfactual exercise, given convex hull as defined earlier, I allow each firm to make 100 characteristic draw each year. Given we evaluate behavior of 15 firms over a period of 10 years, allowing each firm to make 100 characteristic draw each year renders us with 15000 vehicle draws. In Figure 8.1, I plot the k-density curves of the individual characteristics that are realized as part of the independent vehicle draws. These characteristics include Mileage, Battery Range, Area Spanned, and Horsepower/Weight. Figure 8.1 presents the k-density for values of characteristics that are realized across all the years.

To illustrate how vehicle characteristic draws differ across years, Figure 8.2 presents kernel density (k-density) curves for individual characteristics realized as part of the independent vehicle draws specific to each year covered in the analysis. These characteristic draws are representative of the respective convex hulls from which they are drawn, and changes in the set of vehicle characteristics available to firms can be inferred by evaluating how the k-density curves for each characteristic—including Mileage, Battery Range, Area Spanned, and Horsepower/Weight—evolved over time. The year-wise plots indicate that while mileage and the area spanned by vehicles remained relatively stable across years, the battery range of EVs consistently improved year after year, as did the horsepower-to-weight ratio.

In this counterfactual exercise, under the assumption of perfect foresight, I allow each firm at given year to make 100 iterations of a vehicle draw at random, and calculate the probability of introducing a new EV for each of those draw. The steps to conduct the exercise are as follows:

1. For each firm and time, make a random draw of vehicle characteristics from the relevant convex hull of characteristics.

2. Calculate the choice specific value functions under both entry as well no entry with respect to the draw made.

3. The choice-specific value functions can be calculated for each choice as

$$v(a^e_o|\mathcal{M}_{o,t}) = \pi(a^e_o, \mathcal{M}_{o,t}) + \beta\{E_{P^i}\Phi\}\lambda^*$$

   where λ^* is the set of coefficients that approximate value function at conditional choice probabilities that show convergence.

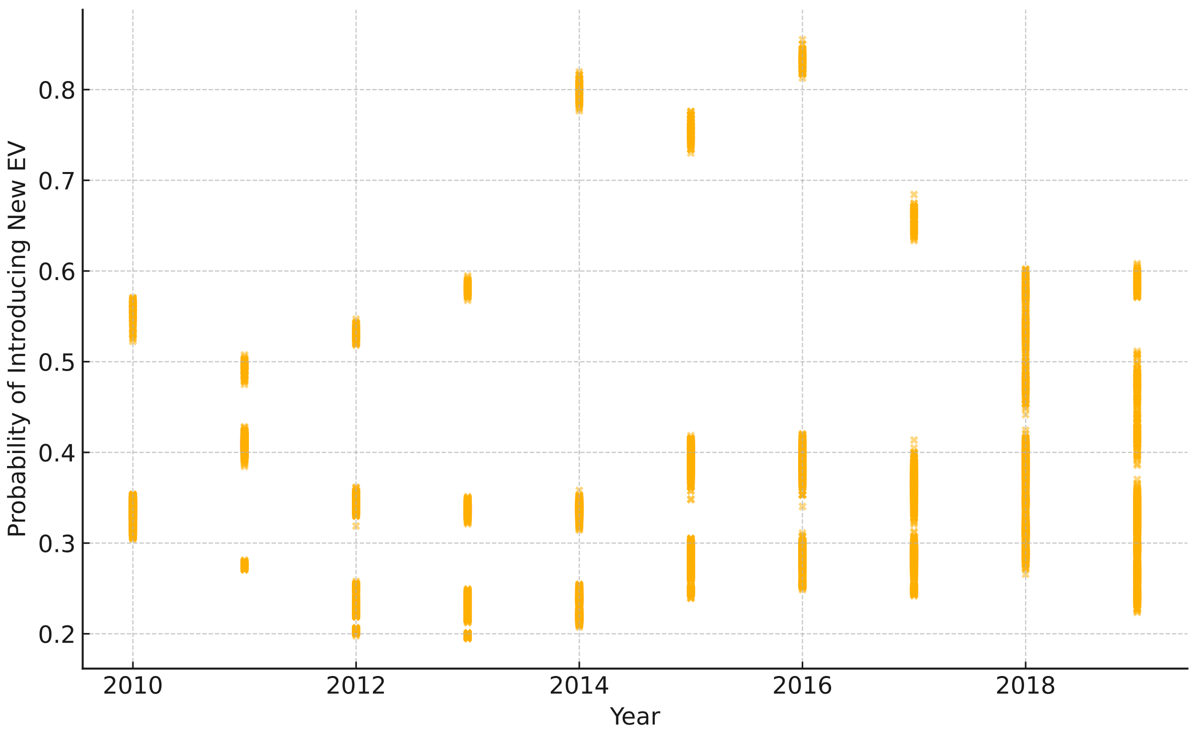


Figure 8.3: The figure provides the scatter plot of the probability of introducing a new EV model across 100 product draws for each firm for the period 2010-2019.

4. Calculate the probability of entry with new EV model for a given draw as

$$P^{'}_{o,t} = \frac{e^{v(1|\mathcal{M}_{o,t})}}{e^{v(1|\mathcal{M}_{o,t})} + e^{v(0|\mathcal{M}_{o,t})}}$$

5. Repeat the exercise 100 times for each firm at a given time and record each realization of $P^{'}_{o,t}$.

The objective of this exercise is to evaluate the probability of entry into a new EV model by each firm in each year for a range of product draws evaluated at the set of coefficients that approximate the value function. By estimating the probability of entry for a range of product draws, I aim to provide a description of each firm's relative likelihood of introducing a new EV, by covering a range of vehicles draw they could have potentially made. The number of EVs available to be purchased from has improved over the years. However, that is not the same as the likelihood of EV entry to have improved. It becomes to crucial to know as the

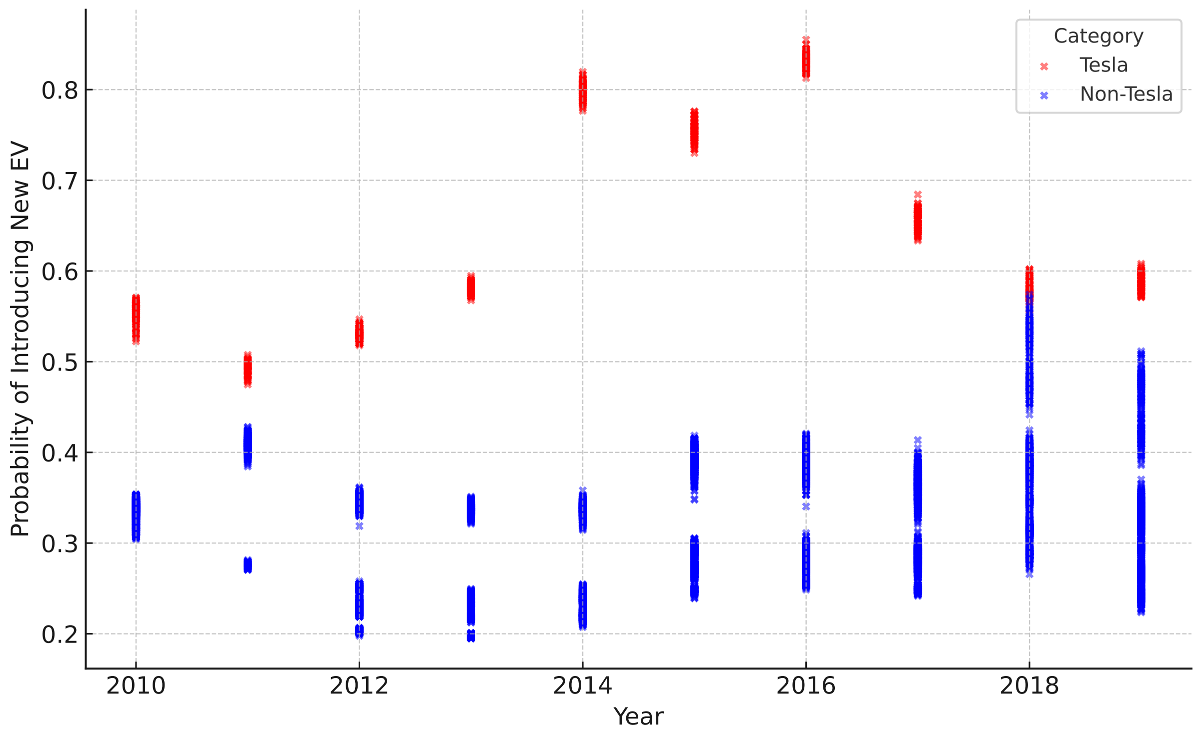


Figure 8.4: The figure provides the scatter plot of the probability of introducing a new EV model across 100 product draws for each firm for the period 2010-2019. The figure labels the estimates separately for Tesla and the rest

EV landscape within the United States have changed over the years, which firms' likelihood to introduce a new EV have improved, remained the same or even declined.

In Figure 8.3, I present estimates of the probability of introducing a new EV model for all firms across the years 2010–2019, iterated across 100 independent draws of vehicle characteristics for each firm-year. Several interesting patterns emerge from this figure. First, in the early two-thirds of the period, there is a sizable gap in the likelihood of EV entry, which worsens over time. Second, towards the latter part of the decade, this gap in EV entry likelihood disappears. Third, for many firms, the likelihood of EV entry does not appear to change significantly over the period.

In Figure 8.4, I separately label the probability estimates for Tesla and the rest of the firms. This figure suggests that both the initial widening gap and the subsequent convergence in entry probability are driven, in part, by Tesla's changing likelihood of model entry during this period. Tesla's probability of introducing a new EV increased between 2010 and 2016, peaking in 2016 before subsequently declining. The figure also indicates that for non-Tesla firms, the likelihood of EV entry has remained relatively stable, with some firms showing improvement, though never to the extent of surpassing Tesla's likelihood.

In Figure 8.5, I report the scatter plot for all firms, excluding Tesla. Visualizing the figure, some interesting patterns emerge. At the period of inception of EV, in 2010, all firms are equally likely to introduce an EV. However, they slowly begin diverging as the years progress. BMW shows an increasing trend in probability from 2010 to 2015, after which it stabilizes at a higher level. Ford and Honda indicates a decline in probability over time, suggesting reduced interest or feasibility in introducing new EV models. General Motors and Tata exhibits an increasing probability over time, particularly post-2015, suggesting a stronger commitment to EV development. Geely, on the other hand, maintains a relatively stable probability across the years with minor variations. Given these non-Tesla firms are subject to the same network of station availability, and the exercise simulates vehicle draw from the same pool, the contrast across firms' likeliness in introducing EV potentially has to do with considerations of cannibalization. Overall, the figure highlights the heterogeneity among non-Tesla firms in entering the EV market. Some firms have increased their likelihood of EV entry over time, while others have remained stable or declined.

8.2 Station build-out

In this section, I use the estimated model parameters to evaluate the impact of a large-scale national policy aimed at expanding the network of charging stations across the United States. The counterfactual exercise involves a full model simulation from 2010 to 2019, assuming that all NEVI funds were exhausted in 2010 to build charging stations at the time of EV introduction. To estimate the number of charging stations resulting from the state-wise allocated spending, I use engineering estimates from the Idaho National Laboratory (INL),

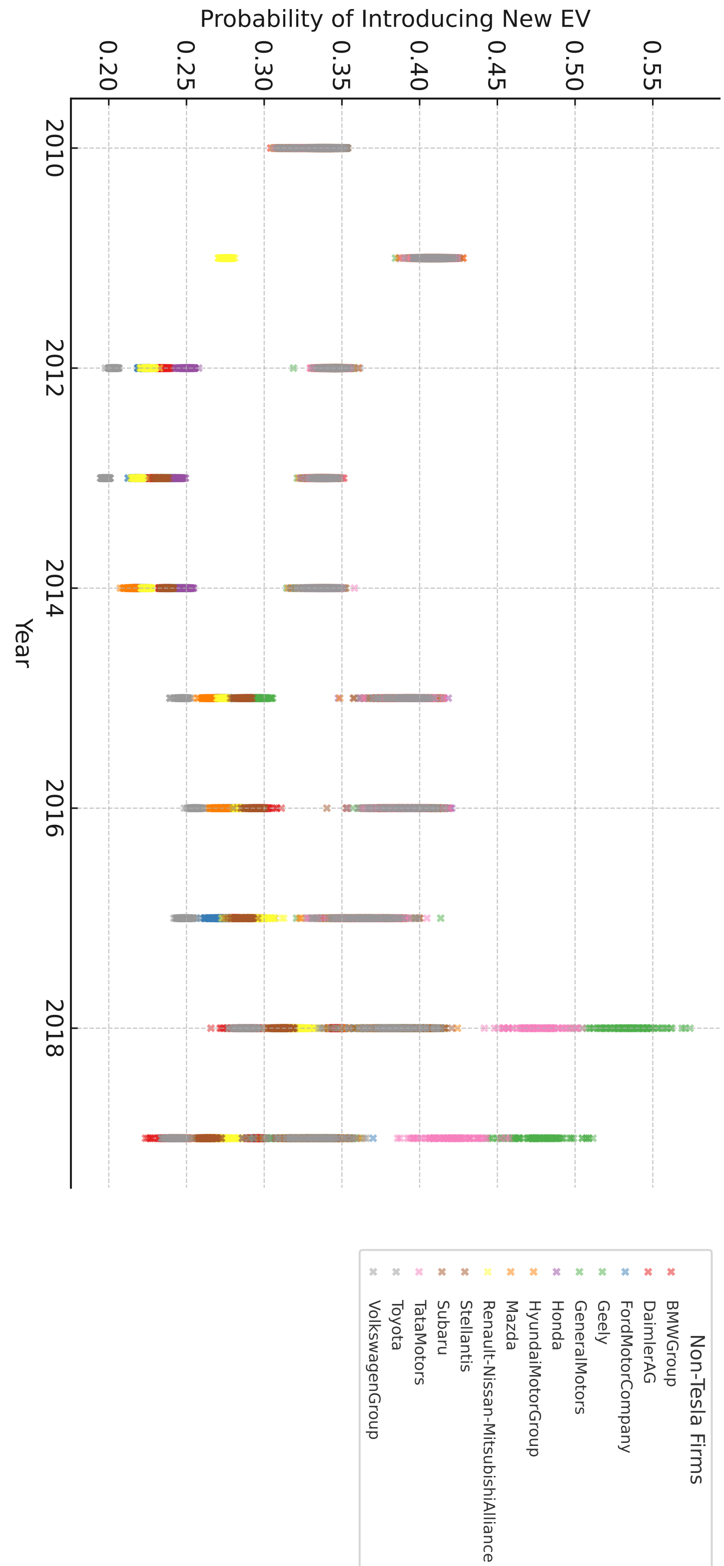


Figure 8.5: The figure provides the scatter plot of the probability of introducing a new EV model across 100 product draws for each of the non-Tesla firms for the period 2010–2019.

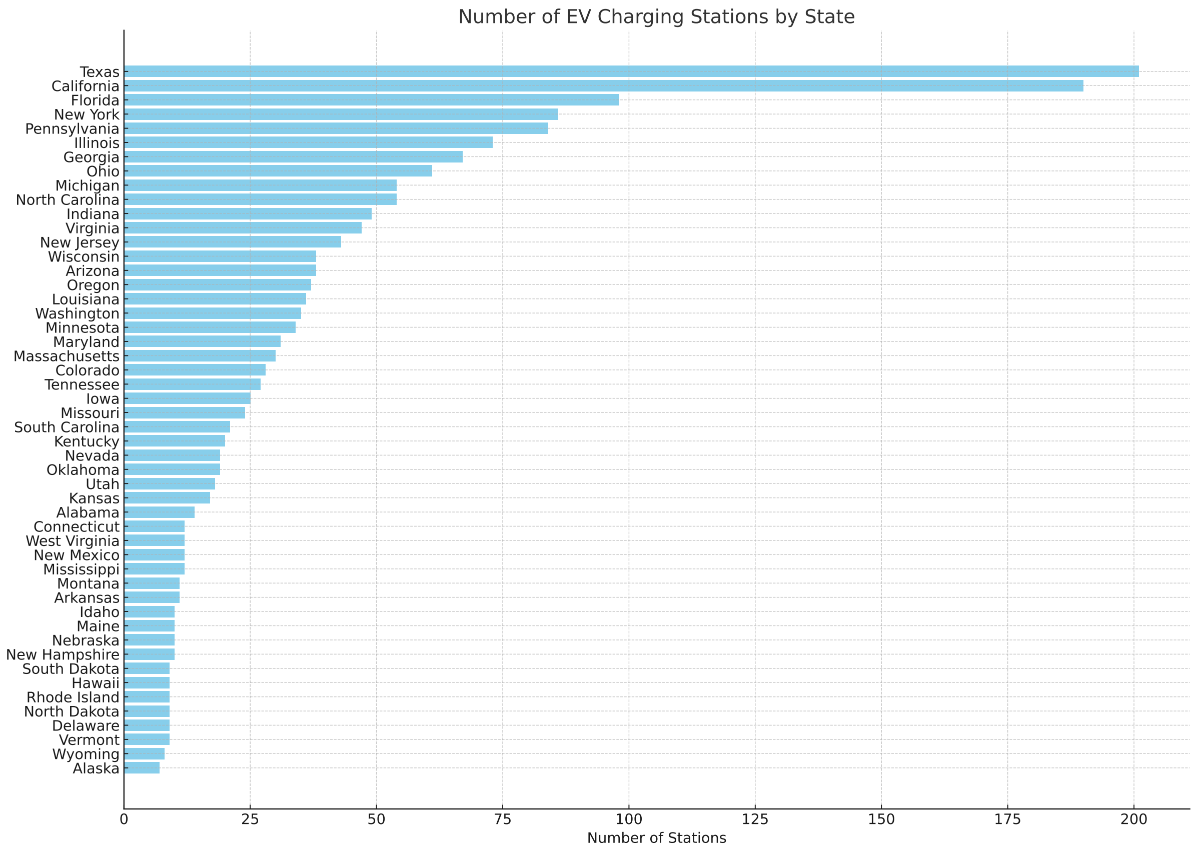


Figure 8.6: The figure reports the imputed number of stations built from respective state's NEVI allocations. The number of charging stations are imputed using engineering estimates from Idaho National Laboratory (INL) at its upper bound at $2.03 million.

which places the upfront cost of a charging station between $0.38 million and $2.03 million. Assuming the upper bound of $2.03 million per station, I impute the number of resulting stations. The policy shock I introduce for this counterfactual exercise assumes that these imputed stations were built as an unanticipated shock in 2010 across the respective states. Figure 8.6 illustrates the number of stations assumed to have been built as a shock in various U.S. states in 2010. The state-wise allocation in total $ value is listed in Figure 3.3.

The steps I follow to conduct this counterfactual exercise are as follows:

1. Assume each US state receives their allocated number of stations from NEVI as a shock in 2010. These would be the number of stations as reported in Figure 8.6.

2. Each firm makes their respective draw of EV characteristics which I treat as public

information.

3. Given the state as observed at current period, supply of third party stations next period is exogenously determined. I used the observed relationship between evolution of third-party charging stations and state variables to determine this relationship and assume the relationship stays the same with the new stations being built as shock. I detail how I capture this relationship in Chapter 8.2.1.

4. I calculate the choice specific value function under both entry and not for each firm.[1]

5. For each firm, I simulate 100 draws of payoff shocks for both entry as well as non-entry and take the average of the payoff shocks. A firm enters with a new EV with the characteristics it drew iff

$$\nu(a^e = 1) + \bar{\epsilon}(\nu(a^e = 1)) \quad > \quad \nu(a^e = 0) + \bar{\epsilon}(\nu(a^e = 0))$$

6. As time period progresses to t+1, introduced EVs are added to the set of vehicles available, third party stations evolve following the relation as estimated, and tesla stations are maintained depending on Tesla's decision to enter with a new model or not. The other state variables modify as observed.

7. At t+1, the process repeats from Step 2.

8.2.1 Third-Party Supply of Charging Stations

A lump-sum build-out of charging stations across all U.S. states not only elicits reaction from both consumers and firms, but will also lead to changes in the supply of other third-party charging stations. In this model, give how firms, that are forward-looking agents maximizing

[1] To account for expectations of behavior of other firms, I take the probability of entry estimated from the first stage OLS I conducted during estimation, with values of state variables being noted as those in counterfactual.

lifetime profits, will internalize these changes in their respective decisions. Therefore, it becomes crucial to provide a robust characterization of third-party stations evolve. To provide an accurate representation of how the market would evolve as a result of the stations built as part of the shock, it is essential to track how other third-party charging stations develop, given that firm and consumer behavior depend on this evolution.

To provide a characterization of the evolution of third-party charging stations, I estimate a policy function predicting third-party charging stations as a function of certain state variables. Firms take this policy function into consideration when forming expectations about the availability of charging stations in the next period. During estimation, I assumed perfect foresight with respect to third party charging stations, as the "true" policy function would ideally predict the next period's station availability based on the current state. For estimation purposes, this would simply involve using the observed data. However, since the scope of the counterfactual exercise extends beyond the existing data, constructing a policy function becomes necessary to meaningfully estimate firms' reactions to the anticipated changes in the market.

To predict the supply function of third-party charging stations, I fit an exponential decay model that predicts the next period's number of third-party charging stations relative to the number of gas stations in a given region in a given year as a function of current state variables. For the purposes of reasonably bounding the prediction of next year's availability of charging stations, I assume number of charging stations in a given state to be always bounded above by the number of gas stations, i.e. charging stations never exceed the number of gas stations in a given state. Using data available on availability of charging and gas stations, gas and electricity prices, and availability of EV and non-EV models from 2010-20,[2] I try to estimate the following equation:

$$Y_{d,t+1} = 1 - exp^{-(\beta_0 + \beta_1 Y_{d,t} + \sum_z \beta_z z_{d,t})} \tag{8.1}$$

[2]I additionally use the data for 2020 to fit this policy function. The rest of the analyses restricts data usage from 2010-2019.

Table 8.1: Estimated Coefficients of the Model Predicting Third-Party Station Availability

Variable	Coefficient
Intercept	-0.0289
	(0.0530)
$\frac{\text{\# of 3rd party charging stations}}{\text{\# of gas stations}}$	1.2748***
	(0.0642)
$(\frac{\text{\# of 3rd party charging stations}}{\text{\# of gas stations}})^2$	0.8773***
	(0.1800)
$\frac{\text{\# of Tesla charging stations}}{\text{\# of gas stations}}$	0.2191
	(0.1649)
$(\frac{\text{\# of Tesla charging stations}}{\text{\# of gas stations}})^2$	0.6774
	(1.1615)
Electricity Price	-0.0032**
	(0.0015)
$(\text{Electricity Price})^2$	0.0002***
	(0.0001)
Gas Price	0.0250
	(0.0370)
$(\text{Gas Price})^2$	-0.0022
	(0.0066)
$\frac{\text{\# of EV models}}{\text{\# of all models}}$	-1.0140**
	(0.4102)
$(\frac{\text{\# of EV models}}{\text{\# of all models}})^2$	16.9764**
	(7.0483)

Note: This table presents the estimated coefficients of the policy function predicting the supply of third-party charging stations relative to gas stations. Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$

where $Y_{d,t+1}$ is the next period's availability of third-party charging stations relative to gas stations in region d, predicted as a function of its current value and other state variables represented with z. The state variables included within z are gas prices, electricity prices and share of vehicles offered that are battery EVs.

In this model, I normalize the availability of the charging stations relative to gas stations, which I assume to be fixed as observed in data. The normalization of charging stations relative to gas stations provides a suitable benchmark by relating the availability of charging stations to the existing infrastructure for gas stations, which serves as a proxy for the overall capacity and network availability need for each state. By fitting a variation of the exponential decay function, I ensure that model does not explode and predicts the number of charging station in limit to be equal to the number of gas stations. The functional form I use to fit the policy function to predict next year's availability of charging station in Equation 8.1 is an exponential decay function. The exponential decay form captures diminishing returns, which is relevant in in charging station build-out. As the network of charging stations becomes less sparse, additional stations contribute less to the network, yielding progressively smaller benefits. This behavior is naturally modeled by the exponential decay function, which approaches an upper limit, which is in this model I predict to be bounded by the number of gas stations. Table 8.1 provide the variables that used to fit the exponential decay model including their respective coefficients. To evaluate how the estimated policy function performs in predicting number of third-party charging stations against the actual number of charging stations as observed in data, I plot the prediction v/s actual data. Figures D.1 and D.2 plot the predicted number of charging stations against against data for the top and bottom 20 states in terms of existing network of charging stations, respectively. From the figures, I infer the policy function as described in this section captures non-linearity as is observed for how charging stations proliferate. The policy function is more stable in prediction as the number of station grows, which serves to my purpose since the policy shock evaluated is a sizable expansion of charging station network.

8.3 Simulation Results from NEVI build-out

Running the full sequence of model simulations, given the large-scale station build-out from NEVI between 2010 and 2020, indicates a sizable increase in the number of EV models offered by firms. In Figure 8.7, I use a grid plot to indicate whether each firm chooses to enter with a new EV model in a given year. The model simulation begins in 2010, the first year in which a firm can decide to introduce a new EV model in the following period.

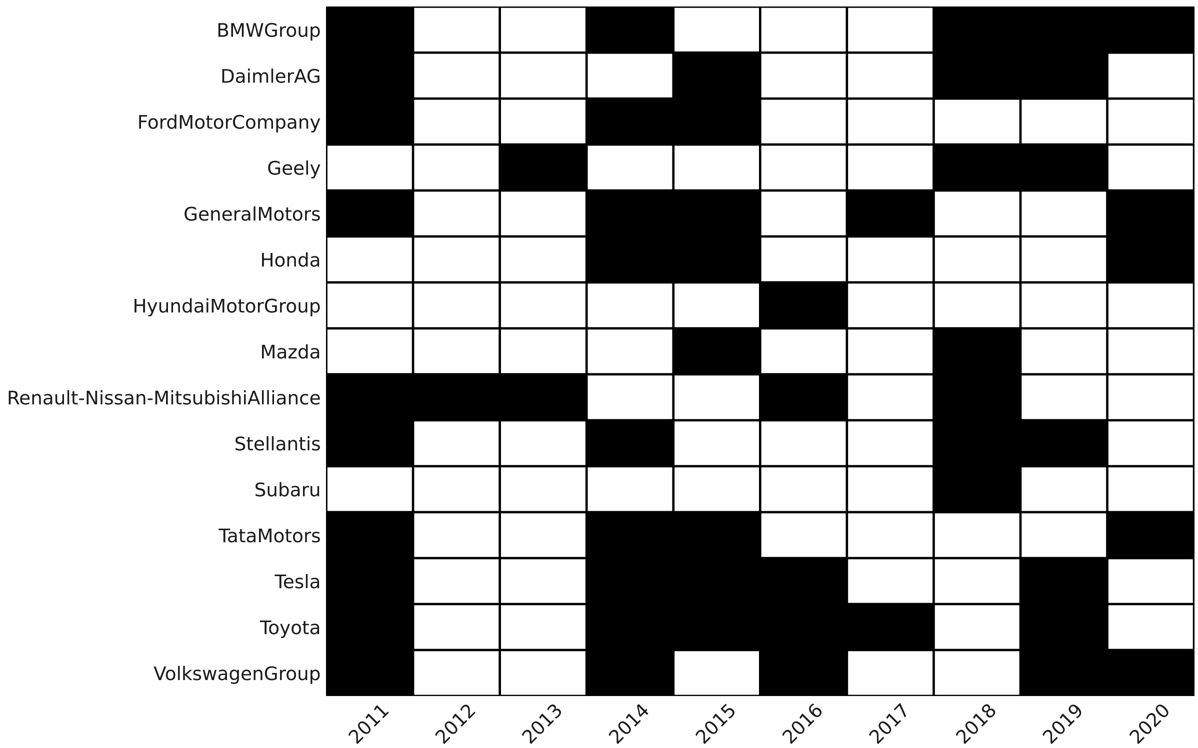
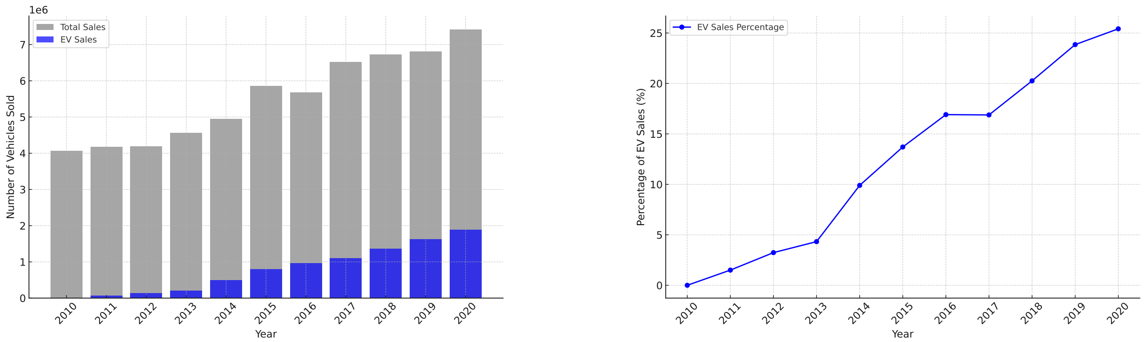


Figure 8.7: The figure presents the grid plot to indicate entry by made by each firm or not in a given year between 2011-2020, inferred from the counterfactual exercise. In the figure, each black block indicates entry whereas a blank space indicates no entry. A new model being introduced in a given year is based upon the decision made by the respective firm the year before. In counterfactual simulation, I predict 56 new models of EV being introduced during the period 2011-2020, compared against 22 in observed data.

The results indicate that a majority of firms choose to introduce a new EV model early in the simulation, likely motivated by the large-scale station build-out, which addresses range anxiety, as well as price incentives provided by the tax credit in place. Entry slows in the following years but sees a surge in 2014 and 2015, possibly due to improvements in EV technology and increasing competitive pressure. Entry then declines in 2016 and 2017 before picking up again in 2018 and 2019. This simulation, as presented in this thesis, highlights the impact of NEVI—a policy that establishes a large-scale charging station network across the United States—in significantly increasing the number of EV models offered. The number of models more than doubles, rising from 22 in the observed data to 56 in the counterfactual scenario.



(a) Total EV sales compared against the total sales of all vehicles.

(b) Percentage of battery-operated EV sales compared to total vehicle sales.

Figure 8.8: Comparison of EV sales trends: absolute sales (left) and percentage of total vehicle sales (right), given the counterfactual exercise. EV sales grow steadily due to increased charging infrastructure, expanded model offerings, and federal and state purchase subsidies.

Driven by an increase in the number of charging stations addressing range anxiety, a growing variety of EV models offering greater differentiation, and a range of purchase subsidies provided by both federal and state authorities, the counterfactual experiment indicates that EV sales have grown steadily—not only in absolute terms but also relative to total vehicle sales. In Figure 8.8a, I plot the predicted number of total vehicle sales alongside EV sales. Overall vehicle sales increase during this period as the number of both EV and non-EV models grows. However, in Figure 8.8b, I plot EV sales as a percentage of total vehicle sales. The percentage of EV sales rises significantly over time, indicating that EVs are steadily replacing internal combustion engine (ICE) vehicles. This trend confirms the effectiveness of the policy in addressing environmental concerns.

To highlight how respective firms contribute to the rise in EV sales between 2011 and 2020, I depict their sales in a stacked bar chart in Figure 8.9. An immediate observation is that there are no obvious market leaders in EV sales within the counterfactual exercise as presented. Firms such as Toyota, Volkswagen, Honda, Ford, and General Motors lead in EV sales and their respective ranks are shuffled over time. In contrast to the dominance in EV sales as observed in data, Tesla exhibits inferior sales compared to the aforementioned firms but demonstrates steady, albeit modest, growth. This suggests that a policy subsidiz-

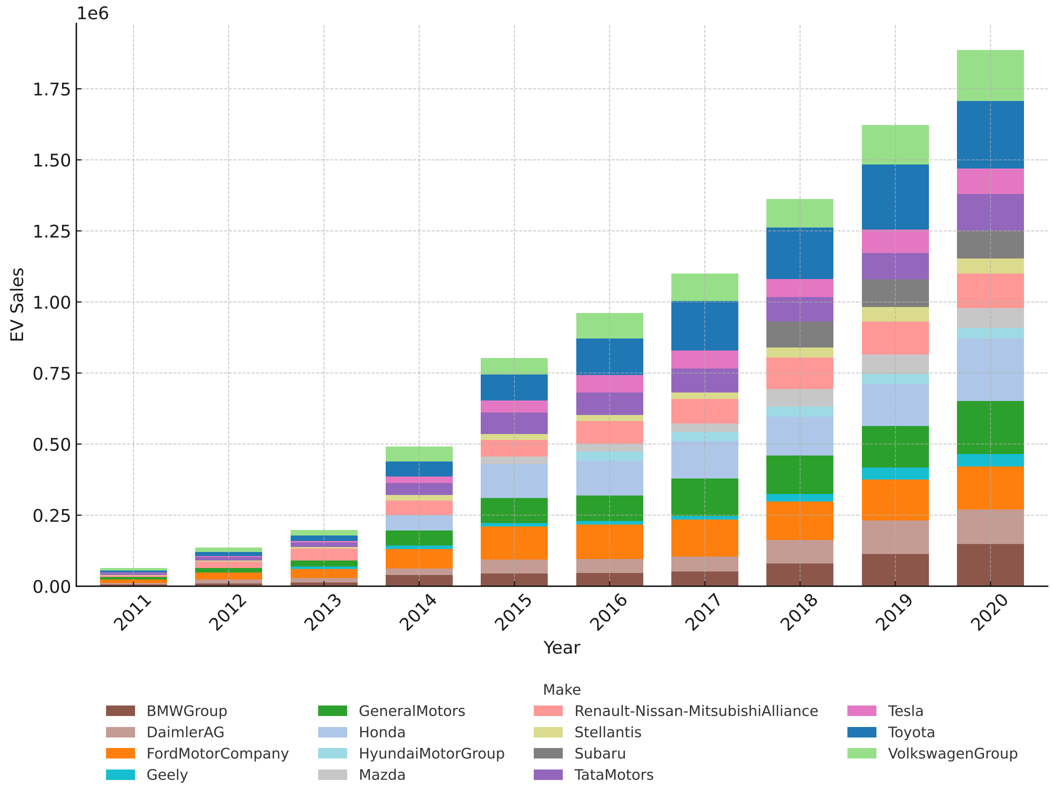


Figure 8.9: The figure provides the stacked bar chart of expected sales of EVs, given the counterfactual exercise, breaking it down by make between the years 2011-2020.

ing station build-out across all firms incentivizes broader market entry, leading to a more competitive EV landscape where sales are expedited across firms, but at the cost of Tesla's market power.

The station build-out program not only initiates a flurry of product entry from firms but leads to further expansion of the charging network itself, which leads to more entry over time. Given the estimation of the supply function of third party stations as an exponential decay function of certain state variables, I am able to predict its evolution in each state as I simulate the entire model. In Figure 8.10, I present how the network of third-part charging stations evolve. The model simulation also involves solving for Tesla's decision to maintain charging stations in each state. Combining the values, in the same figure I also present how the network of Tesla charging stations evolved and compare the two contrasting evolution in the counterfactual exercise and evaluate how different it is compared to the actual evolution

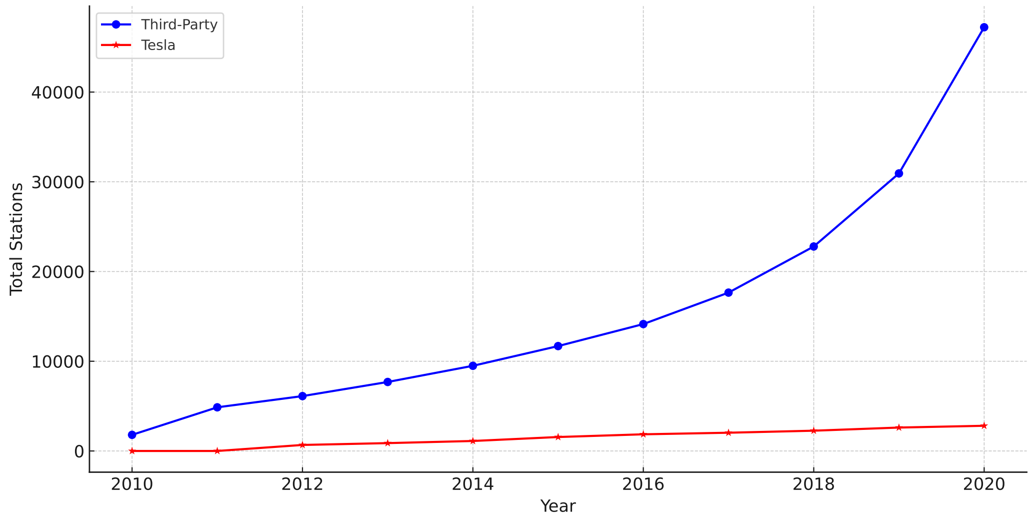


Figure 8.10: The figure represents the evolution of third-party charging station as well as the evolution of Tesla charging stations in the counterfactual exercise.

(Figure 3.1. The evolution of third-party charging stations in counterfactual follow a similar pattern to actual data but have scaled bigger. The shape being as preserved as observed in data is a result of estimating the supply of third-party charging stations. What is startlingly different from data is how relatively small Tesla's network is. Although Tesla's network does grow over time, on account of increased competition, it is only a tiny fraction of the overall size of the third-party charging network, and therefore does not contribute much to its overall market power, reconciling its modest sales in the counterfactual estimation. I record the state-wise evolution of the network in charging stations in Figure F.1 and F.2.

Chapter 9

Conclusion

The transition from gas-powered to electric vehicles remains a critical concern for contemporary environmental policy. Despite a range of federal and state-level policies subsidizing EV purchases over the past decade, EV sales accounted for only 9% of all new vehicle purchases in 2024.[1] Anecdotal evidence suggests that range anxiety—stemming from the limited availability of charging stations—remains a key deterrent to greater EV adoption. Tesla's relatively success in this segment is related to the exclusive charging network it provides to its users. In addition, recent policy initiatives aimed at accelerating EV adoption, such as the National Electric Vehicle Infrastructure (NEVI) Formula Program, actively address range anxiety by promoting the nationwide charging infrastructure.

In this thesis, I model and estimate a forward looking game of entry in new EV models by auto-manufacturers within the US. Additionally, to account for Tesla's unique product positioning, I allow Tesla to maintain exclusive charging stations in each US state. Using micro-data on purchase patterns from a nationally representative sample of households, I find range anxiety to be a key factor negatively impacting a household's utility from the purchase of a new vehicle. Given the complementarity between the size of the charging network available to a consumer and their utility from operating an EV, increasing the

[1] *See*: U.S. share of electric and hybrid vehicle sales reached a record in the third quarter, U.S. Energy Information Administration, December 4, 2024, available at https://www.eia.gov/todayinenergy/detail.php?id=63904

availability of charging stations drives greater adoption of EVs by consumers, encouraging firms to enter the market with newer varieties of EVs, leading to a compounding effect on sales, driven by both the increase in charging stations and the expansion of available models. Another dimension to evaluate in this context is competition from gas vehicles. Despite the size of charging network improving, firms on account of concerns of cannibalization of sales into their existing gas vehicles, might potentially choose to avoid introducing a new EV.

Analysis from the demand side shows that as the charging station network expanded over the years, the compensating variance with respect to both the number of stations and increased travel requirements declined in absolute value. Since Tesla users had access to a larger network due to the additional Tesla-exclusive stations, their compensating variances in both dimensions were smaller than those of non-Tesla users. This suggests that while an increase in charging stations improves overall utility, the marginal value of each additional station diminishes. A publicly funded charging station expansion reduces Tesla's market power and makes it less competitive. On the other hand, expansion of charging network benefits other firms that may have previously been deterred from entering the market due to concerns about cannibalization.

Using the model primitives as estimated, I engage in a counterfactual exercise where I allow firms to make random draws of characteristics of EVs and evaluate their relative likelihood of entry. Between the period 2010-2019, the likelihood on entry of Tesla is consistently higher than the rest. For non-Tesla firms, early entry likelihoods are similar, but over time, their paths diverge with some firms increasing their likelihood and some reducing over time. To evaluate how a large scale national project to build stations, in another counterfactual exercise, I conduct a full model simulation between 2010-2020 and find a large supply shock in stations to greatly boost EV models being offered, subsequent stations being built as well as the resulting sales. A substantial expansion of third-party charging infrastructure diminishes the value of exclusive charging access, impacting Tesla's market power and leading to a more attractive and equitable EV landscape. As a result, EV adoption accelerates, driven by early entry by most firms and market leadership becomes more evenly distributed among firms.

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Appendix

A Accounting Price Derivatives

Accounting for price derivatives is not straightforward given the exposition as presented in this thesis. First, The demand system as presented in this thesis follows a nested structure, households first decide as to whether or not they wish to be in the market for the purchase of new automobiles and if so, they subsequently choose the vehicle that maximizes their utility. Second, I integrate the expected demand at the household levels over the distribution of households accounting for their respective locations, incomes and travel requirements. Therefore, any price derivative aggregated at the national level which firms take into account their price settings need to also integrate derivatives accounted for at the household level. I present the formulation of own-price derivation of demand in A.1 and the formulation of cross-price derivation of demand in A.2.

A.1 Own-Price Derivative of Demand

From Equation 5.5, demand for household i's demand for vehicle j at time t is

$$s_{ijdt} = \underbrace{\frac{exp(ln(\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K)}{1 + exp(ln(\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K)}}_{\text{Probability HH } i \text{ goes to the inside}} \quad \times \quad \underbrace{\frac{exp(V_{ijdt})}{\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})}}_{`xtProbabilityibuysjonceinside}$$

Take the derivative of s_{ijdt} with respect to price of vehicle j at time t

$$\begin{aligned}
\frac{\partial}{\partial p_{jt}} s_{ijdt} &= \frac{\partial}{\partial p_{jt}} \left[\frac{exp(ln(\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K)}{1 + exp(ln(\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K)} \right] \times \frac{exp(V_{ijdt})}{\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})} \\
&\quad + \frac{exp(ln(\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K)}{1 + exp(ln(\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K)} \times \frac{\partial}{\partial p_{jt}} \left[\frac{exp(V_{ijdt})}{\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})} \right] \\
&= \left[\frac{\frac{\partial}{\partial p_{jt}} (exp(ln(\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K))}{\{1 + exp(ln(\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K)\}^2} \right] \times \frac{exp(V_{ijdt})}{\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})} \\
&\quad + \frac{exp(ln(\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K)}{1 + exp(ln(\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K)} \\
&\quad \times \left[\frac{(\frac{\partial}{\partial p_{jt}} exp(V_{ijdt}))(\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})) - exp(V_{ijdt}) \frac{\partial}{\partial p_{jt}} (\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt}))}{\{\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})\}^2} \right]
\end{aligned}$$

From our equation specification 5.1, we know that $\frac{\partial}{\partial p_{jt}} V_{ijdt} = \alpha \frac{1}{Y_i}$ and $\frac{\partial}{\partial p_{jt}} V_{ij'dt} = 0$, for vehicle j' different from vehicle j. Continuing the simplification of the derivative of s_{ijdt} with respect to p_{jt}

$$\frac{\partial}{\partial p_{jt}} s_{ijdt} = \left[\frac{(exp(ln(\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K)) \times \frac{exp(V_{ijdt})}{\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})} \times \frac{\alpha}{Y_i}}{\{1 + exp(ln(\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K)\}^2} \right] \times \frac{exp(V_{ijdt})}{\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})}$$
$$+ \frac{exp(ln(\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K)}{1 + exp(ln(\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K)} \times \frac{\alpha}{Y_i} \times \frac{exp(V_{ijdt})}{\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})} \left[1 - \frac{exp(V_{ijdt})}{\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})} \right]$$

Referring to equation 5.5 that defines s_{ijdt}, its derivative with respect to p_{jt} can be further simplified as

$$\begin{aligned}
\frac{\partial}{\partial p_{jt}} s_{ijdt} &= \frac{\alpha}{Y_i} \times s_{ijdt} \times \frac{1}{1 + exp(ln(\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K)} \times \frac{exp(V_{ijdt})}{\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})} \\
&\quad + \frac{\alpha}{Y_i} \times s_{ijdt} \times \left[1 - \frac{exp(V_{ijdt})}{\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})} \right] \\
&= \frac{\alpha}{Y_i} \times s_{ijdt} \times \left[1 - \frac{exp(V_{ijdt})}{\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})} \left\{ 1 - \frac{1}{1 + exp(ln(\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})} \right\} \right] \\
&= \frac{\alpha}{Y_i} \times s_{ijdt} \times \left[1 - \frac{exp(V_{ijdt})}{\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})} \times \frac{exp(ln(\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})}{1 + exp(ln(\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})} \right] \\
&= \frac{\alpha}{Y_i} \times s_{ijdt} \times [1 - s_{ijdt}]
\end{aligned}$$

Given the formulation of aggregate demand, as per Equation 5.6, the own-price derivative of aggregate demand can be written as

$$\begin{aligned}
\frac{\partial}{\partial p_{jt}} S_{jt} &= \frac{\partial}{\partial p_{jt}} \int s_{ijdt} d\mathcal{G}(\mathcal{I}) \\
&= \int (\frac{\partial}{\partial p_{jt}} s_{ijdt}) d\mathcal{G}(\mathcal{I}) \\
&= \int (\frac{\alpha}{Y_i} \times s_{ijdt} \times (1 - s_{ijdt})) d\mathcal{G}(\mathcal{I})
\end{aligned}$$

A.2 Cross-price Derivative of Demand

From Equation 5.5, demand for household i's demand for vehicle j at time t is

$$s_{ijdt} = \underbrace{\frac{exp(ln(\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K)}{1 + exp(ln(\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K)}}_{\text{Probability HH } i \text{ goes to the inside}} \times \underbrace{\frac{exp(V_{ijdt})}{\sum_{j'\epsilon \mathbf{J}_t} exp(V_{ij'dt})}}_{\text{Probability } i \text{ buys j once inside}}$$

Take the derivative of s_{ijdt} with respect to price of another vehicle k at time t

$$\begin{aligned}
\frac{\partial}{\partial p_{kt}} s_{ijdt} &= \frac{\partial}{\partial p_{kt}} \left[\frac{exp(ln(\sum_{j' \epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K)}{1 + exp(ln(\sum_{j' \epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K)} \right] \times \frac{exp(V_{ijdt})}{\sum_{j' \epsilon \mathbf{J}_t} exp(V_{ij'dt})} \\
&\quad + \frac{exp(ln(\sum_{j' \epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K)}{1 + exp(ln(\sum_{j' \epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K)} \times \frac{\partial}{\partial p_{kt}} \left[\frac{exp(V_{ijdt})}{\sum_{j' \epsilon \mathbf{J}_t} exp(V_{ij'dt})} \right] \\
&= \left[\frac{\frac{\partial}{\partial p_{kt}} (exp(ln(\sum_{j' \epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K))}{\{1 + exp(ln(\sum_{j' \epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K)\}^2} \right] \times \frac{exp(V_{ijdt})}{\sum_{j' \epsilon \mathbf{J}_t} exp(V_{ij'dt})} \\
&\quad + \frac{exp(ln(\sum_{j' \epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K)}{1 + exp(ln(\sum_{j' \epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K)} \\
&\quad \times \left[\frac{(\frac{\partial}{\partial p_{kt}} exp(V_{ijdt}))(\sum_{j' \epsilon \mathbf{J}_t} exp(V_{ij'dt})) - exp(V_{ijdt}) \frac{\partial}{\partial p_{kt}} (\sum_{j' \epsilon \mathbf{J}_t} exp(V_{ij'dt}))}{\{\sum_{j' \epsilon \mathbf{J}_t} exp(V_{ij'dt})\}^2} \right] \\
&= \left[\frac{(exp(ln(\sum_{j' \epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K)) \times \frac{exp(V_{ikdt})}{\sum_{j' \epsilon \mathbf{J}_t} exp(V_{ij'dt})} \times \frac{\alpha}{Y_i}}{\{1 + exp(ln(\sum_{j' \epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K)\}^2} \right] \times \frac{exp(V_{ijdt})}{\sum_{j' \epsilon \mathbf{J}_t} exp(V_{ij'dt})} \\
&\quad + \frac{exp(ln(\sum_{j' \epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K)}{1 + exp(ln(\sum_{j' \epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K)} \times \left[\frac{0 - exp(V_{ijdt}) \times exp(V_{ikdt}) \times \frac{\alpha}{Y_i}}{\{\sum_{j' \epsilon \mathbf{J}_t} exp(V_{ij'dt})\}^2} \right] \\
&= \frac{\alpha}{Y_i} \times \frac{s_{ikdt}}{\{1 + exp(ln(\sum_{j' \epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K)\}} \times \frac{exp(V_{ijdt})}{\sum_{j' \epsilon \mathbf{J}_t} exp(V_{ij'dt})} \\
&\quad - \frac{\alpha}{Y_i} \times s_{ikdt} \times \frac{exp(V_{ijdt})}{\sum_{j' \epsilon \mathbf{J}_t} exp(V_{ij'dt})} \\
&= \frac{\alpha}{Y_i} \times s_{ikdt} \times \left[\frac{exp(V_{ijdt})}{\sum_{j' \epsilon \mathbf{J}_t} exp(V_{ij'dt})} \left(\frac{1}{1 + exp(ln(\sum_{j' \epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K)} - 1 \right) \right] \\
&= \frac{\alpha}{Y_i} \times s_{ikdt} \times \left[\frac{exp(V_{ijdt})}{\sum_{j' \epsilon \mathbf{J}_t} exp(V_{ij'dt})} \left(\frac{-exp(ln(\sum_{j' \epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K)}{1 + exp(ln(\sum_{j' \epsilon \mathbf{J}_t} exp(V_{ij'dt})) + K)} \right) \right] \\
&= -\frac{\alpha}{Y_i} \times s_{ikdt} \times s_{ijdt}
\end{aligned}$$

Given the formulation of aggregate demand, as per Equation 5.6, the cross-price derivative of aggregate demand can be written as

$$\begin{aligned}
\frac{\partial}{\partial p_{kt}} S_{jt} &= \frac{\partial}{\partial p_{kt}} \int s_{ijdt} d\mathcal{G}(\mathcal{I}) \\
&= \int (\frac{\partial}{\partial p_{kt}} s_{ijdt}) d\mathcal{G}(\mathcal{I}) \\
&= \int (-\frac{\alpha}{Y_i} \times s_{ikdt} \times s_{ijdt}) d\mathcal{G}(\mathcal{I})
\end{aligned}$$

B Polynomials used to approximate Value Function

According to the Stone-Weierstrass Theorem, any continuous function can be approximated arbitrarily well by a uniform series of polynomials. However, while the theorem guarantees the existence of such an approximating polynomial sequence, it does not construct or specify this sequence explicitly. The task of identifying a suitable polynomial approximation is left to the economist. In this thesis, I approximate the value function using first- and second-degree Chebyshev polynomials of the relevant state variables. Chebyshev polynomials are particularly useful due to their favorable numerical properties, including their ability to minimize the Runge phenomenon, which can cause large oscillations in polynomial approximations of high degree.

The ideal polynomial approximation, in a uniform sense, is the minimax polynomial, which provides the best uniform approximation of a given degree within the class of polynomials. By definition, the minimax polynomial minimizes the maximum deviation from the true function over the entire state space. However, computing the minimax polynomial is computationally challenging, as it requires solving a global minimization problem across all points in the state space. Instead, I use least-squares Chebyshev approximation, which offers a close approximation to the minimax solution while being significantly easier to compute. Least-squares Chebyshev approximation optimally distributes approximation errors in a least-squares sense, making it a practical and effective alternative for approximating the value function in dynamic economic models.

Chebyshev polynomials are a special class of orthogonal polynomials that play a crucial role in approximation theory and numerical analysis. They are orthogonal over the interval $[-1, 1]$ with respect to the weight function $\frac{1}{\sqrt{1-x^2}}$, making them particularly well-suited for interpolation and function approximation. These polynomials are defined using a trigonometric representation:

$$T_n(x) = \cos(n \cdot \arccos(x))$$

This definition leads to the recursive structure of Chebyshev polynomials, which can be expressed as:

$$\begin{aligned}
&T_0(x) = 1, \\
&T_1(x) = x, \\
&T_2(x) = 2x^2 - 1, \\
&T_{n+1}(x) = 2xT_n(x) - T_{n-1}(x).
\end{aligned}$$

This recurrence relation makes it computationally efficient to generate higher-order Chebyshev polynomials. Moreover, the derivatives of Chebyshev polynomials also follow a recursive pattern, which facilitates their use in numerical differentiation and spectral methods:

Table B.1: State Variables Used in Value Function Approximation

Firm-Specific Variables
- Number of EVs in the firm's existing portfolio
- Number of competing EVs
- Number of non-EVs in the firm's existing portfolio
- Number of competing non-EVs
Vehicle Characteristics
- Mean, median, and standard deviation (sd) of the following for the firm's portfolio:
· Horsepower-to-weight ratio
· Mileage for EVs
· Mileage for non-EVs
· Area spanned
· Battery range
- Mean, median, and sd of the following for all competing products:
· Horsepower-to-weight ratio
· Mileage for EVs
· Mileage for non-EVs
· Area spanned
· Battery range
Energy Prices
- Percentiles (10th, 25th, 50th, 75th, 90th) of gas prices across all U.S. states
- Percentiles (10th, 25th, 50th, 75th, 90th) of electricity prices for transportation
Charging Infrastructure
- Number of relevant charging stations in each U.S. state $\times$ Median battery range
Household Demographics
- Population in each U.S. state
Policy Variables
- State-wise subsidy on EV
- National eligibility on EV

$$\begin{aligned} T_0'(x) &= 0, \\ T_1'(x) &= 1, \\ T_{n+1}'(x) &= 2T_n(x) + 2xT_n'(x) - T_{n-1}'(x). \end{aligned}$$

Chebyshev polynomials are particularly useful for function approximation due to their min-max property, which ensures that they provide near-optimal polynomial approximations with minimal maximum error. For the full list of state variables whose first and second order polynomials are used in the approximation of value function, refer to Table B.1.

C Hessian Matrix of Dynamic Parameters

To estimate the standard error for the dynamic parameters the maximize the likelihood of data as observed, I analytically solve for the variance-covariance matrix of θ^*, which is calculated as the inverse of the Information matrix, which in turn is the negative of the expected value of the Hessian matrix of the log-likelihood function with respect to θ^*. The log-likelihood function given θ^* for the set of data covering N observations can be represented as:

$$lnL(\theta^*) = \sum_{i=1}^{N} lnL_i(\theta^*) \tag{C.1}$$

The likelihood for each observed data point for a given firm and time period represents the probability with which they would introduce a new EV model in the market. Given the approach I adopt to rationalize the forward-looking game that is characteristic of this model, the likelihood of model entry for a given firm-period can be calculated by comparing the conditional choice value functions with respect to entry v/s not. Both the conditional choice value functions with respect to entry v/s not is calculated as the sum of the respective flow payoffs and the discounted conditional value function approximated as a linear combination of polynomials using the set of coefficients calculated at equilibrium beliefs. The likelihood for a data-point for given firm-time can be represented as:

$$\begin{aligned} L_i(\theta^*) &= \frac{exp(v(a^e = 1|\mathcal{M}_{o,t}, \theta^*))}{exp(v(a^e = 1|\mathcal{M}_{o,t}, \theta^*)) + exp(v(a^e = 0|\mathcal{M}_{o,t}, \theta^*))} \\ &= \frac{exp(\tilde{\pi} - \tau_o - \tilde{\tau} N^e.\mathbf{I}(Tesla) + \beta\phi^e\lambda^*)}{exp(\tilde{\pi} - \tau_o - \tilde{\tau} N^e.\mathbf{I}(Tesla) + \beta\phi^e\lambda^*) + exp(\tilde{\pi} - \tilde{\tau} N^{ne}.\mathbf{I}(Tesla) + \beta\phi^{ne}\lambda^*)} \end{aligned} \tag{C.2}$$

The above representation generalizes the formulation of likelihood for both Tesla as well as non-Tesla firms. Given Tesla's unique position to also provide stations exclusive to its users, Tesla incurs the cost of maintaining stations respective to path differential. The indicator variable $\mathbf{I}(Tesla)$ indicates that the related term is only applicable for Tesla and not other firms, with N^e representing the set of stations built under entry and N^{ne} representing the set of stations built under no entry. Before I analytically solve for the Hessian matrix of the log-likelihood function at the equilibrium values of the dynamic parameter, it is convenient to derive the first order derivative of the likelihood expression as shown in Equation C.2 with respect to sunk cost of product entry, τ.

$$\frac{\partial L_i}{\partial \tau} = \frac{\partial}{\partial \tau}\frac{exp(\tilde{\pi} - \tau_o - \tilde{\tau}N^e.\mathbf{I}(Tesla) + \beta\phi^e\lambda^*)}{exp(\tilde{\pi} - \tau_o - \tilde{\tau}N^e.\mathbf{I}(Tesla) + \beta\phi^e\lambda^*) + exp(\tilde{\pi} - \tilde{\tau}N^{ne}.\mathbf{I}(Tesla) + \beta\phi^{ne}\lambda^*)}$$

$$= \frac{-1 \times exp(\tilde{\pi} - \tau_o - \tilde{\tau}N^e.\mathbf{I}(Tesla) + \beta\phi^e\lambda^*)}{exp(\tilde{\pi} - \tau_o - \tilde{\tau}N^e.\mathbf{I}(Tesla) + \beta\phi^e\lambda^*) + exp(\tilde{\pi} - \tilde{\tau}N^{ne}.\mathbf{I}(Tesla) + \beta\phi^{ne}\lambda^*)} \tag{C.3}$$

$$+ \left[\frac{exp(\tilde{\pi} - \tau_o - \tilde{\tau}N^e.\mathbf{I}(Tesla) + \beta\phi^e\lambda^*)}{exp(\tilde{\pi} - \tau_o - \tilde{\tau}N^e.\mathbf{I}(Tesla) + \beta\phi^e\lambda^*) + exp(\tilde{\pi} - \tilde{\tau}N^{ne}.\mathbf{I}(Tesla) + \beta\phi^{ne}\lambda^*)}\right]^2$$

$$= -L(1 - L)$$

The first order derivative of the likelihood expression with respect to the fixed cost of maintaining a Tesla station, $\tilde{\tau}$ can also be solved for.

$$\frac{\partial L}{\partial \tilde{\tau}} = \frac{\partial}{\partial \tilde{\tau}}\frac{exp(\tilde{\pi} - \tau_o - \tilde{\tau}N^e + \beta\phi^e\lambda^*)}{exp(\tilde{\pi} - \tau_o - \tilde{\tau}N^e + \beta\phi^e\lambda^*) + exp(\tilde{\pi} - \tilde{\tau}N^{ne} + \beta\phi^{ne}\lambda^*)}.\mathbf{I}(Tesla)$$

$$= \Big\{\frac{-N^e exp(\tilde{\pi} - \tau_o - \tilde{\tau}N^e + \beta\phi^e\lambda^*)}{exp(\tilde{\pi} - \tau_o - \tilde{\tau}N^e + \beta\phi^e\lambda^*) + exp(\tilde{\pi} - \tilde{\tau}N^{ne} + \beta\phi^{ne}\lambda^*)}$$

$$+ \frac{exp(\tilde{\pi} - \tau_o - \tilde{\tau}N^e + \beta\phi^e\lambda^*)\{N^e exp(\tilde{\pi} - \tau_o - \tilde{\tau}N^e + \beta\phi^e\lambda^*)\}}{[exp(\tilde{\pi} - \tau_o - \tilde{\tau}N^e + \beta\phi^e\lambda^*) + exp(\tilde{\pi} - \tilde{\tau}N^{ne} + \beta\phi^{ne}\lambda^*)]^2} \tag{C.4}$$

$$+ \frac{exp(\tilde{\pi} - \tau_o - \tilde{\tau}N^e. + \beta\phi^e\lambda^*)\{N^{ne} exp(\tilde{\pi} - \tau_o - \tilde{\tau}N^{ne} + \beta\phi^e\lambda^*)\}}{[exp(\tilde{\pi} - \tau_o - \tilde{\tau}N^e + \beta\phi^e\lambda^*) + exp(\tilde{\pi} - \tilde{\tau}N^{ne} + \beta\phi^{ne}\lambda^*)]^2}\Big\}.\mathbf{I}(Tesla)$$

$$= \left[-N^e L + L\{N^e L + N^{ne}(1 - L)\}\right].\mathbf{I}(Tesla)$$

$$= (N^{ne} - N^e)L(1 - L).\mathbf{I}(Tesla)$$

Given the formulation of the likelihood function as presented in C.2, the log-likelihood function can be updated as

$$
\begin{aligned}
lnL(\theta^*) &= \sum_{i=1}^{N} lnL_i(\theta^*) \\
&= \sum_{i=1}^{N} ln\{\frac{exp(\tilde{\pi} - \tau_o - \tilde{\tau}N^e.\mathbf{I}(Tesla) + \beta\phi^e\lambda^*)}{exp(\tilde{\pi} - \tau_o - \tilde{\tau}N^e.\mathbf{I}(Tesla) + \beta\phi^e\lambda^*) + exp(\tilde{\pi} - \tilde{\tau}N^{ne}.\mathbf{I}(Tesla) + \beta\phi^{ne}\lambda^*)}\} \\
&= \sum_{i=1}^{N} \{ln(exp(\tilde{\pi} - \tau_o - \tilde{\tau}N^e.\mathbf{I}(Tesla) + \beta\phi^e\lambda^*)) \\
&\quad - ln(exp(\tilde{\pi} - \tau_o - \tilde{\tau}N^e.\mathbf{I}(Tesla) + \beta\phi^e\lambda^*) + exp(\tilde{\pi} - \tilde{\tau}N^{ne}.\mathbf{I}(Tesla) + \beta\phi^{ne}\lambda^*))\} \\
&= \sum_{i=1}^{N} \{\tilde{\pi} - \tau_o - \tilde{\tau}N^e.\mathbf{I}(Tesla) + \beta\phi^e\lambda^* \\
&\quad - ln(exp(\tilde{\pi} - \tau_o - \tilde{\tau}N^e.\mathbf{I}(Tesla) + \beta\phi^e\lambda^*) + exp(\tilde{\pi} - \tilde{\tau}N^{ne}.\mathbf{I}(Tesla) + \beta\phi^{ne}\lambda^*))\}
\end{aligned}
\tag{C.5}
$$

Taking the derivative of the log-likelihood with respect to the sunk cost of model entry

$$
\begin{aligned}
\frac{\partial lnL(\theta^*)}{\partial \tau} &= \frac{1}{\partial \tau} \sum_{i=1}^{N} lnL_i(\theta^*) \\
&= \sum_{i=1}^{N} \{-1 \\
&\quad + \frac{exp(\tilde{\pi} - \tau_o - \tilde{\tau}N^e.\mathbf{I}(Tesla) + \beta\phi^e\lambda^*)}{exp(\tilde{\pi} - \tau_o - \tilde{\tau}N^e.\mathbf{I}(Tesla) + \beta\phi^e\lambda^*) + exp(\tilde{\pi} - \tilde{\tau}N^{ne}.\mathbf{I}(Tesla) + \beta\phi^{ne}\lambda^*)}\} \\
&= -N + \sum_{i=1}^{N} L_i(\theta^*)
\end{aligned}
\tag{C.6}
$$

Taking the derivative of the log-likelihood with respect to the fixed cost of maintaining stations

$$\begin{aligned}
\frac{\partial lnL(\theta^*)}{\partial \tilde{\tau}} &= \frac{\partial}{\partial \tilde{\tau}} \sum_{i=1}^{N} lnL_i(\theta^*) \\
&= \sum_{i=1}^{N} \{-N^e.\mathbf{I}(Tesla) \\
&\quad + \left[\frac{N^e.\mathbf{I}(Tesla)exp(\tilde{\pi} - \tau_o - \tilde{\tau}N^e.\mathbf{I}(Tesla) + \beta\phi^e\lambda^*)}{exp(\tilde{\pi} - \tau_o - \tilde{\tau}N^e.\mathbf{I}(Tesla) + \beta\phi^e\lambda^*) + exp(\tilde{\pi} - \tilde{\tau}N^{ne}.\mathbf{I}(Tesla) + \beta\phi^{ne}\lambda^*)}\right] \\
&\quad + \left[\frac{N^{ne}.\mathbf{I}(Tesla).exp(\tilde{\pi} - \tilde{\tau}N^{ne}.\mathbf{I}(Tesla) + \beta\phi^{ne}\lambda^*)}{exp(\tilde{\pi} - \tau_o - \tilde{\tau}N^e.\mathbf{I}(Tesla) + \beta\phi^e\lambda^*) + exp(\tilde{\pi} - \tilde{\tau}N^{ne}.\mathbf{I}(Tesla) + \beta\phi^{ne}\lambda^*)}\right]\} \\
&= \sum_{i=1}^{N} \{(-N^e + N^eL + N^{ne}(1-L)).\mathbf{I}(Tesla)\}
\end{aligned} \tag{C.7}$$

Now that we have the analytical solution of the first order derivatives of the log-likelihood functions with respect to our dynamic parameters $\theta^* = (\tau, \tilde{\tau})$, as presented in Equations C.6 and C.6, deriving the Hessian matrix is relatively straightforward. Given there are two dynamic parameters that characterize the model, the Hessian would be a 2×2 matrix. The diagonal elements would correspond to taking double derivative of the log-likelihood function with respect to the individual parameters. The non-diagonal term corresponds to the cross-derivatives of the two parameters. Using the formulations as presented from Equations (C.1) - (C.7), individual elements of the Hessian can be derived as:

$$\begin{aligned}
\frac{\partial^2 lnL(\theta^*)}{\partial \tau^2} &= \frac{\partial^2}{\partial \tau^2} \sum_{i=1}^{N} lnL_i(\theta^*) \\
&= \frac{\partial}{\partial \tau}\left[-N + \sum_{i=1}^{N} L_i(\theta^*)\right] \\
&= \sum_{i=1}^{N} \left[-L_i(\theta^*)(1 - L_i(\theta^*))\right]
\end{aligned} \tag{C.8}$$

$$\begin{aligned}
\frac{\partial^2 lnL}{\partial\tilde{\tau}^2} &= \frac{\partial^2}{\partial\tilde{\tau}^2}\sum_{i=1}^{N} lnL_i(\theta^*) \\
&= \frac{\partial}{\partial\tilde{\tau}}\sum_{i=1}^{N}\{(-N^e + N^e L_i(\theta^*) + N^{ne}(1 - L_i(\theta^*)).\mathbf{I}(Tesla)\} \\
&= \sum_{i=1}^{N}(N^e - N^{ne})\frac{\partial L_i(\theta^*)}{\partial\tilde{\tau}}.\mathbf{I}(Tesla) \\
&= -\sum_{i=1}^{N}\{(N^e - N^{ne})^2.L_i(\theta^*)(1 - L_i(\theta^*)\}.\mathbf{I}(Tesla)
\end{aligned} \tag{C.9}$$

$$\begin{aligned}
\frac{\partial^2 lnL}{\partial\tau\partial\tilde{\tau}} &= \frac{\partial^2}{\partial\tilde{\tau}\partial\tau}\sum_{i=1}^{N} lnL_i(\theta^*) \\
&= \frac{\partial}{\partial\tau}\sum_{i=1}^{N}\{(-N^e + N^e L_i(\theta^*) + N^{ne}(1 - L_i(\theta^*)).\mathbf{I}(Tesla)\} \\
&= \sum_{i=1}^{N}(N^e - N^{ne})\frac{\partial L_i(\theta^*)}{\partial\tau}.\mathbf{I}(Tesla) \\
&= -\sum_{i=1}^{N}\left[(N^e - N^{ne}).L_i(\theta^*)(1 - L_i(\theta^*))\right].\mathbf{I}(Tesla)
\end{aligned} \tag{C.10}$$

D Evaluating evolution of Third-Party Stations

To evaluate how the estimated policy function performs I plot the predicted number of third-party charging stations against the actual number of charging stations as observed in data. Proliferation of network of charging stations follows a non linear pattern, indicating sluggish growth in early years, followed by a rapid growth and then again followed by sluggish progression towards a potential saturation point. Figures D.1 and D.2 plot the predicted number of charging stations against against data for the top and bottom 20 states in terms of existing network of charging stations, respectively. From the figures, I infer the policy function as described in this section captures non-linearity as is observed for how charging stations proliferate. The policy function is more stable in prediction as the number of station grows, which serves to my purpose since the policy shock evaluated is a sizable expansion of charging station network.

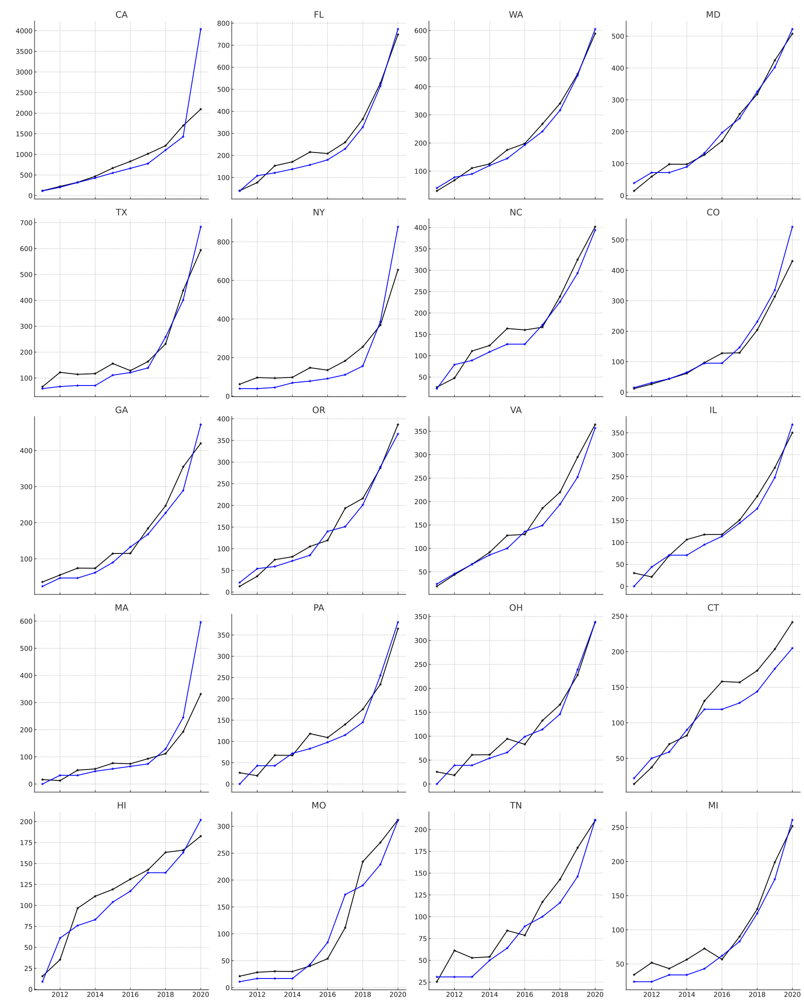

Figure D.1: The figure reports the predicted number of third-party charging stations from the policy function estimated above and compares against the data. This figures reports the prediction and compares against the true numbers for the top 20 states in terms of existing network of charging stations.

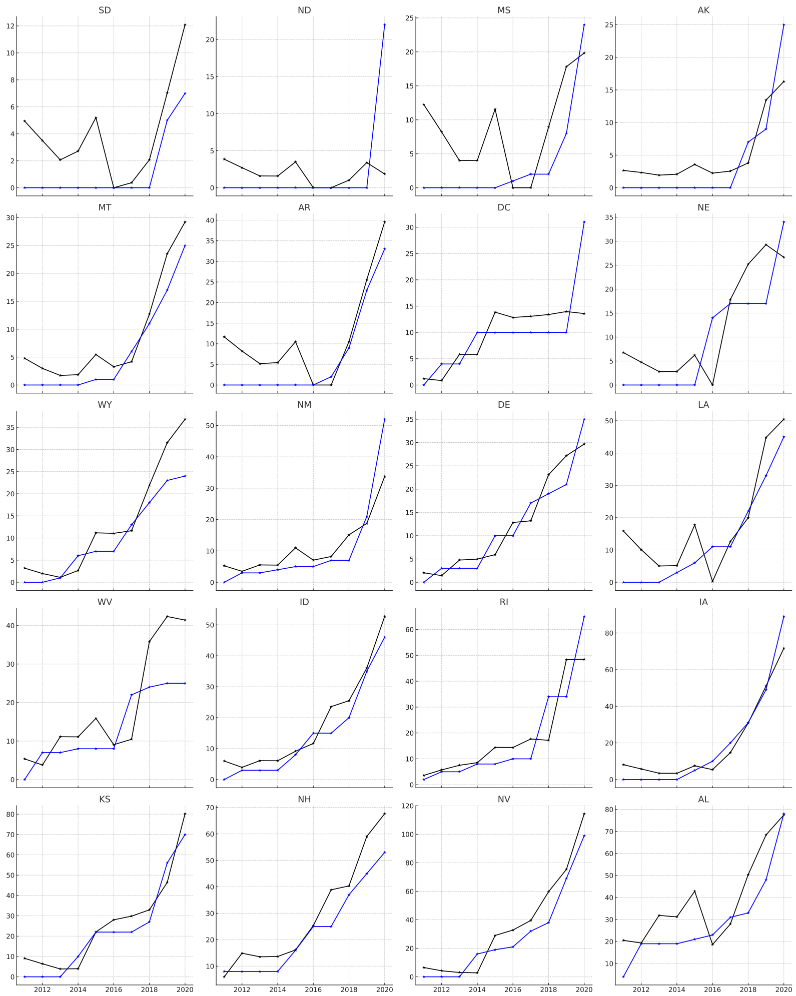

Figure D.2: The figure reports the predicted number of third-party charging stations from the policy function estimated above and compares against the data. This figures reports the prediction and compares against the true numbers for the top 20 states in terms of existing network of charging stations.

E Estimating Marginal Costs of New EVs

To solve for the Bertrand Nash pricing game within the model presented in this thesis, it is necessary to have the respective marginal costs. In Section 8.2, we simulate the full model dynamics from 2010-2020 given a policy shock that sizably expands the network of charging station in 2010. Beyond solving for the entry game with firms choosing to enter with a new EV or not each period, it is also imperative to solve for the pricing sub-game in a given realization of state. I predict the marginal costs based on the linear relationship of marginal costs estimated in Section 7.3 and the characteristics of electric vehicles as observed. The results of the linear regression of marginal costs estimated characteristics as observed is reported below in Table E.1.

Table E.1: Linear Model Estimating Marginal Costs from Observed Characteristics

Variable	Estimate	Standard Error
Area	709.21	(5920.49)
Horsepower/Weight	156155.7	(61282.41)
4 Passenger Doors	-11944.66	(3494.18)
MPGe	-253.47	(44.53)
Battery Range	85.73	(21.58)
Constant	40983.88	(8432.73)

Note: This table presents the estimated coefficients of a linear regression model fitting predicted marginal costs on vehicle characteristics from data as observed.

F State-wise Counterfactual evolution of stations

The supply function of third party stations allows me to predict state-wise evolution of charging stations, concurrently also accounting for other changes the model solves for such as electric vehicles available, network size of Tesla, etc. In Figure F.1 and F.2, I present how the network of third-party charging stations evolve in the top 20 and bottom 20 states given the size of initial NEVI allocation. The model simulation also involves solving for Tesla's decision to maintain charging stations in each state. The network of third-party stations grow consistently in each station over time during the period, preserving the shape as observed in aggregate data. Tesla's network does grow over time, on account of increased competition, it is only a tiny fraction of the overall size of the third-party charging network.

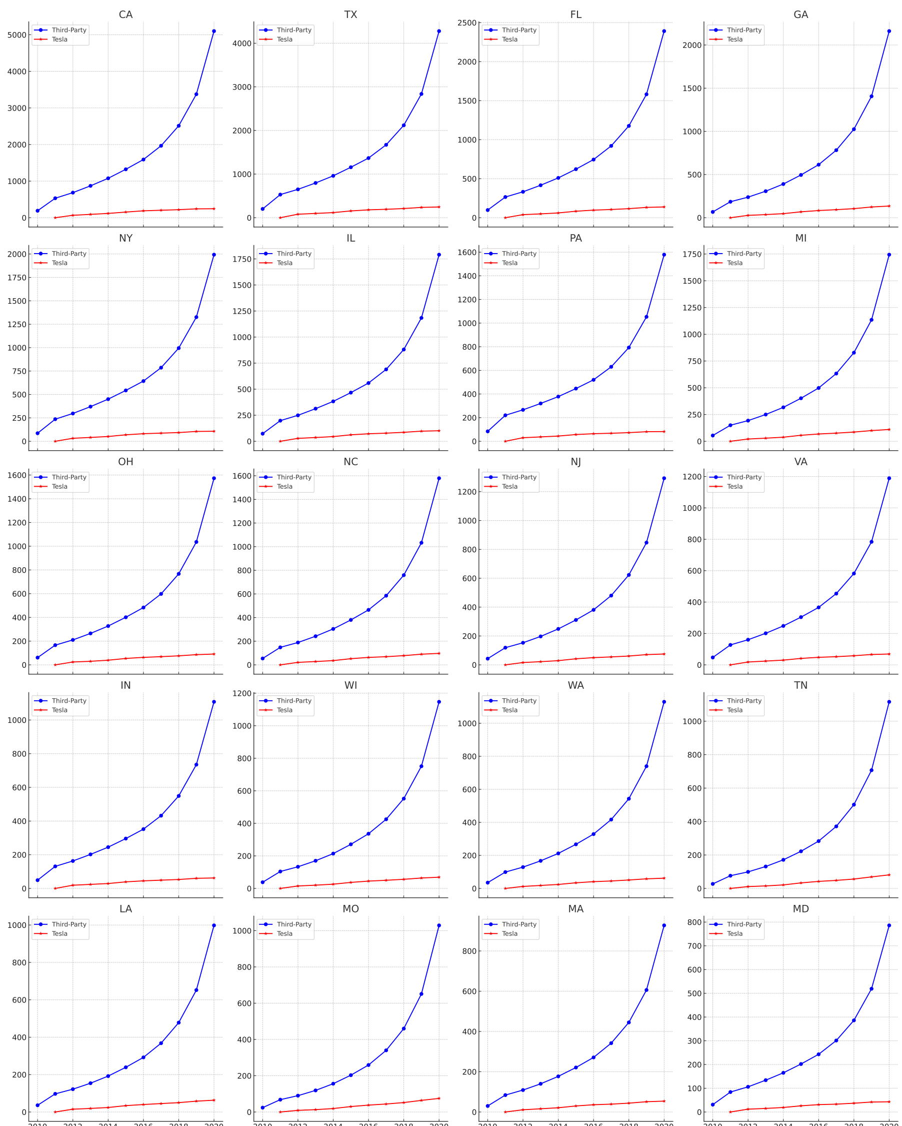

Figure F.1: The figure provides the predicted evolution of network of charging stations in top 20 US states as per size of NEVI allocation.

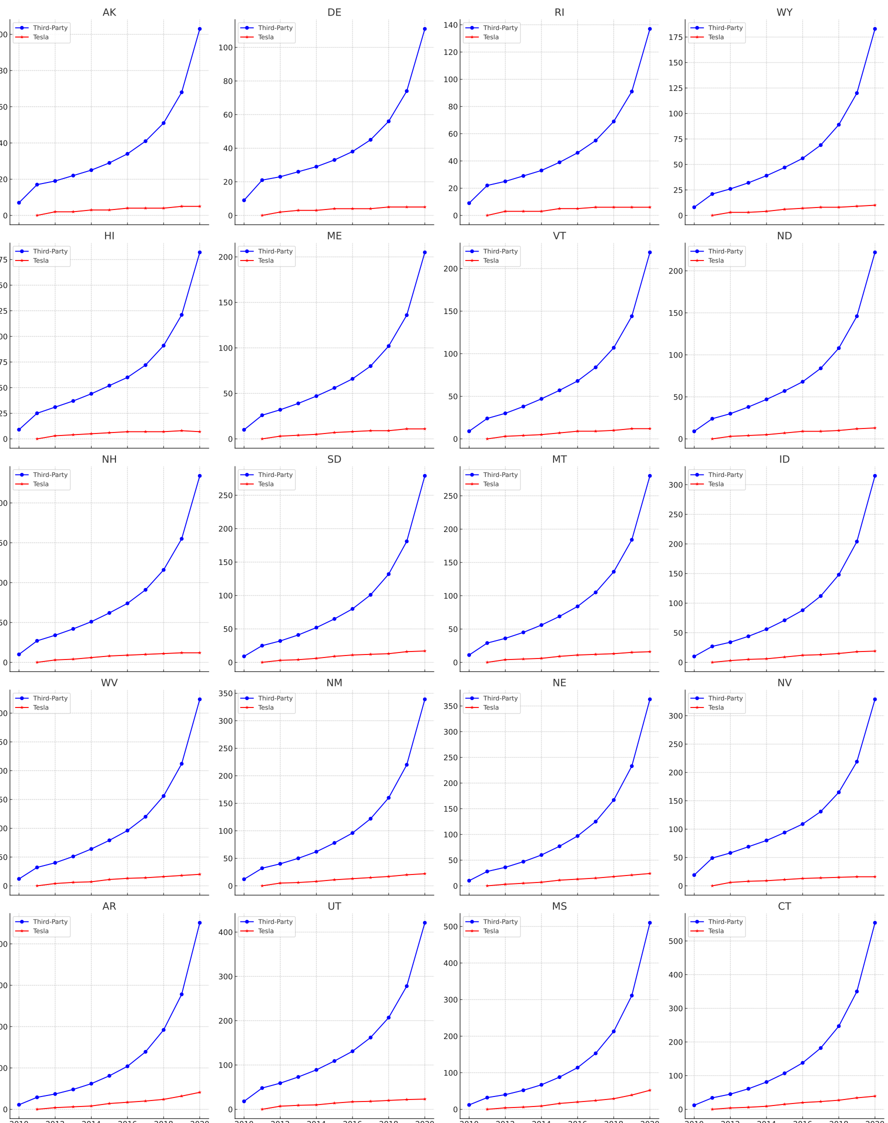

Figure F.2: The figure provides the predicted evolution of network of charging stations in bottom 20 US states as per size of NEVI allocation.

G Additional Tables and Figures

G.1 Relevant State Variables

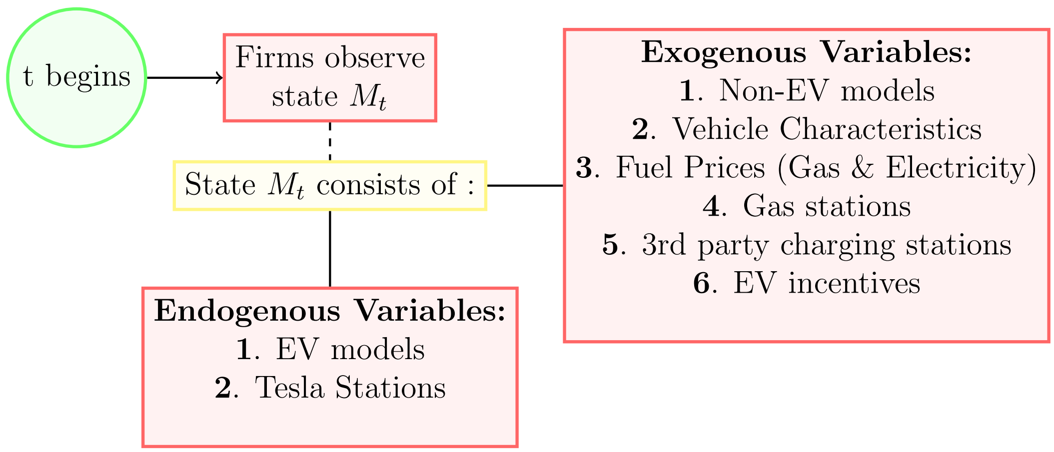

Figure G.1: Relevant State Variables

G.2 Competition Structure

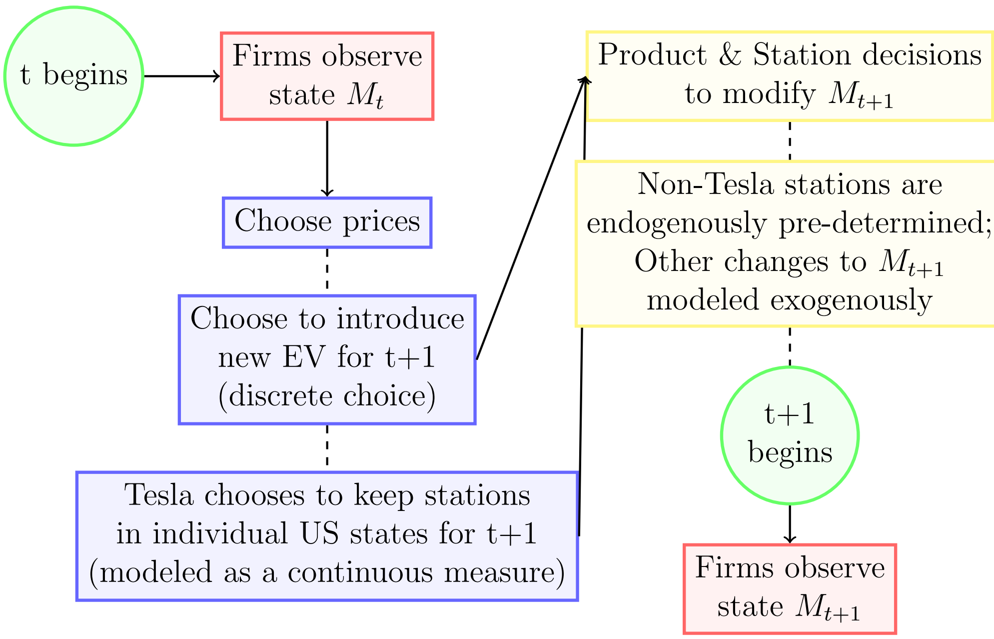

Figure G.2: Decision process of firms in period t and transition to $t+1$