Discrete Choice Modeling of Plug-in Electric Vehicle Use and Charging Behavior Using Stated Preference Data

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Abstract

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Plug-in Electric Vehicles (PEVs) have the potential of reducing gasoline consumption and greenhouse gas emissions in the transportation sector. The net impacts of PEVs – including upstream emissions from electricity generation and the impact these vehicles place on the electricity grid – depend on both the amount of travel conducted by PEV and locations that those PEVs are charged. This dissertation investigates the vehicle use choices and charging decisions of both battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) for both home-based trip tours and long-distance trips using stated preference (SP) data. It presents a novel dynamic discrete choice modeling (DDCM) framework that explicitly accounts for the stochastic nature of the vehicle choice and charging decisions of PEV users: earlier choices on vehicle use and charging influence the utility of the future choices; the expectation of the future options influences those earlier decisions; and choices are made under uncertainty about actual energy consumption and availability of chargers.

For home-based trip tours, my results show that BEV users are willing to pay $10-$24 to avoid having to deviate from the originally planned route, which indicates that “range anxiety” of BEV owners – the fear of being stranded in the middle of a trip – is not a crucial issue for home-based trips. Using charging infrastructure development to encourage BEV adoption might be more beneficial than reducing “range anxiety” among the current users, which could entail building charging stations at locations that have more public exposure, such as public parking garages in a city center. When BEVs are on long-distance trips, the cost of deviation is significantly higher: $244, which indicates that BEV owners are likely to be more cautious and view finding a charger off the route much more costly when they are on long-distance trips. Comparing the cost of deviation for home-based tours and long-distance trips, to support the existing users, the most cost-effective places to invest in charging infrastructure are inter-city corridors instead of in-city locations. By comparing the relative size of the coefficient estimates, in this dissertation, I also analyze the monetary value of increasing charging power, moving the charging stations closer to highway exits, and having amenities such as restrooms, restaurants, and Wi-Fi near the charging stations.

The comparison between the DDCMs and SDCMs based on simpler decision heuristics shows that for home-based tours, DDCMs only offer a little better prediction rate with a significant cost when it comes to computation time and complexity of model development. For the purpose of demand forecasting of a charging network or site selection for the charging facilities, the SDCMs based on simpler heuristics are recommended for home-based trip tours. For long-distance trips, the charging choices are largely decided by the state of charge (SOC) and deviation, and the characteristics of the charging stations only contribute to a small portion of predictive power. SDCMs outperform the DDCMs for the current sample. However, this could change in the future when the charging network is dense and the characteristics of the charging stations have higher prediction power.

For both the home-based tours and long-distance trips, and for both vehicle choices and charging decisions, the decision patterns are likely to be heterogeneous among the PEV owners. The efforts related to the prediction of the future EV charging demand, the policy-making on battery and charging infrastructure development, and the planning/design of the charging network all need to consider these different preferences of the consumers. Due to the heterogeneity of users' preferences, both increasing battery pack size and reducing station spacing can encourage current BEV owners to use their BEVs for long-distance trips, and one of the two does not substitute the other. Even if a lot of the BEV models offered by the market have 500 miles of range, the density of the public charging network can still play an important role in enabling BEVs for long-distance trips, especially when the battery remains expensive.

Keywords: PEV charging behavior, stated preference data, discrete choice modeling, DDCMs, heterogeneity, range anxiety

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Glossary

ASC	Alternative specific constant
BEV	Battery electric vehicle
DCFC	Direct Current Fast Charge
DDCM	Dynamic discrete choice model
DEV	Deviation
EV	Electric vehicle
GHG	Greenhouse gas
L1	Level 1 charger
L2	Level 2 charger
PEV	Plug-in electric vehicle
PHEV	Plug-in Hybrid electric vehicle
RP	Revealed preference
SDCM	Static discrete choice model
SOC	State of charge
SP	Stated preference

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0 Read Me First

To make it easier for the readers to find the information they are looking for in this long document, I want to provide a summary of each of the first nine chapters.

Chapter 1 is on an introduction of the concepts related to plug-in electric vehicles (PEVs), what the general trend of PEV adoption is like, and what the charging facilities are.

Chapter 2 states a broader goal of the dissertation and its merit.

Chapter 3 describes the literature review on PEV charging behavior modeling and dynamic discrete choices models (DDCMs).

Chapter 4 includes an overview of the research questions, the data source, and the details of the frameworks and estimations of the statistical models used in this dissertation.

Chapter 5 includes the details of the survey design, the experiment design, and the data collection of the choice experiments for home-based trip tours.

Chapter 6 includes three analyses based on the data from the survey described in Chapter 5.

Chapter 7 includes the details of the survey design, the experiment design, and the data collection of the choice experiments for long-distance trips.

Chapter 8 includes two analyses based on the data from the survey described in Chapter 7.

Chapter 9 lists the main conclusions of this research work.

1 Background

1.1 An introduction of Plug in Electric Vehicles (PEVs)

Plug-in electric vehicles (PEVs) are vehicles that can be powered by electricity and can be recharged by plugging into an external source of electricity such as a wall socket. There are two categories of PEVs: battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs). BEVs only have the electricity powertrain. PHEVs combine the electric powertrain with a conventional internal combustion engine. In this study, PEV only refers to private cars, but does not include plug-in electric trucks.

1.1.1 Benefits of PEVs

Compared to conventional internal combustion engine vehicles (ICEVs), PEVs have a few advantages. First, they can potentially reduce air pollution and greenhouse gas emissions in transportation sector because they do not emit harmful pollutants at the tailpipe during operation *(1)*. When the source of the electricity that is used to recharge the batteries is clean, the operation of PEVs has significantly less GHG emission. Some cities with Chronic air pollution problems may also gain local clean air benefits by shifting the harmful emission to electric generation plants located outside the cities. The magnitude of the benefits of greenhouse gas emissions is influenced by the energy source. The life-circle emissions of PEVs come from vehicle manufacturing and the source of electricity. Another source of greenhouse gas emission of PEVs is during manufacturing. Therefore, the environmental benefits of PEVs largely depend on the source of electricity. According to the full life cycle assessments of the environmental impact of PEVs, even though PEVs have a higher carbon footprint during production than ICEVs, when the electricity is from clean resources (including solar, wind, hydrogen, nuclear) PEVs have significantly lower emissions than ICEVs *(2,3)*. When the PEVs are recharged from coal-fired plants, they usually produce slightly more greenhouse gas emissions than ICEVs, which causes the discrepancy of the benefits of PEVs according to countries and regions *(4)*. Even when the energy source is not clean, it is meaningful to switch to electricity because focusing the change of the electricity source is a lot easier than the effort to reduce the usage of gasoline. Besides the environmental benefits of replacing gasoline with electricity, vehicle electrification can help reduce oil dependency in transportation sector, which is beneficial to national security *(5)*.

Compared to ICEVs, PEVs have lower operation cost because of the high energy efficiency of electric motors and the low cost of electricity. Electric motors are more efficient at converting stored energy into driving a vehicle. Typically, only 15% of the fuel energy content of gasoline engines is effectively used to move the vehicle or to power accessories, and the on-board efficiencies of diesel engines can reach 20%. Electric drive vehicles, on the other hand, can typically have on-board efficiencies of around 80% *(6)*. Assume the electricity consumption rate of a Nissan Leaf is 30 kWh/100 mi and the fuel economy of an ICEV is 30 mpg, when the electricity price is the national average $0.10 per kWh (the stable national average), the cost of an ICEV is 2-5 times of a PEV running on electricity for every miles they travel depending on the gasoline price. An analysis of PEVs shows that right now with the subsidies of the government to encourage PEV adoption, even when considering the high initial costs of PEVs, the life-cycle cost of PEVs is lower than ICEVs *(7)*. The maintenance cost is also lower than ICEVs because the electric motors usually break down less frequently than the mechanical systems in ICEVs. The net-cost of PEVs is generally more stable than ICEVs since the price of electricity barely changes over the years but the gasoline price could fluctuate greatly.

Another advantage of the PEVs is the convenience of skipping visits to gasoline stations and routine maintenance checks. PEVs usually offer better driving experiences when they are running on electricity because they usually have higher acceleration rate compared to ICEVs (e.g. The Tesla Roadster 2.5 Sport can accelerate from 0 to 60 mph in 3.7 seconds) and the noise is minimum in the vehicle when running on electricity. A vehicle-to-grid (V2G) system can offer the PEV owners the option to sell the stored electricity back to the grid, which can help improve the operation efficiency of the utilities during demand peaks *(8,9).*

1.1.2 Disadvantages of PEVs

The initial cost of PEVs are generally rather high compared to ICEVs due to the expensive lithium-ion battery packs, which remains as a major barrier of PEV adoption *(10).* But the battery price is dropping these years with the development of technology. According to the data collected by the Bloomberg New Energy Finance, the battery price dropped from $1000/Kwh in 2010 to around $400/Kwh in 2015. Tom Randall did a prediction of the battery cost in the following 15 years, as shown in Figure 2. This prediction though appears to be too optimistic, is backed up by the recent reports on the battery cost claimed by the industry: product chief of GM claimed that the company will only pay $145/Kwh of battery cost for the new 2017 new EV model. If the battery price drops to $120/Kwh, the initial price of EV will be competitive with ICEV models *(11).*

The electric ranges of PEVs are generally much lower than their gasoline counterparts and the time needed to recharge a battery is an order of magnitude greater than the time to refuel with petroleum fuel for a comparable range, which is another major barrier of broad BEV adoption. Tesla Model S (AWD - 90D) has the largest range among the BEV models available in the market till the year 2016: 294 mi. Range around 50mi ~100mi is rather common among

BEVs. The most popular BEV models are the Tesla Model S (rated range 149mi~294mi) and Nissan Leaf (rated range around 73mi-84 mi). The most popular PHEV model is the Chevrolet Volt with the rated electric range of 53mi, which is the highest among the PHEV models available in the market (Figure 1). The fear of the battery being fully depleted and becoming stranded in the middle of a trip is a major barrier to BEV adoption and usage, a condition described as "range anxiety" *(12).* To mitigate the effect of the limited range of BEVs, a lot of BEV adopters may keep the choice of choosing an ICEV for relatively long-distance travel, which is referred to as hybrid ownership of vehicles. PHEVs offer the potential to overcome these barriers, combining an internal combustion engine, an electric powertrain and onboard charging equipment, offering to reduce gasoline use and GHG emissions while retaining the ability to travel long distances and refuel quickly and conveniently *(13-15).* PHEVs are inherently less dependent on recharging infrastructure than are battery electric vehicles (BEVs) because they have an internal combustion engine.

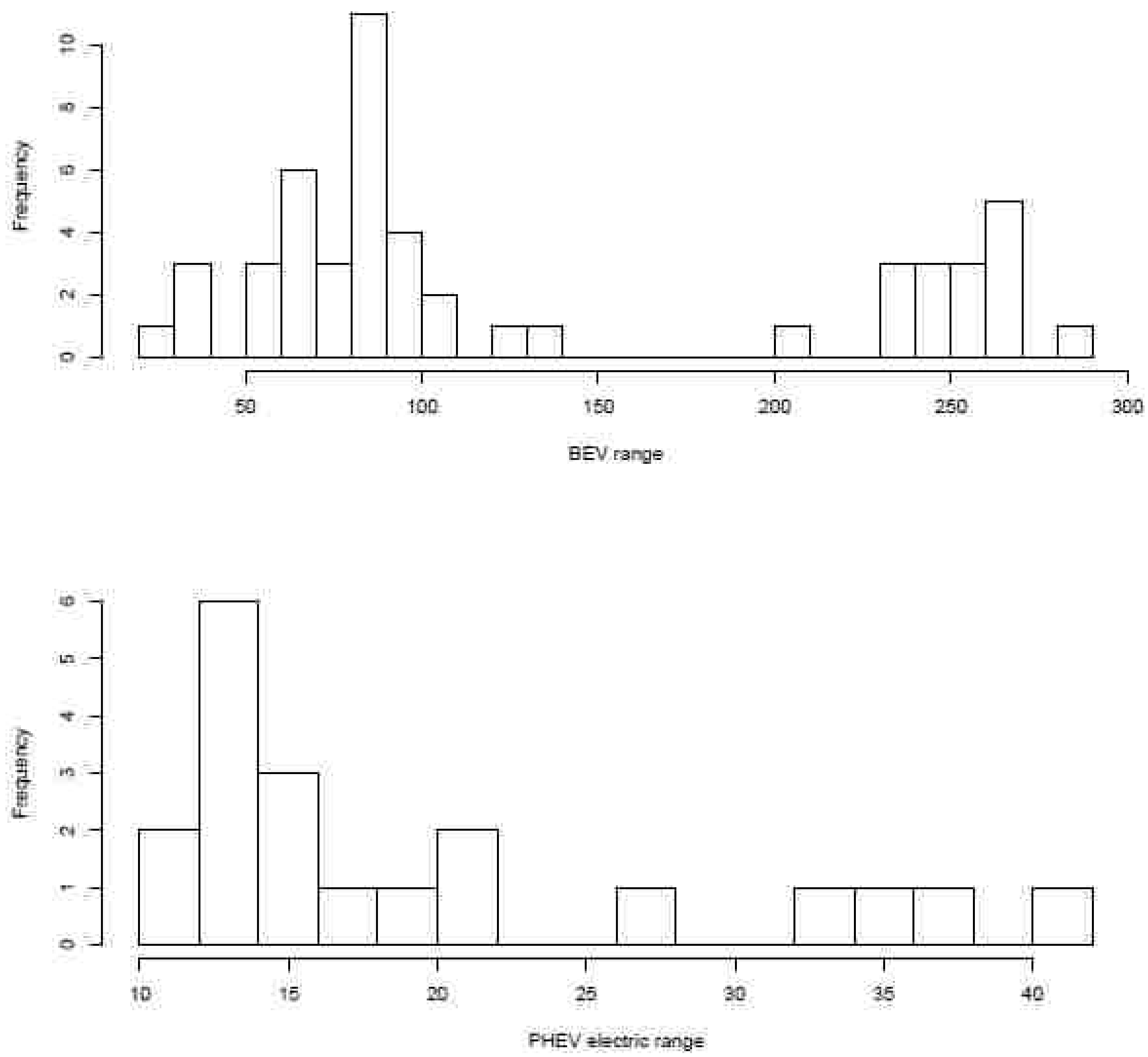


Figure 1. Range of the PEV models available in US in 2016[1]

1.2 PEV adoption

According to the Global EV Outlook 2017 report by the International Energy Agency, the PEV adoption in the world has been increasing rapidly. The global PEV stock is increasing exponentially (Figure 2): since the global PEV stock crossed the one- million threshold in 2015,

[1] Data source: US Department of Energy http://www.fueleconomy.gov/feg/ws/index.shtml

it increased to more than two million vehicles till the end of 2016. By the end of the 2016, the market share of PEVs was over one percent, from 0.85% in 2015. The following six countries in the world have PEV market share more than one percent: Norway (28.8%), Netherlands (6.39%), Sweden (3.41%), France (1.46%), United Kingdom (1.41%), and China (1.37). China has 32% of the PEV stock in the world, ranking at the top of the portion of global PEV stock, following by United States (28%) *(16)*. Several countries in the world share the political aspiration of ditching gasoline vehicles and replace them with EVs by 2025-2040, including Norway, India, France and Britain. Some other countries including China, Denmark, Germany, etc. have EV car sales target in place *(17)*.

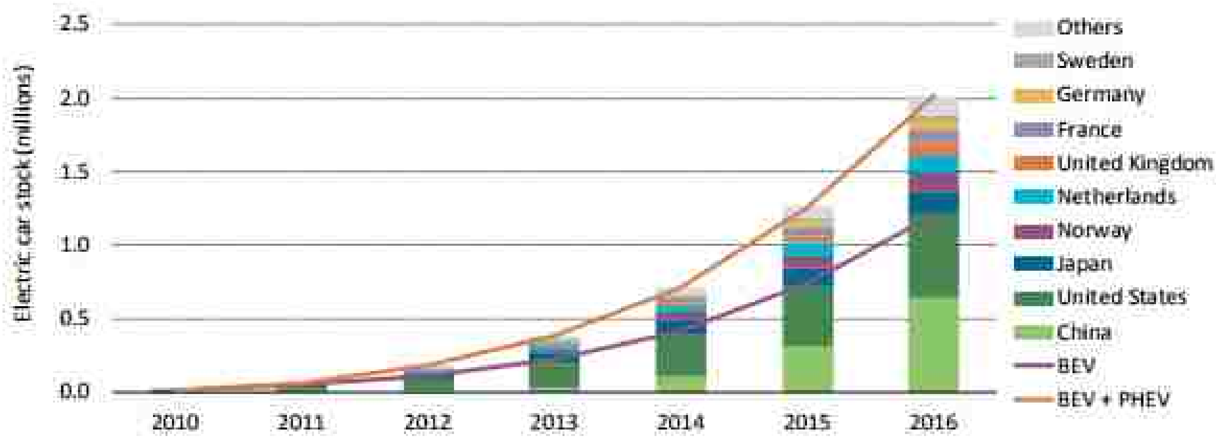


Figure 2: Global PEV stock *(16)*

Same with other countries in the world, American government offers great support for EV adoption by providing tax credits (both on federal and state level) for reducing the initial costs. and some states offer other incentives such as vehicle registration fee reductions, low-cost charging rates, access to high-occupancy vehicle lane and parking facilities, etc *(18)*. The PEV sales in US has been increasing rapidly after hitting a speed bump in 2014*(19)*. The market share of EVs increased to 1.20% in 2017 from 0.91% in 2016 *(16).* In the year 2018, PEV sales have been increasing rapidly with models with high range leading the race, such as the Tesla model 3 and Chevrolet Bolt EV.

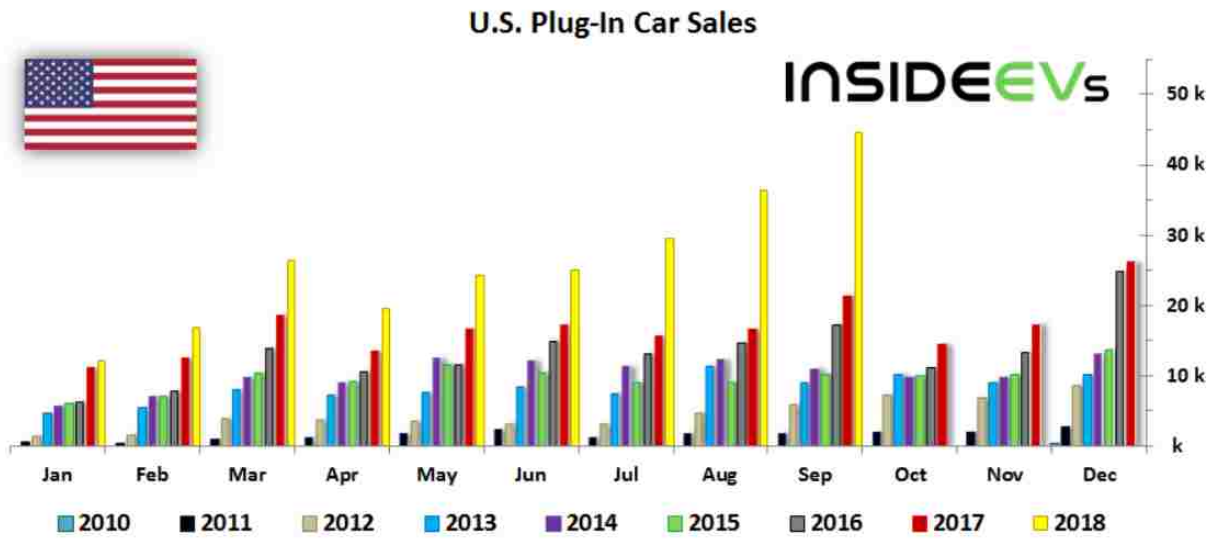


Figure 3: PEV sales in US *(19)*

1.3 Charging facilities

1.3.1 PEV chargers

Charging facility is indispensable for the operation of PEVs: they can increase the range of BEVs and increase the replacement of gasoline by electricity of PHEVs. PEV chargers that are used to recharge PEVs, also known as electric vehicle supply equipment (EVSEs) are classified as fast chargers and slow chargers according to the charging speed, as shown in table 1. There are three levels of chargers corresponding to the maximum current/power: Level 1, Level 2 and Level 3. The PEVs also have a maximum current that can be accepted, which is referred to as maximum acceptance rate. The final charging current is the minimum current of the maximum current that the charger can provide and the maximum current that the car can receive.

TABLE 1: PEV chargers

Category	Level	Current Type	Voltage	Amps	Power range	Most common power
Slow Chargers	Level 1	AC	120 volts	8 to 15 amps	<=1.9kW	Most common 1.4kW
	Level 2	AC	240 volts	16-40 amps	>3.7kW and <=19.2kW	Most common 3.3kW or 7.2kW
Fast Charger	Level 3	AC			>20kW and ≤43.5kW	
	Level 3	DC Fast Charger (DCFC)			<200kW	CHAdeMO 40kW-50kW Tesla Fast Charger 90kW-135kW (50-120kW)

Level 1 charger generally refers to plugging into household outlet. It can provide 2-5 miles per hour and can top the range of PEVs in 12-24 hours depending on the range. They are mostly used to recharge at home or for workplace charging. Level 2 requires installation of dedicated standard electrical outlet. It can provide 10-25 miles of range per hour and can charge the PEVs to full range in 3-10 hours depending on the range. Level 2 chargers can be used to charge PEVs at home and are popularly used for public charging stations in the cities. DC fast chargers, also called Level 3 chargers, can deliver 80% charge within half an hour. *(16)* Today, most publicly available chargers using the CHAdeMO and CCS standards have an output of 50 kilowatts or less; Tesla's Superchargers run at up to 135 kw. The DC chargers are currently mostly used for long distance interstate trips along high ways. Very few DC fast chargers are available in the public charging network in cities. 170 miles for Tesla charging get be obtained in half an hour

The PEV chargers are deployed at residential areas, work places, public charging facilities. The chargers include residential chargers, chargers at work place, public chargers, and residential chargers shared by PlugShare members. The Department of Energy has conducted two programs to deploy residential chargers and public charging PEV facilities. The EV Project partnered with city, regional and state governments, utilities, and other organizations in 18 cities to deploy about 12,500 Level 2 and more than 100 Level 3 charging units at workplaces and public areas *(20).* Another project EV Everywhere worked on deploying charging stations at workplaces and some residential areas to increase the coverage of PEVs *(21).* According to the data collected by DOE, employees with access to workplace charging are 20 times more likely to purchase and EV and workplace charging is proving to be the most helpful promoter of PEVs through awareness and incentives *(22)*. To the end of 2016, there are 35,089 slow chargers and 5,384 fast chargers that are publicly accessible. The average number of PEVs served per station is high than most of other countries and similar to Norway, where PEV has the highest market share amongst PEV owning countries in the world. In US, PEV users use real-time charging network (such as ChargePoint) to locate and check the real-time availability of public chargers. Some PEV owners share their private chargers at the residential locations through platforms such as PlugShare.

1.3.2 Charging choices of PEV users in US

According to the EV project report, 60%-80% of all PEV charging is done at home, 30%-40% is down at work if there is workplace charging available and only 3%-4% was done in public by the last quarter of 2014. BEV drivers are charging only once per day on average- significantly less frequent than PHEV drivers despite having no alternative power source besides electricity. Because the time to recharge is longer for Level 1 and Level 2 chargers, they are usually used when there are natural stops around the chargers, for example recharge the PEVs when the drivers are at work. It rarely happens when the drivers have to stop specifically for charging. Since DC fast chargers offer high recharging speed, drivers can stop for a reasonable short time (around half an hour) to gain 80% of range. Therefore, DC Fast charging is used as an alternative to home-charging for whom home charger is not an option and is usually used as a solution for long distance trips. Statistics show that Compared to PHEVs with no away-from home charging, the percentage of miles driven per day in EV mode is a lot higher *(22)*.

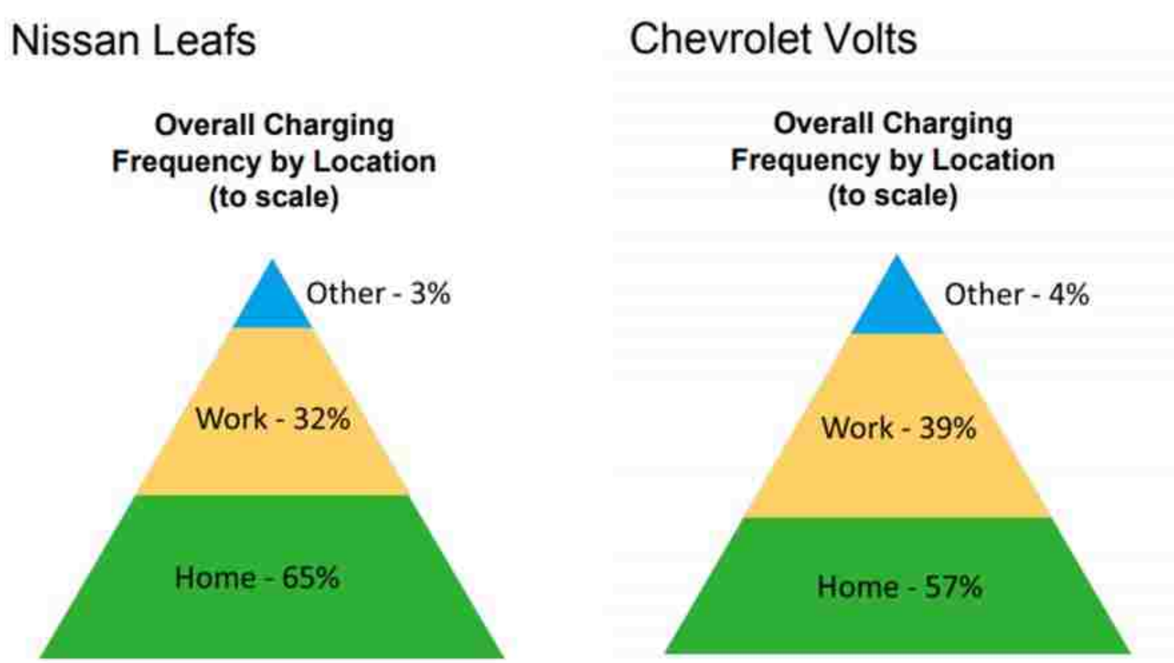


Figure 4： Where do PEV users charge currently *(22)*

2 Research Objective and Its Merit

2.1 The objective

The statistics on PEV charging choices by the EV Project show that the public charging facilities does not appear to be critical for the successful PEV operation. As addressed by some BMW board member Herbert Diess: “Very few people would use public charging …this public charging infrastructure is not really very important because people are charging their cars at home”. However, some believe that “A critical factor for successful PEV adoption is the development and use of charging infrastructure in non-residential location.” The charging choices of the PEV users need to be further explored to respond to these claims. There could be two opposing theories to explain why public charging infrastructures are not used frequently: (1) the demand is low for public charging infrastructure, as in PEV users prefer not to charge out of residential area or workplace; (2) or the supply charging infrastructures is too low. In an extreme case, when there is only one public charger in Seattle, the share of public charging is low even though it is fully utilized. Some BEV users might choose to drive an unlimited range alternative when they observe low supply of public chargers.

The specific objectives of this project are to (1) use statistical modeling to gain understandings of how PEV users make decisions on which vehicle to use and where to charge for home-based trip tours and long-distance trips (2) develop interactive survey tools to elicit choice processes involving complex, interconnected decisions, and (3) develop and evaluate the dynamic discrete modeling framework with the consideration of heterogeneity and compare the model performance with static models based on simpler heuristics. The dependent variables of the study include the PEV use and charging choices. PEV use refers to whether a PEV owner chooses their PEV for a travel day, and PEV charging choices refer to the decision of whether to charge at each charging opportunity during the travel day. The independent variables include the characteristics of the vehicle, the characteristics of the trips, and the characteristics of the charging opportunities along the trip.

2.2 The merit of the study

This research explores the influence of the characteristics of the trips of a travel day and the charging opportunities on vehicle use and charging choices, which is essential for the estimation of charging demand and energy demand (both gasoline demand and electricity demand), the estimation of emissions associated with electricity generation for charging and the consumption of gasoline, the extent to which charging infrastructure is utilized, and the strain the PEV charging places on the electric grid. The understanding of the charging behavior also helps the government to forecast the impacts of changes in tax levels and the tax revenues. Change of energy consumption level based on charging decision patterns.

This study can help understand how PEV drivers make decisions about PEV use including choices related to vehicle usage and charging and help to understand further how these choices interact with the development of charging infrastructure, and how these interactions determine the overall environmental impacts of PEVs. This understanding will support the design of vehicles and acceptance of PEVs. It will also provide a foundation for identifying public policies that can effectively and efficiently guide a transition toward a more environmentally and economically sustainable transportation system. Governmental and non-governmental organizations from national to local level: to forecast transport demand (in which case these models are integrated with traditional four-step models for transport demand), energy demand and emission levels, and to stimulate policy impacts on the demand.

Dynamic discrete choice model (DDCM) is a common analysis tool in a lot of areas such as economics and social science, but not in transportation due to the high computation costs. Another important contribution of this research is to discuss whether DDCM improves the prediction of PEV use and charging choices from static discrete choice models by considering the intertemporal payoffs and if so, whether the benefits justify its high estimation effort. In the research project, I will list out clearly the estimation methods of DDCM based on the materials in the other fields and publish my code for the estimation, which hopefully will benefit the broader applications of DDCM in transportation.

3 Literature Review

3.1 The signs of the lack of charging behavior analysis

A large and growing body of research established that PEVs could significantly reduce petroleum consumption and environmental pollution from automobiles *(14, 15, 18)*. However, the time, location, rate and duration of PEV charging influences the amount of petroleum that can be displaced, the planning of charging infrastructures, the emission associated with electricity generation for charging, the extent to which charging infrastructure is utilized, and the strain that the charging places on the electric grid. Modeling of vehicle usage and charging demand is essential for the forecasting of charging demand, the estimation of energy consumption, the forecast of emission levels from electricity generation and gasoline consumption, and the load that PEVs place on the electric grid. Thus, it is critical to understand how PEV owners' charging decisions are affected by the cost, speed, and availability of charging opportunities. Such knowledge enables the design of infrastructure systems so as to minimize the number of gasoline-fueled miles driven in PEVs. At the earlier stage of research on the charging demand of PEVs, aggregated methods, also called top-down methods are usually applied. These methods are all based on assumptions about the vehicle usage and charging behavior and sometimes descriptive analysis of the current situation.

During the early stage of the development of PEV market, there are not enough users and not comprehensive data to analyze the PEV use and charging behavior. To evaluate the energy conservation potential and environmental impact of PEVs and forecast the demand of public charging infrastructure, earlier research efforts on these topics assumed some deterministic rules on when the PEVs will be used and when the PEVs will be charged.

The energy consumption of PHEVs and the amount of gasoline replaced by electricity depends on how often the vehicles are recharged. To assess the energy consumption and charging demand of PHEVs, early studies relied heavily on assumptions about the charging behavior of PHEV owners. For example, in some studies it was presumed that PHEVs were only charged at home *(23, 24, 25).* Based on the Daily travel distances for over a year of 255 households in Seattle, Khan, .etc. found that for one-vehicle households, using PHEV with 40 miles of range (also called PHEV40), 80% of their VMT will be electrified; for two-vehicle households, using a PHEV40, 50 to 70% of household miles can be electrified while meeting all trip-distance needs *(24).* Based on daily driving distances of 12 households in California, Williams found “20 miles of charge-depleting range would have been fully utilized on 81% of days driven, whereas 40 miles would not have been fully utilized on over half of travel days” *(25).* Lin (2012) analyzed the energy demand under the assumption that PHEVs were plugged in whenever the CD range was depleted *(26).* Axsen and Kurani (2010) estimated the energy impacts of PHEVs assuming that PHEVs would be recharged whenever parked within 25 feet of an electrical outlet *(27).* What these models of charging behavior had in common was that they were generally simple and deterministic. Several authors have since shown that charging choices are heterogeneous across users and depend on much more than just an empty battery or an available plug *(28-30).*

For BEVs, the question of petroleum displacement hinges not on the split between electricity and gasoline for a single vehicle since BEVs only consume electricity, but on the fraction of travel days that can be satisfied by a BEV. The calculation of gasoline consumption is usually based on common assumption that BEVs are only charged once-per-day mostly at home. Pearre, et.al used longitudinal GPS travel data to calculate the fraction of travel days that could be fully satisfied by a BEV, versus those that would require adaption by foregoing travel or using a conventional vehicle. They employed common assumption of once-per-day charging *(31).* Recently, Don and Lin (2014) explored the potential for mid-trip charging to increase the feasibility of BEVs for covering days with larger travel distance. However, as with all other investigations, they relied on assumptions to define when charging infrastructure would be utilized *(32).* Wang, Lin and Chen (2010) found that even a small increase in uncontrolled charging could have a substantial impact on marginal electricity costs. These assumptions are all conservative *(33).* On the other end on the spectrum, Wu, Aliprantis, and Gkritza (2011) estimated an upper bound of power demand by PEVs by assuming uncontrolled, “opportunistic” charging at every stop *(34).* The basic assumptions of these analyses show the lack of empirical models on vehicle and charging choices of PEV owners.

3.2 Charging choices and charging behavior modeling

3.2.1 Descriptive analysis of charging choices

Because of the short history of PEVs in the automobile market and the low adoption rate, the paucity of real-world data of PEV use and charging behavior makes the results quite limited *(25).* Even when real-world information is available, it is rare for the data to be sufficient to test the new technology and policy scenarios with the rapidly evolving market. So earlier research efforts on PEV charging behavior are mostly based on descriptive methods *(36-38).* Davies and Kurani reported results from a study of 40 vehicles for a one-week period during which the author identified a mean of one daily charge, including two participants that did not recharge at all *(39).* The EV project published aggregated data on the charging pattern of 2,900 Nissan Leaf BEVs *(40)* and 900 Chevrolet Volt PHEVs *(41).* They found that public charging does not have a high utilization rate so far: BEV drivers are recharging only once per day, on average-significantly less frequent than PHEV drivers-despite having no alternative power source besides electricity. Chevrolet Volts are most commonly recharged when the battery is below 10% state of charge (SOC), and that most charging events end with the SOC above 90%. In contrast, for Nissan Leafs, the SOC at the start of charging was more evenly distributed, and substantially fewer charging events ended with a full battery. They also revealed considerable heterogeneity in travel and charging behavior across PEV drivers. While some possible explanations have been proposed, they are not, on their own, sufficient to develop a model of drivers' choices about charging that could be used to predict charging behavior and infrastructure utilization as the availability, speed, and cost of charging change over time. Zoepf, et.al. reported on a yearlong study of 125 instrumented PHEV prototypes. They found that charging events were spread throughout the day with a peak around 2pm-6pm, rather than occurring exclusively overnight. They also found that many vehicles charged infrequently, and that the actual fraction of miles powered by electricity was about 25% less than if all vehicles charged overnight *(28).*

These descriptive analyses is important for researchers to have some insights about the PEV use and charging behavior, which is a great improvement from the deterministic charging rules commonly assumed in PEV impact assessments discussed in Chapter 3.1. However, these results essentially only show a picture of the status quo, which is of limited use to predict the future demand of electric vehicle use and charging choices because the market is evolving rapidly. Only statistical models offer sufficiently flexibility to information decision in a quickly changing context.

3.2.2 Statistical modeling of charging choices

Several studies applied statistical models to analyze the charging choices of PEV users with the consideration of the characteristics of trips and charging opportunities, the details related to the models' functional form, utility specification, preference heterogeneity and choice set is summarized in Table 2.

Based on a year-long study of PHEVs instrumented for detailed data collection in the United States, Zoepf et al. developed a mixed logit model of charging choices, finding that current state of charge (SOC), completed trip distance, and dwell time all influenced the choice of whether to charge at the end of a trip *(14).* The results revealed heterogeneity in charging behavior across PHEV users, which has also been demonstrated using stated preference surveys *(29, 30)* and instrumented vehicle studies *(21).* Jabeen et al. analyzed the influence of charging cost, charging duration and time of day on people's charging preferences among charging at home, work, and public recharging stations using both multinomial logit and mixed logit models *(29).* Using stated preference data from UK drivers, Daina estimated a multinomial logit model to determine the influence of SOC, price, trip purpose, distance and dwell time on charging choices *(13).* Using a mixed multinomial logistic regression model, Sun et al. examined the influence of SOC and VMT of the next travel day on the charging time choice (no charging, charging immediately after arrival at home or workplace, nighttime charging or charging at other times) *(30).* Daina & Polak estimated a hazard-based model to predict the durations between charging events and concluded that vehicle state of charge, cumulative average driving speed, and individual characteristics significantly influence charging rate *(46).* These studies show that multiple factors influence the charging decisions of PEV drivers: the trip characteristics including trip distance, trip purpose, the destination and time of the day, and the characteristics of the charging opportunities including the price, dwell time at the station and the SOC of the PEVs.

Both mixed logit regression models and latent class models help capture the heterogeneity of decision-making. Earlier efforts to model the heterogeneity of charging preferences across PEV drivers mainly used mixed logit regression models and latent class logit models *(13, 17, &18).* In a mixed logit regression model, the random taste of coefficients (denoted as β) follows a continuous random distribution across the population. The estimation of the coefficients involves the assumption about the distribution of the distribution (most commonly choices include uniform distribution and normal distribution) and integration of the parameters over this defined distribution.

$$p_{nj} = \int \frac{e^{\beta x_{nj}}}{\sum_{k=1}^{K} e^{\beta x_{nk}}} f(\beta|\theta) \tag{1}$$

Latent class models assume that all individuals can be grouped into a finite set of classes (Q classes). Here, taste heterogeneity is captured by allocating respondents to different classes in a probabilistic manner, allowing the probability of class membership to depend upon the respondents' sociodemographic information. Each class has different taste coefficients, but within each class, the taste parameters are assumed to be homogeneous *(24).*

Within class *q*, the conditional probability of charging by individual *i* in choice situation *t* is:

$$\mathrm{P}(Charge_{it}|\, \beta_q, \text{class q}) = \frac{e^{\beta_q X_{it}}}{e^{\beta_q X_{it}+1}} \tag{2}$$

where $\beta_q$is a vector of coefficients for class *q*, and X_{it} is a vector of observed variables characterizing the choice faced by individual *i* in situation *t*.

A class allocation model defines the probability that the respondent *i* falls into class *q* as π_{iq}, which can be calculated using the multinomial logit equation:

$$\pi_{iq} = \frac{e^{\gamma_q Z_i}}{\sum_{q=1}^{Q} e^{\gamma_q Z_i}} \quad (3)$$

where γ_q is a vector of coefficients for the class allocation model and Z_i is a vector of observed socioeconomic variables used to predict class membership for respondent *i*.

Then the charging probability for individual *i* under scenario *t* is given by:

$$\mathrm{P}(\mathrm{Charge_{it}}) = \sum_{q=1}^{Q} \pi_{iq} \cdot \frac{e^{\beta_q X_{it}}}{e^{\beta_q X_{it}+1}} \quad (4)$$

Recent studies have found that latent class models generate richer patterns of heterogeneity, yielding better fitting models of revealed and stated PEV charging choices while providing an easy to interpret, intuitive segmentation of respondent types *(43, 44).* In contrast to mixed logit models that assume a continuous distribution of taste parameters, latent class models assume that individuals can be separated into finite sets of classes, with preference heterogeneity captured by allocating respondents to different classes based on sociodemographic information. Yu & MacKenzie analyzed the charging decisions of PHEV users based on the data of the instrumented pre-market Prius PHEVs in US using both mixed logit model and latent class logit model and found that the estimates of the latent class logit model fit the data better according to the Bayesian Inference Criteria (BIC). They also found that the derived variable charge energy- the percentage of range that the PHEVs can get by charging at a stop is a better predictor of charging activities than SOC itself *(43)*. Wen et al. conducted a stated preference (SP) survey among BEV users and asked the respondents to make choices about charging at a stop characterized by SOC, distance to home, charging price, dwell time, power of the charger, and gasoline price. They identified three modes of charging behavior among BEV drivers, also found that a latent class logit model provided a better fit to the data than a mixed logit model *(44).*

Ge and MacKenzie conducted a SP survey among PHEV drivers *(45)*, and similarly to Wen et al *(45)*, they presented the respondents with charging station scenarios characterized by remaining range, distance to home, gasoline and charging price, dwell time and charging power and asked them to choose whether to charge or not if they were in that situation. They analyzed the data with latent class logit model and found two charging behavior patterns among the respondents: later adopters with primarily financial motivation of owning an EV tend to make decisions to minimize fuel cost, but earlier adopters with other motivations such as environmental concern and vehicle performance tend to place much more value on gasoline cost than charging cost, which is consistent with the concept of “gas anxiety”- the desire of PHEV users to avoid using gasoline.

A new study came out recently modeled the charging mode (fast or normal) and location choice (home, work or public charging stations) using mixed logit model based on revealed preference data collected from 500 BEV users in Japan *(49)*. It is concluded that charging mode choice and location choice are mainly determined by battery capacity, time of the day (midnight), SOC and number of past fast charging events.

However, these models consider each charging decision as an isolated case: the charging decisions at different locations by one individual are independent, which is apparently not the case.

TABLE 2 Development of empirical literature on charging behavior of PEV users

Authors	Data Source	Output	Independent Variables	Heterogeneity	odel	Ref.
Zoepf, S., et al (2013)	Instrumented pre-market Prius PHEVs in U.S.	Charge or not at the end of a trip	SOC, dwell time, day & time, location, last trip	Yes. Consider the heterogeneity using continuous random variable	Mixed logit	*(28)*
Jabeen, F., et al (2013)	Stated preferences of Australian PEV owners	Location and timing of charging	Price, location, duration, time of day	Yes. Consider the heterogeneity using continuous random variable	Mixed logit	*(29)*
Sun, X., et al (2015)	Instrumented PEVs (120-180 km range) in Japan	Timing of end-of-day charging	SOC, days until next trip, VMT next travel day, work day, night time, fast charging experience	Yes. Consider the heterogeneity using continuous random variable	Mixed logit	*(30)*
Sun, X., et al (2014)	Instrumented PEVs (120-180 km range) in Japan	SOC at start of mid-trip fast-charge events	Charging station density, region, battery size, daily trips & VMT, speed, HVAC	Not considered	Stochastic frontier modeling	*(42)*
Yu, H. and MacKenzie, D. (2016)	Instrumented pre-market Prius PHEVs in U.S.	Charge or not at the end of a trip	Charge energy (the energy that could be taken on during a stop) , day & time, location, last trip	Compare two different ways of accounting for heterogeneity: mixed logit and latent class logit	Mixed logit and latent class logit	*(43)*
Wen, Y., et al (2016)	Stated preferences of U.S. BEV owners	Charge or not at a public charging station	Recharging price at the station, electricity cost to get a full charge at home, dwell time, charging power	Compare two different ways of accounting for heterogeneity: mixed logit and latent class logit	Mixed logit and latent class logit	*(44)*
Ge,Y., et al (2016)	Stated preferences of U.S. PHEV owners	Charge or not at a public charging station	Recharging price at the station, electricity cost to get a full charge at home, dwell time, charging power, gasoline price	Using latent classes to account for the observed heterogeneity.	latent class logit model	*(45)*

Daina, N. and Polak, J. (2016)	Instrumented Nissan Leaf vehicles and a questionnaire among the drivers	Duration between charging events	SOC, gender, age, range anxiety indicator, whether to use PEV to go to work/school	This paper does not consider heterogeneity. Top-down approach.	Hazard model	*(46)*
Ge, Y. and MacKenzie, D (2017)	Stated preferences of U.S. PHEV owners	Charge or not at all the charging opportunities of the whole travel day	Recharging price at the station, electricity cost to get a full charge at home, dwell time, charging power, gasoline price, availability of chargers	Using latent classes to account for the observed heterogeneity; Consider intertemporal tradeoff using DDCM framework.	DDCM with observed heterogeneity	*(47)*

3.3 From charging behavior to charging demand modeling

The summation of the decisions at the charging stations generates the charging demand, which is also called bottom-up approach. The benefit of this approach is that compared to top-down approach (aggregate analyses), bottom-up methods allow the flexibility to do the counterfactual analysis: it can be used to predict the demand with the change of policy, infrastructure supply and market scenarios. The limitation of static models discussed in Section 3.2.2 exposes more explicitly within the context of the generation of the charging demand because the static models assume the individual charging decisions are independent and they do not consider the decision of vehicle choice.

The availability of public charging infrastructure intuitively appears to be a key enabler of Plug-in Electric Vehicle (PEV) adoption, increasing the operating radius of Battery-Electric Vehicles (BEVs), and increasing the fraction of electric powered miles in Plug-in Hybrid Electric Vehicles (PHEVs). The low utilization of public chargers *(20)* does not necessarily mean the demand of pubic charging is low because it could be due to the lack of public charging opportunities. To mitigate the effect of the limited range of BEVs, a lot of BEV adopters may keep the choice of choosing an internal combustion engine vehicle (ICEV) for relatively long-distance travel. When they observe the lack of public charging supply and the possibility of being stranded in the middle of the day, they could either choose to use their own ICEV/ PHEV or rent an ICEV vehicle (RENT) if they do not own one *(48).*

For a travel day that needs to be completed by driving, PEV owners usually face two stages of decisions as presented by Figure 5: whether to use PEV for the day (stage 1 decision), and if so, whether to charge the PEV at the stops as the day progresses (stage 2 decision). The decisions of the two stages are inseparable intuitively: the vehicle choice influences whether they will face the charging decisions later, and the expectation of future charging opportunities influences the vehicle choice. Modeling the stage 2 decisions of charging choices alone may lead to underestimation of charging demand. The charging decisions at any two stops in the travel day are not independent either: the charging decision at one stop influences whether the vehicle needs to be charged at the following stops, and the expectation of future charging opportunities influences the charging decision at the current stop. This dependence between an earlier decision and a later one can be translated into the following according to the utility theory: a decision at an earlier stop may affect not only the current utility, but the expected utility later of the following stops; the value of the expected future utility may affect the decision at the current stop. The earlier studies discussed in section 3.2.2 cannot capture these inter-temporal payoffs.

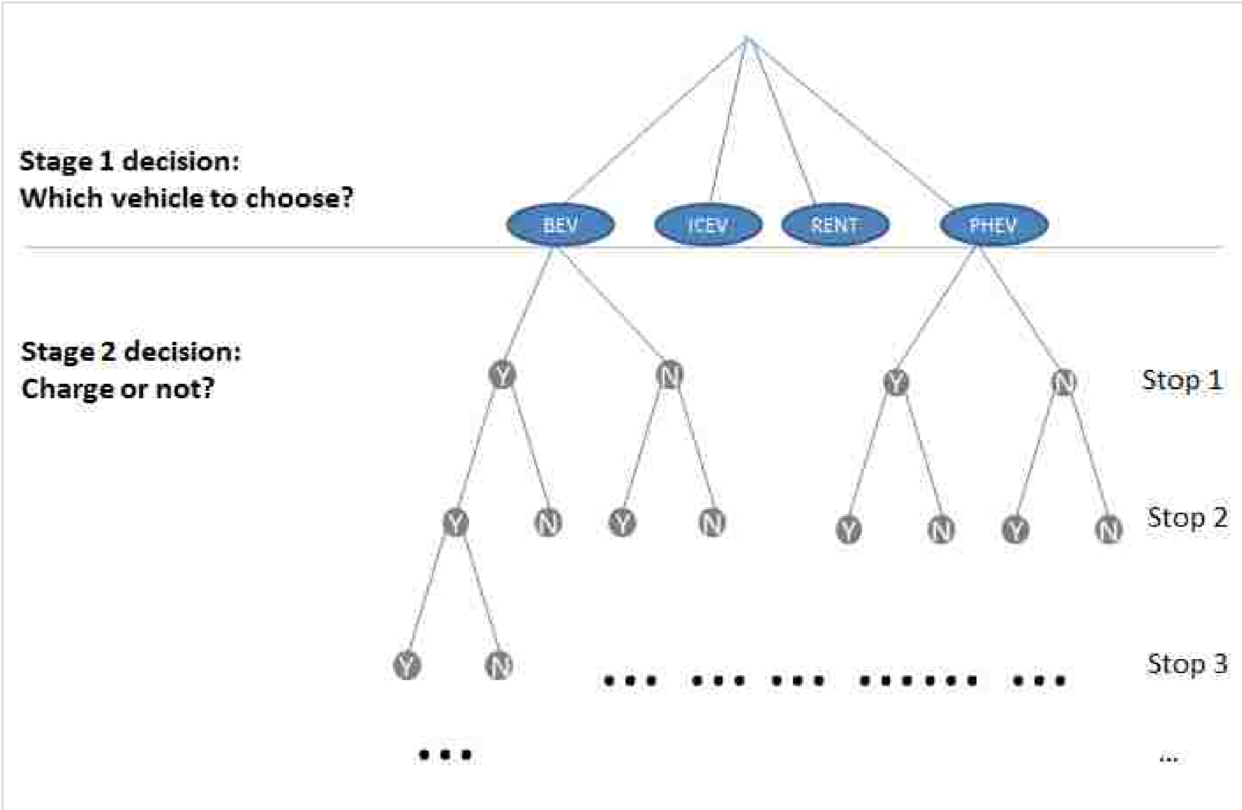


Figure 5 Decision tree of PEV owners for a particular travel day

Static models discussed in Chapter 3.2.2 only consider the Stage 2 decisions and assume the charging decisions at the stations are independent, which could lead to significant underestimation of the charging demand, especially with the rapidly evolving market of vehicle electrification. In a survey on the charging choices conducted by our lab in 2013 where the respondents were asked to make decisions on the characteristics of one individual charging station, the respondents' feedback shows that their charging decisions are based on earlier or later stops, not just the current stop. Dynamic discrete choice modeling (DDCM) can be used to model the vehicle choice and charging choices jointly under the uncertainty of energy consumption and the uncertainty of availability of chargers with the consideration of unobserved heterogeneity. The fundamental principle in DDCM analysis is that choices in any period are assumed to be made in a dynamic programming framework such that the choices made will maximize the net present value of the current utility and expected future utility *(49)*. A DDCM is more suitable when the utility of a decision maker's choices depend on choices previously made, and when those earlier choices were made knowing that there would be uncertain future payoffs. At each time t, decision-maker i with characteristics X_i observes the state variables s_{it} (e.g. the remaining range of the PEV) and chooses his action d_{it}^* (e.g. choose among BEV, PHEV, ICEV, and RENT; choose to charge or not) so as to maximize his expected net utility over the current period and all future periods, as shown in equation (5):

$$d_{it}^*(S_{it}) = argMax_{d_{it} \epsilon D} E_t \left[\sum_{j=0}^{T-t} \beta^j U\left(S_{i,t+j}, d_{i,t+j}, \theta\right) \right] \tag{5}$$

$U\left(s_{i,t}, d_{i,t}, \theta\right)$ is the flow utility of decision-maker *i* at time period *t*, which depends on the structural parameters θ in addition to the choices d_{it} and states s_{it}. $\mathrm{E_t}$ represents the function that calculates the expected value of the intertemporal payoff from period *t* to the final period *T*. The earlier choices will influence the future utility because the current decision d_{it} influences the future state variables $s_{i,t+1}$ via a process captured by the state transition probability $F(s_{i,t+1}|s_{i,t}, d_{i,t})$. The expected future opportunities influence the earlier choices through the expected utility value. Parameter β is a discount factor between 0 and 1, and the transition function represents the uncertainty of the future states (e.g. due to variability in in-use energy consumption and the uncertain availability of charging stations).

3.4 The concepts, estimation and applications of DDCM

There are generally three types of DDCMs: (1) single agent problem (2) Equilibrium problem (3) dynamic games. Single agent problems assume the decision makers are independent from each other, take the classic bus engine replacement problem discussed by Rust as an example: the decision to replace or keep the engine of one bus is independent from the decision on other buses *(51)*. The PEV charging problem in this study falls into this category because the vehicle choice and charging decisions are independent across individuals. Equilibrium problem solves problems that require the interactions between two sides: service providers and service receivers. For example, in an online freelance market, the bidders and the hirers both make decisions that maximize their utility and their decisions have impacts on each other *(52)*. Dynamic games have multiple agents interacting with each other.

DDCM of single agent problems has been widely used in economic analysis and social science *(49)*. It models choices based on intertemporal tradeoffs, which has obvious benefits for a lot of economic problems. For durable goods such as bus engines, DDCM considers the intertemporal trade-offs between the current replacement cost and future maintenance cost, which is one classic problem analyzed by Rust *(51)*. For storable goods such as ketchup, it considers the intertemporal trade-offs between savings from a low price today and high storage cost in the future *(53)*. DDCM problems are also broadly applied in some social science topics such as job search problem *(54)* and reproductive choices *(55)*. In transportation area, there are not a lot of applications until recently partly due to the massive computation cost *(50)*. In 2013, Cirillo et al. used DDCM to analyze car ownership behavior with consideration of consumers' expectations of future product characteristics *(56, 57)*. DDCM is more suitable for vehicle adoption topics than static discrete choice models because the car buyers are usually forward-looking and the expectation about future market plays a great role in the decision making.

In this chapter, I first explain in Section 3.4.1 some basic concepts related to dynamic discrete choice models and the basic model set-up of a single agent problem based on the notations demonstrated in the Rust model *(51).* Then I will talk about the estimation methods and the implications of certain departures from the basic assumption in the DDCM presented in the *(51)* addressed in the literature.

3.4.1 Concepts and Framework of a single agent DDCM

This study applies DDCM to model the vehicle choice and charging choices jointly under the uncertainty of energy consumption and the uncertainty of availability of chargers with the consideration of unobserved heterogeneity. The fundamental principle in DDCM analysis is that choices in any period are assumed to be made in a dynamic programming framework such that the choices made will maximize the net present value of the current utility and expected future utility *(50)*. DDCM considers individual decision-maker as a forward-looking and rational agent. The agents are forward-looking because they make decisions with the consideration of the effect of their current choices on their future stream of utility. They are rational because the way in which they handle uncertainty about the future variables is by doing the best possible forecast using the information that is available at the time of decision. A DDCM is more suitable when the utility of a decision maker's choices depends on choices previously made, and when those earlier choices were made knowing that there would be uncertain future payoffs.

At decision period *t*, individual *i* chooses among *J* mutually exclusive alternatives to maximize the net utility, as in: $d_{it} = \{j: j\epsilon D = \{1,2,..J\}\}$. The expression $d_{it} = j$ means that the respondent *i* choose alternative *j* at period *t*. Denote the choice indicator I as equation (6):

$$\mathrm{I}(d_{it} = \mathrm{j}) = \begin{cases} 1, & if\ d_{it} = \mathrm{j} \\ 0, & if\ d_{it} \neq \mathrm{j} \end{cases} \tag{6}$$

The utility at each period t depends on the vector of state variables denoted as S_{it}. S_{it} consists of two parts: a vector of state variables that are known to the researcher (s_{it}) and the component of the state variables that are known to the decision-makers but are not observed by the researcher (denoted as ε_{it}). The observable state variables can be time-varying variables or time-invariant variables, and they can be random variables that follow certain distributions or deterministic.

$$S_{it} = \{s_{it}, \varepsilon_{it}\} \tag{7}$$

$$\varepsilon_{it} = \left(\varepsilon_{it1}, .., \varepsilon_{itJ}\right)' \tag{8}$$

The agents choose the alternative to maximize his expected net utility over the current period and all future periods, as shown in equation (9):

$$d_{it}^{*}(s_{it}) = argMax_{j\epsilon D} E_t\left[\sum_{\tau=t}^{T} \beta^{\tau-t} U_{itj}(s_{it}, \varepsilon_{itj}, \theta\ )\right] \tag{9}$$

In equation (9), $U_{itj}(s_{i\tau})$ is the flow utility (also called the one-period payoff) of decision-maker *i* at time period *t* for respondent *j*, which depends on the structural parameters θ in addition to the alternative j, states s_{it} and random error ε_{itj}. $\mathrm{E_t}$ represents the function that calculates the expected value of the intertemporal payoff from period *t* to the final period *T*. The expected future opportunities influence the earlier choices through the expected utility value. Parameter β is a discount factor between 0 and 1, and the transition function represents the uncertainty of the future states (e.g. due to variability in in-use energy consumption and the uncertain availability of charging stations). The earlier choices will influence the future utility because the current decision d_{it} influences the future state variables $S_{i,t+1}$ via a process captured by the state transition probability $F(S_{i,t+1}|S_{i,t}, d_{i,t}, \alpha)$. F is the agents' belief about the transition of the future state variables based on the value of the state variables and the choice at the current period. α here is the vector of parameters of the state transition function.

$$S_{i,t+1} \sim F\left(S_{i,t+1} \middle| S_{it}, d_{it}, \alpha\right) \tag{10}$$

There is not a general class of DDCM models. In 1987, Rust first came up with the method of Nested Fixed Point Algorithm (NFPA) that can generate consistent estimates for the engine replacement problem, which was applied in multiple empirical analyses shortly after. Engine replacement problem is generally referred to as a classic example of DDCM and the later theoretical development and estimation methods can all be considered as the extensions from the framework discussed by Rust (Rust framework). Based on the Rust framework, a single-agent DDCM uses the following baseline assumptions for the convenience of estimation.

Assumption 1(Additive Separability) The flow utility is additively separable between the observable and the unobserved state variables, and the unobserved state variables (random errors) are identically and independently distributed (IID) across the individuals and time period. $u_{itj}(s_{it})$ is the systematic part of the utility of respondent *i* at time period *t* for choice j and it values depends on the state variable s_{it}. ε_{itj} is the random error of respondent i at period t for alternative *j*.

$$U_{itj}(s_{it}, \varepsilon_{itj}, \theta) = u_{itj}(s_{it}, \theta) + \varepsilon_{itj} \tag{11}$$

Assumption 2 (Conditional Independence of future state vector *s*) Conditional on the decision at the current decision and observable state variables, next period observable variables do not depend on current unobserved state variable ε_{it}. The unobservable state variables ε_t are independent and identically distributed across agents and decision periods. See equation (12).

$$F_{s,\varepsilon}\left(s_{i,t+1}, \varepsilon_{i,t+1} \middle| d_{it}, s_{it}, \varepsilon_{it}, \alpha\right) = F_s\left(s_{i,t+1} \middle| d_{it}, s_{it},\right) F_\varepsilon\left(\varepsilon_{i,t+1}\right) \tag{12}$$

The intertemporal payoff function based on current and expected future utility is defined as value function V_{it} (equation (13)).

$$V_{it}(s_{i,t}) = E_t\left[\sum_{\tau=t}^{T_i} \beta^{\tau-t} U_{itj}(s_{it}, \varepsilon_{itj}, \theta)\right] \tag{13}$$

At each period t, the decision made at station t will make respondent *i* achieve the biggest expected utility, as shown in equation (14). The optimal choice can also be defined as $\mathrm{d}^*_{\mathrm{ijt}} \equiv 1\{\mathrm{d}^*_{\mathrm{it}}(\mathrm{s_t}) = \mathrm{j}\}$.

$$d^*_{it}(s_{it}) = argMax_{j\epsilon D} V_{it}(s_{i,t}) = argMax_{j\epsilon D} E_t\left[\sum_{\tau=t}^{\tau=T_i} \beta^{\tau-t} U_{itj}(s_{it}, \varepsilon_{itj}, \theta)\right] \tag{14}$$

The summation of the utilities is broken into sub problems according to the principle of optimality: the remaining decisions only depend on the current state instead of the initial decisions and earlier states that result in the current state *(58)*. Bellman's curve of optimality uses the principle of optimality and rewrites the value functions of respondent *i* at period *t* as an iterative process as shown by equation (15) *(59)*.

$$V_{it}(s_{it},\theta) = \max_{j\epsilon D}\left(u_{itj}(s_{i\tau},\theta) + \varepsilon_{itj} + \beta\int V_{i,t+1}(s_{i,t+1},\theta)dF_{is}(s_{i,t+1}|d_{it},s_{it},\alpha)\right) \tag{15}$$

Define the conditional value function of respondent i at period *t* as the choice specific value function of alternative *j* denoted by $v_{itj}(s_{it})$. It can be calculated according to equation (16).

$$\begin{aligned} v_{itj}(s_{it}) &= u_{itj}(s_{it},\theta) + \beta\int V_{i,t+1}(s_{i,t+1},\theta)dF_{is}(s_{i,t+1}|d_{it},s_{it},\alpha) \\ &= u_{itj}(s_{it},\theta) + \beta\int ln\sum_{h\epsilon D}\exp\{v_{i,t+1,j}(s_{i,t+1},\theta)\}\,dF_{is}(s_{i,t+1}|d_{it},s_{it},\alpha) \end{aligned} \tag{16}$$

According to random utility theory, the individual *i* chooses choice *j* in period *t* if and only if:

$$v_{itj}(s_{it},\theta) + \varepsilon_{itj} \geq v_{itk}(s_{it},\theta) + \varepsilon_{itk} \quad \forall\, k \neq j \tag{17}$$

Therefore, the conditional probability of the choice *j* by respondent *i* at stop *t* based on the value of the state variables can be expressed as equation (18) under the following third assumption of Rust framework.

Assumption 3: The distribution of the unobserved state variables ε_{itj} is type-I extreme value distribution.

$$P_r(d_{it} = j|\, s_{it}) = \frac{e^{v_{ijt}(s_{it},\theta)}}{\sum_{h\epsilon D} e^{v_{iht}(s_{it},\theta)}} \tag{18}$$

The framework of a single agent DDCM is simple and straightforward enough, but the complexity of estimation and the high computational cost prove to be a long time struggle on the road of further development of the theory and applications of the model. Rust first developed Nested Fixed Point Algorithm (NFPA) for the estimation of a single agent dynamic model *(16)*, which generates consistent estimates but suffers from a dimension curse: in general, DDCM with high dimensions of state variables are usually intractable by NFPA *(51)*. Two-Step method that came out later has relatively lower computation cost because the value functions do not need to be calculated based on the state transition distributions but simulated based on the conditional choice probabilities. Two-Step method offers consistent estimates with reasonable efficiency but it has higher requirement on the data: there should be enough repetition of the combination of state variables *(60)* to ensure enough accuracy of the conditional choice probability. In Section 3.4.2 and 3.4.3, I will explain in detail how the NFPA and Two-Step method work and talk about the pros and cons, also the applications of these methods in empirical analyses. Then I will talk about the extended literatures on the consideration of heterogeneity.

3.4.2 NFPA estimation and its applications

Equation (16) describes the iteration of the choice-specific value functions, according to which, the value functions of a problem with limited time periods (a finite horizon problem) can be calculated using backwards induction, and those of a problem with infinite horizon can be calculated using fixed point algorithm *(51).* According to the two assumption of the Rust framework, the full likelihood includes the likelihood of the decisions on choice at each time period and the likelihood of the observable state variables. The full log-likelihood for the respondent *i* is shown in equation (19) and (20):

$$ll_i(\theta) = \sum_{t=1}^{T_i} \ln \left[Pr\left(s_{it}, d_{it} \middle| s_{i,t-1}, d_{i,t-1}, \alpha, \theta\right)^{I(d_{it}=1)} \right] \tag{19}$$

$$ll_i(\theta) = \sum_{t=1}^{T_i} \ln \Pr(d_{it}|s_{it}, \theta)^{I(d_{it}=1)} + \sum_{t=2}^{T_i} lnPr\big(s_{it}\big|s_{i,t-1}, d_{i,t-1}, \alpha\big) \tag{20}$$

The log-likelihood of the full sample is shown in equation (21).

$$ll(\theta) = \sum_{i=1}^{N} ll_i(\theta) \tag{21}$$

The two assumptions of Rust Framework listed in Section 3.4.1 facilitate the transition from equation (19) to equation (20), which makes it possible to estimate the parameters in the state transition function α (second term of equation (20)) and the structural parameters (first term of equation (20)) separately. Rust *(51)* proved that by estimating the state transition function variables and the structural variables separately, then adding a single Newton-Raphson iteration for the full likelihood optimization, the final estimators are asymptotically equivalent to the full likelihood estimator.

To estimate the structural parameters, Rust came up with the NFPA. NFPA entails an inner loop that calculates the value function iteratively according to equation (also called dynamic programing problem) *(16)* and an outer loop that updates the structural parameters using the optimization algorithm of BHHH. Instead of computing the hessian, BHHH approximates the hessian using information matrix equality *(61)*. Essentially, NFPA needs to calculate the value functions whenever θs are updated, which proves to be very costly especially with the increase of the dimension of the state variables *(51)*. The time to calculate the value functions increases exponentially with the increase of the number of state variables. The application papers of NFPA usually try to control the number of the state variables *(53-55)* or condense the multiple state variables into an inclusive value if it is reasonable *(62)*. In transportation area, Lapparent and Gernicchiaro applied NFPA and studied the duration of vehicle ownership and distance driven considering the uncertainty of energy price and income *(63)*.

3.4.3 Two-Step method for the estimation of a single agent problem

Two-Step method proposed by Hotz and Miller *(60)* avoids the computation of the value functions directly but approximates them through simulations. They noticed that the value functions can be represented as a function of the probability of the choice conditional on the value of the state variables (CCPs) because there is a one-to-one mapping relationship between the CCPs and the value functions according to equation (18). The estimates of the CCPs can be obtained either non-parametrically or parametrically based on the data. For example, when the combinations of all the state variables appear fairly frequently in the data, non-parametric estimates of the CCPs when the state variable vector is s'can be as shown in equation (20). The denominator of equation (22) is the totally number of observations with the state variables s', and the numerator is the number of observations with state variable s' and the choice j. However, when all the combinations of the state variables cannot be covered by the data or for some cases there are few observations, this method can be hard to implement. In this case, it is possible to use semi-parametric measures to account for the CCPs, but the convergence of the model can be challenged because the CCPs are not accurate.

$$\hat{p}_j(s_{it} = s') = \frac{\sum_{i=1}^{N} \sum_{t=1}^{T_i} \mathrm{I}(d_{it} = \mathrm{j})\{s_{it} = s'\}}{\sum_{i=1}^{N} \sum_{t=1}^{T_i} 1\{s_{it} = s'\}} \tag{22}$$

Two-Step method approximates the value function by replacing the integration with simulations based on the CCPs given state vector as shown by equation (22) and state transition probabilities $F(s_{i,t+1}|s_{i,t}, d_{i,t})$ according to equation (23). In equation (23), γ is the Euler's constant and the part of the utility $\gamma - log\left(\hat{p}\left(j^{'m}\middle|s^{'m}\right)\right)$ equals to the expectation of the error term ($E[\varepsilon_j|j^{'m}, s^{'m}]$) under the assumption that the error terms of the utility are distributed according to Type 1 extreme value. One simulation can be pictured as drawing a path of $(s_{i,t+1}, d_{i,t+1})$ for the future periods conditional on the current $(s_{i,t}, d_{i,t})$: draw an outcome of $s_{i,t+1}$ based on the transition probabilities $F(s_{i,t+1}|s_{i,t}, d_{i,t})$, and then draw an outcome of $d_{i,t+1}$ based on the simulated $s_{i,t+1}$ according to the CCPs. M is the total number of simulations (or paths) and the total number of periods simulated (T) for every path is to be decided by the researchers. Larger M and T result in smaller simulation errors and truncation errors.

$$\begin{aligned}
&\widetilde{v}_{itj}(s_{it}, \theta) \\
&\qquad \approx \frac{1}{M}\sum_{m}\Big[u_{itj}(s_{it}, \theta) \\
&\qquad + \beta\left[u_{i,t+1,j^{'m}}(s^{'m}{}_{i,t+1}, \theta) + \gamma\right. \\
&\qquad \left.\left. - \log\left(\hat{p}\left(j^{'m}\middle|s^{'m}\right)\right) + \beta\left[u_{i,t+2,j^{''m}}(s^{''m}{}_{i,t+1}, \theta) + \gamma - \log\left(\hat{p}\left(j^{''m}\middle|s^{''m}\right)\right) + \beta \ldots\right]\right]\right],
\end{aligned}$$

$$\text{Where } \; E\left[\varepsilon_j\middle|j^{'m}, s^{'m}\right] = \gamma - log\left(\hat{p}\left(j^{'m}\middle|s^{'m}\right)\right) \tag{23}$$

For some problems a decision can reset the state space to a known state that is independent from past choices, also called a renewable state. Take the engine replacement problem as an example, when the bus engine is replaced, the state, which is the mileage of the engine goes back to zero no matter what the sequence of choices made to the bus in earlier stages. This kind of problem is also called regenerative problem *(51)* and this quality is referred to as finite dependence *(64)*. For a regenerative problem, the simulation process can be simplified greatly because of the existence of the renewable state (equation (24)) *(65)*. In equation (24), j^0 is the decision that resets the state vectors.

$$\begin{aligned}
&\tilde{v}_{itj}(s_{it},\theta) \\
&\qquad \approx u_{itj}(s_{it},\theta)+\beta\gamma \\
&\qquad +\beta\int\left[-\ln(\hat{p}(j^0|s_{i,t+1})+u_{i,t+1,j^0}(s_{i,t+1},\theta)\right]dF_{is}(s_{i,t+1}|d_{it},s_{it},\alpha) \\
&\qquad +\beta\int\int V_{i,t+2}(s_{i,t+2},\theta)\,dF_{is}(s_{i,t+2}|d_{i,t+1}=j^0,s_{i,t+1})dF_{is}(s_{i,t+1}|d_{it},s_{it},\alpha)
\end{aligned} \tag{24}$$

The calculation of the value functions is the only fundamental difference between the NFPA and the Two-Step method, however this one difference greatly improves the tractability of DDCMs because Two-Step method releases the NFPA from the dimension curse: even when the number of state variables is large, it can generate consistent estimates as long as the dataset is comprehensive enough *(66)*. Because of this development of estimation method of DDCM, several relatively more complex DDCM problems were estimated *(67- 69)*. However, the simulation error of the Two-Step method generates simulation errors and truncation errors, so the estimates are not efficient. If the state-size is reasonable, the efficiency of the estimates can benefit from iterations of the full model using NFPA. Another drawback of the Two-Step method is that the CCPs are conditioned to the agents' decisions under the conditions observed in the data, so even though it is completely sufficient to answer substantive questions on the structural parameters, it sometimes does not generate counterfactual predictions *(65)*.

3.4.4 Departures from the Rust framework: DDCM with unobserved heterogeneity

The Assumption 1 of Rust framework assumes that all the unobserved state variables are IID. However, a lot of problems are more complicated than that. For the bus replacement problem, different bus brands may have different maintenance and engine replacement fee, which will influence the engine replacement choices. Because of the computational cost and theoretical complexity of bringing in unobserved heterogeneity, earlier researchers dealt with heterogeneity by avoiding heterogeneous groups in the data set *(51, 62)*. For example, Rust tested the within and between groups differences of buses of different brands and decided to only use part of the dataset that appears to be homogeneous. However, this is not always applicable considering the fact that most of the times the heterogeneity cannot be observed. Take the career choice problem by Keane and Wolpine (70) as an example, when observed state variables such as education and work experiences are considered in the model, the innate "capability" of the individuals cannot be observed but intuitively it will influence the career choices significantly. When there is preference heterogeneity in the decision making, the unobserved state variables are correlated across time periods, which are also referred to as persistent unobservables by Arcidiacono and Jones when these unobservables persist with time *(71)*. Persistent unobservables cause the self-selection of the agents, which is referred to as "Dynamic Selection" problem *(71)*. For example, when the brands of the buses are different, the set of buses in any period is not random anymore but self-selected because the brands with higher maintenance cost are less likelihood to have high mileage values.

Econometrically, persistent unobservables cause the correlation of error terms, which makes the Assumption 1 of Rust framework unrealistic. The clean separation of the likelihoods shown in equation (20) is not correct anymore in this case. Then, the evaluation of the likelihood and the estimation of the parameters are much more complicated than the DDCM problem without heterogeneity. The estimation method of the DDCM with the consideration of heterogeneity was developed not long ago by Arcidiacono and Jones *(71)*. They built the estimation algorithm of DDCM with heterogeneity on top of the NFPA algorithm by Rust and the expectation-maximization algorithm (EM algorithm).

Assume the unobserved state variable is c_i that is drawn from a set of Q types: $c_i = q \in \{1,2, \dots, Q\}$. Denote the percentage of agents with q as π_q. π_q is also commonly referred to as population probability. The probability of agent *i* having the unobserved state probability as $c_i = q$ is π_{iq}.

$$\pi_{q=} \frac{\sum_{i=1}^{N} \pi_{iq}}{N} \tag{25}$$

The utility of the respondent *i* at period *t* for alternative *j* now depends on the type c_i besides the state variable s_{it} and random error vector ε_{itj}, as shown in equation (26).

$$U_{itj}\left(s_{it}, c_i, \theta, \varepsilon_{itj}\right) = u_{itj}(s_{it}, c_i, \theta) + \varepsilon_{itj} \tag{26}$$

The state transition can also depend on the class indicator c_i: $S_{i,t+1} \sim F\left(S_{i,t+1} \middle| S_{it}, d_{it}, c_i, \alpha\right)$. The state transitions are not directly observable from the data as in the Rust framework because they are functions of unobservable state variable c_i. This makes the estimation completely different from the Rust model using NFPA *(51)* because it precludes the possibility of estimating the parameters in the state transition function α in the first step.

The calculation of the value functions and conditional probability need to updated accordingly, see equation (27) and equation (28).

$$v_{itj}(s_{it},\theta,c_i) = u_{itj}(s_{it},\theta,c_i) + \beta\int V_{i,t+1}\big(s_{i,t+1},\theta,c_i\big)dF_{is}\big(s_{i,t+1}\big|j,s_{it},\alpha,c_i\big)$$

$$= u_{itj}(s_{it},\theta,c_i) + \beta\int ln\sum_{h\epsilon D}\exp\big\{v_{i,t+1,j}\big(s_{i,t+1},\theta,c_i\big)\big\}\,dF_{is}\big(s_{i,t+1}\big|j,s_{it},\alpha,c_i\big)$$

$$(27)$$

$$P_r(d_{it} = j|\,s_{it},c_i) = \frac{e^{v_{ijt}(s_{it},\theta,c_i)}}{\sum_{h\epsilon D} e^{v_{iht}(s_{it},\theta,c_i)}} \quad (28)$$

Then the full likelihood function is given by equation (29).

$$ll_i(\theta) = ln\sum_{q=1}^{Q}\pi_{iq}\sum_{t=1}^{T_i}Pr\big(s_{it},d_{it}\big|s_{i,t-1},d_{i,t-1},c_i = q,\alpha,\theta\big)^{I(d_{it}=1)}$$

$$= \ ln\sum_{q=1}^{Q}\pi_{iq}\prod_{t=1}^{T_i}Pr(d_{it}|s_{it},c_i = q,\theta)^{I(d_{it}=1)}\cdot f(s_{it}|s_{i,t-1},d_{i,t-1},c_i = q,\alpha)$$

$$(29)$$

The estimation of α and θ based on equation (29) has a few challenges: (1) There are more parameters to estimate: for each type q, the parameters need to be estimated and π_{iq}s need to be estimated too; (2) the value functions and the conditional probabilities are both functions of the unobserved state variable c_i. (3) The summation inside the function of ln precludes the possibility of sequential estimation of the state transitions and the choice probabilities.

Arcidiacono and Jones *(71)* propose using NFPA in combination with EM algorithm *(72)* to estimate the parameters based on equation (29). EM algorithm facilitates the equivalence of the full likelihood shown in equation (30) and separates one difficult maximization problem into separate smaller maximization problems. It re-introduces additive separability in the log likelihood for the choice probabilities and the state transition parameters and makes it possible to sequentially estimate the parameters again.

$$\{\hat{\theta}, \hat{\alpha}\}$$

$$= argmax \sum_{i=1}^{N} ln \sum_{q=1}^{Q} \pi_{iq} \prod_{t=1}^{T_i} Pr(d_{it}|s_{it}, c_i = q, \theta, \alpha)^{I(d_{it}=1)} \cdot f(s_{it}|s_{i,t-1}, d_{i,t-1}, c_i = q, \alpha)$$

$$= argmax_{\theta} \sum_{i=1}^{N} \sum_{t=1}^{T_i} \sum_{q=1}^{Q} \pi_{iq} \cdot \ln\left[Pr(d_{it}|s_{it}, c_i = q, \theta, \hat{\alpha})^{I(d_{it}=1)}\right]$$

$$+ argmax_{\theta} \sum_{i=1}^{N} \sum_{t=1}^{T_i} \sum_{q=1}^{Q} \pi_{iq} \cdot \ln\left[f\left(s_{it}\middle|s_{i,t-1}, d_{i,t-1}, c_i = q, \alpha\right)\right] \tag{30}$$

Arcidiacono and Miller recently developed the algorithm based on Two-Step method and EM algorithm *(65)*. The procedure is similar to the Arcidiacono and Miller *(71)* with two differences: the calculation of the value functions is based on simulation; and the CCPs conditional on the type c_i need to be updated for each iteration.

3.5 Summary

The literature review shows that the modeling of vehicle uses and charging behavior of PEV users is of great importance for the assessment of the demand of public charging infrastructure, the demand forecasting of the energy consumption, and the evaluation of the environmental impact of driving. Earlier research papers on the charging behavior of both BEV and PHEV collectively show that the following factors play a great role in the decision-making of whether to charge or not at a station: remaining range of the PEV, distance to home, charging price, gasoline price, dwell time and charger level. They also show evidence of preference heterogeneity of charging decisions. The static models used to analyze charging behavior (mainly mixed logit models and latent class logit models) assume the charging decision at one station is only influenced by the characteristics of the current station and independent from the earlier or later charging opportunities in the day. However, the decisions of vehicle choice and PEV charging fall into one dynamic process: the expectation of the future charging opportunities influences the charging decision at the current station, and the charging decisions at the earlier stations influence the SOC of the PEV at the current station, thus influence the charging choice at the current stop. The existence of charging opportunities during the day influences whether one wants to drive a PEV. DDCM can capture this evaluation of intertemporal tradeoff. Recent development of DDCM shows that there are methods that offer consistent and efficient estimates for DDCM with the consideration of heterogeneity.

4 Methodology

4.1 Overview

The analyses of the dissertation are based on the data from web-based interactive surveys where the respondents are firstly asked about their socio-demographic information and the specific information of vehicles they own, then presented with travel day scenarios characterized by planned distance and stops, gasoline price, charging price, charger level and the availability of chargers. In each scenario, the respondents were asked to choose from one of the vehicles they own or renting a car to complete the travel day, and if they choose to use their PEV, whether to charge their PEV at each stop as the day progresses.

The data collections and analyses were conducted relatively independently for home-based trip tours and long-distance trips. A home-based trip tour is a tour with multiple natural destinations, where the main activity is not charging. For example, a home-based trip tour could have three trips: (1) from home to workplace; (2) from workplace to shopping mall; and (3) from shopping mall to home. This tour has two destinations: the workplace and shopping mall, where the main activities are respectively work and shopping instead of charging. Therefore, on a home-based tour PEV users tend to charge on natural trip destinations instead of stopping specifically for charging. A long-distance trip is a road trip with only one final destination, for example a road trip from Seattle to San Francisco. On a long-distance trip, PEV drivers usually stop specifically for charging.

Two of these surveys were respectively designed to simulate home-based trips and long-distance trips (interstate trips), which will be described in detail in Chapter 5 and Chapter 7. The analyses are done respectively for home-based and long-distance trips since the characteristics of the charging opportunities are different for these two situations. For long distance trips, the drivers stop specifically for charging and the time it takes to reach a full charge and the time to access the charging stations are likely to influence the charging choices. For home-based trips, recharging usually happens at natural stops of the travel day, therefore the dwell time at the natural stops is likely to influence the charging choices.

The data from both surveys are analyzed using discrete choice models, including DDCMs with the consideration of heterogeneity using methods proposed by Arcidiacono and his coauthors *(65,71)*. Both the vehicle choices and charging decisions are analyzed, and the DDCMs are compared with static discrete choice models (SDCMs) based on much simpler decision heuristics. In total, five analyses were presented in this dissertation. Specifically, based on the data collected from the choice experiment for home-based trip tours described in Chapter 5, Chapter 6 presents three topics (Analysis 1-3), and based on the data collected from the choice experiment for long-distance trips described in Chapter 7, Chapter 8 presents two topics (Analysis 4-5).

Analysis 1: Modeling vehicle choices and charging behavior of BEV owners jointly using DDCM for home-based trip tours;

Analysis 2: Modeling charging choices of PHEV users using DDCM for home-based trip tours;

Analysis 3: Comparison between DDCM and static models based on simple decision heuristics for home-based trips;

Analysis 4: Modeling vehicle choice decisions of BEV owners for long-distance trips;

Analysis 5: Modeling charging choices of BEV drivers on a long-distance trip, and comparison between DDCM and static models based on simple decision heuristics.

4.2 Data source

The surveys were administrated to a sample of PEV drivers recruited trough their membership in the Electric Auto Association (EAA) and snowball sampling through social media platforms such as Facebook and other EV forums such as Plug-in America. Despite the fact that EAA members may differ from current or future mainstream PEV owners, the low adoption rate of PEVs in US (still less than one percent) makes it very costly to sample from the whole PEV owner population. There are several advantages to using EAA members as subjects, despite of the fact that they may differ from future mainstream PEV owners. First, EAA members tend to be highly interested in the technology and willing to participate in studies of this sort, even without tangible compensation. Second, because many of them have owned PEVs for longer than other owners, there is less risk that their charging behavior is shaped by a lack of familiarity with the technology. Third, EAA chapters are spread all around the country, providing high geography diversity. Fourth, a representative sample of all current PEV owners would not necessarily be more representative of mainstream consumers than a sample of EAA members because of the low adoption rate. Since the market share of PEVs is still below 1% in US, the current adopters are generally still the early adopters, a niche group with tastes and preferences substantially different than those of the majority. Developing a theory to explain PEV use and charging choices is important, despite any potential dissimilarity between the current and future PEV owners. The respondents of the study were all added to a prize draw to win an Apple iPad, or an Apple Watch, or a Microsoft Surface tablet of a $499 value.

Although stated preference (SP) data is considered inferior to revealed preference (RP) data that observe real-world choices, the collection of RP data is a huge challenge for a study like this because of the low adoption rate of PEVs (less than 1% in US) and as a consequence, the scarcity of data of individual level charging decisions. The dataset involved in this analysis needs to include the individual level data (the specific information of the vehicles and the socio-demographic information of the respondents), the trip data (the distances between the stops, the duration at the stops), and the data on the characteristics of the charging opportunities (the power, price and availability of the chargers). A RP study of charging choices would require detailed data about the PEV, including its state of charge and its location, in order to identify the availability, price and power of the charging infrastructure. For the goal of this research project, SP data have several advantages. (1) The SP approach avoids collecting a lot of data about the PEV including the state of charge and its location, which is essential for a RP study; (2)A RP study of charging behavior will reply on data of the charging infrastructure such as charging price, the availability of chargers and charger power at each charging stop visited. Quite apart from the practical challenges of obtaining and integrating charger data from multiple infrastructure providers, it would be effectively impossible to identify every single charging opportunity, since most PEVs can be charged from ordinary 110V wall outlets, in addition to dedicated EVSEs. (3) Even though the data about the charging opportunities, and PEV and the trips can be obtained, it is difficult to identify the effect of electricity price, gasoline price, and public charging price on charging choices because may or may not fluctuate significantly over the course of a RP study period. An important disadvantage of SP studies is the potential for hypothetical biases: the risk that respondents cannot or do not respond in a way that reflects how they would act in a real-world choice situation. The risk of hypothetical bias in the proposed survey is expected to be small because the respondents will be asked about routine choices with which they are very familiar, rather than being asked to make decision about products or services that are not available or with which they have no experience.

4.3 Modeling methods

4.3.1 Conditional logit model

Conditional logit model is one type of discrete choice model based on utility theory proposed by McFadden (1973) *(79)*. It is a static discrete choice model (SDCM) because the decisions are made based on the current utility instead of the intertemporal payoffs: the fundamental assumption is that the choice made achieves the highest utility (equation (32)) $U(d_{it}, X_{it}, \theta)$. $U(d_{it}, X_{it}, \theta)$ has systematic component $u(d_{it}, X_{it}, \theta)$ and a random component ε_{ijt}, then under the assumption that the error terms are independently and identically Gumbel distributed (equation (31)), the probability of alternative *j* getting chosen is shown as equation (33) *(79)*.

$$f(\varepsilon) = \exp\{-\varepsilon - exp\{-\varepsilon\}\} \tag{31}$$

$$d_{it}^{*} = argMax_{d_{it} \epsilon D_{it}} U(d_{it}, X_{it}, \theta) \tag{32}$$

$$\mathrm{P}(d_{it} = j) = \frac{e^{u(d_{it}=j, X_{it}, \theta)}}{\sum_{k=1}^{D_{it}} e^{u(d_{it}=k, X_{it}, \theta)}} \tag{33}$$

4.3.2 Latent class logistic regression model

As discussed in Section 3.2.2, early efforts to model the heterogeneity of charging preferences across PEV drivers mostly used mixed logit regression models *(13, 17, 18)*. In a mixed logit regression model, the random taste of coefficients (denoted as β) follows a continuous random distribution across the population.

Latent class models, however, assume that all individuals can be grouped into a finite set of classes (Q classes). Here, taste heterogeneity is captured by allocating respondents to different classes in a probabilistic fashion that allows the probability of class membership to depend upon the respondents' sociodemographic information. Different classes haave different taste coefficients, but within each class, the taste parameters are assumed to be homogeneous *(24)*. For example, for the decision of chargin, within class q, the conditional probability of charging by individual *i* in choice situation *t* can be defined as equation *(34)*. β_q represents the coefficients for class q, and X_{it} represents a the independent variables that influence the choice faced by individual *i* in situation *t*. Function (35) shows the probability of one individual falls into class q, which depends on multiple variables denoted by Z_i.

$$P(Charge_{it}|\, \beta_q, \text{class q}) = \frac{e^{\beta_q X_{it}}}{e^{\beta_q X_{it}}+1} \tag{34}$$

$$\pi_{iq} = \frac{\mathrm{e}^{\Upsilon_q Z_i}}{\sum_{\mathrm{q}=1}^{\mathrm{Q}} \mathrm{e}^{\Upsilon_q Z_i}} \tag{35}$$

Then the charging probability for individual *i* under scenario *t* is given by equation (36).

$$\mathrm{P}(\mathrm{Charge_{it}}) = \sum_{\mathrm{q}=1}^{\mathrm{Q}} \pi_{iq} \cdot \frac{e^{\beta_q X_{it}}}{e^{\beta_q X_{it}+1}} \tag{36}$$

4.3.3 DDCM

4.3.3.1 DDCM model framework

In this dissertation, DDCM is used to (1) jointly model BEV owners' vehicle choices and charging choices for a home-based trip tour in the face of uncertain energy consumption and uncertain availability of chargers, (2) analyzing charging choices of PHEV drivers on a home-based tour, and (3) analyzing charging choices of BEV users on a long-distance trip. The fundamental principle in DDCM analysis is that choices in any period are assumed to be made in a dynamic programming framework such that the choices made will maximize the net present value of the current utility plus expected future utility *(71)*. A DDCM is more suitable when the utility of a decision-maker's choices depends on choices previously made, and when those earlier choices were made knowing that there would be uncertain future payoffs. At each decision period t, decision-maker i with characteristics X_i observes the state variables s_{it} (factors that can influence the value of utility, and thus influence the choices, e.g. the remaining range of the BEV) and chooses his action d_{it}^* among choice set D_{it} (e.g. choose among BEV, ICEV, and rent a car (RENT) for stage 1 decision; choose to charge or not for stage 2 decisions) so as to maximize his expected net utility over the current stop and all future stops, as shown in equation (37):

$$d_{it}^*(s_{it}) = argMax_{d_{it} \epsilon D_{it}} E_t \left[\sum_{j=0}^{T-t} \beta^j U\left(s_{i,t+j}, d_{i,t+j}, X_i, \theta\right) \right] \tag{37}$$

$U(s_{it}, d_{it}, X_i, \theta)$ is the flow utility (the utility at one decision period) of decision-maker *i* at decision period *t*, which depends on the structural parameters θ in addition to the choices d_{it} and states s_{it}. $\mathrm{E_t}$ represents the function that calculates the expected value of the intertemporal payoff from period *t* to the final period *T*. Parameter β is a discount factor. The specification of the function $\mathrm{E_t}$ and the estimation of the model will be explained a later section.

4.3.3.2 Value function derivation

The intertemporal payoff function based on current and expected future utility is defined as value function V_{it} (equation (38)).

$$V_{it}(s_{i,t}) = E_t\left[\sum_{j=0}^{T-t} \beta^j U(s_{i,t+j}, d_{i,t+j}, \theta)\right] \tag{38}$$

At each station *t*, the choice is assumed to be the one that makes respondent *i* achieve the biggest expected utility, as shown in equation (39). The optimal choice can be defined as $d_{ijt}^* \equiv 1\{d_{it}^*(s_t) = j\}$.

$$d_{it}^*(s_{it}) = argMax_{d_{it}\epsilon D_{it}} V_{it}(s_{i,t}) = argMax_{d_{it}\epsilon D_{it}} E_t\left[\sum_{j=0}^{T-t} \beta^j U\big(s_{i,t+j}, d_{i,t+j}, X_i\big)\right] \tag{39}$$

Bellman's curve of optimality shows that the value function of respondent *i* at period *t* can be rewritten as equation (40).

$$V_{it}(s_{i,t}) = \max_{j\epsilon D_{it}}\left(u_{itj}(s_{i\tau}) + \varepsilon_{itj} + \beta \int V_{i,t+1}(s_{i,t+1}) dF_{is}(s_{i,t+1}|d_{it}, s_{it})\right) \tag{40}$$

The conditional value function of respondent i at decision period *t* is defined as the choice specific value function of alternative *j* denoted by $v_{itj}(s_{it})$. It can be calculated according to equation (41).

$$\begin{aligned} v_{itj}(s_{it}) &= u_{itj}(s_{it}) + \beta \int V_{i,t+1}\big(s_{i,t+1}\big) dF_{is}\big(s_{i,t+1}\big|j, s_{it}\big) \\ &= u_{itj}(s_{it}) + \beta \int ln \sum_{h\epsilon D_{i,t+1}} \exp\{v_{i,t+1,j}\big(s_{i,t+1}\big)\}\, dF_{is}\big(s_{i,t+1}\big|j, s_{it}\big) \end{aligned} \tag{41}$$

According to random utility theory, individual *i* chooses choice *j* at decision period *t* if and only if:

$$v_{itj}(s_{it}) + \varepsilon_{itj} \geq v_{itk}(s_{it}) + \varepsilon_{itk} \quad \forall\, k \neq j \tag{42}$$

Similar to static conditional logit model described in section 4.3.1, the probability of choosing alternative *j* based on the value function can be calculated according to the following equation.

$$\mathrm{P}(d_{it} = j) = \frac{e^{v_{itj}(s_{it})}}{\sum_{k=1}^{D_{it}=J} e^{v_{itk}(s_{it})}} \tag{43}$$

4.3.3.3 Latent class model for DDCM

To capture the heterogeneity of charging preferences among PEV drivers, the DDCM was extended into a latent class framework. Latent class models assume that all individuals can be separated into a finite set of classes (Q classes) and estimate a set of structural parameters for every class. Here, taste heterogeneity is captured by allocating respondents to different classes in a probabilistic manner, allowing the probability of class membership to be based on the choices made by the respondents.

Under the assumption that the distribution of the error term ε_{itj} is type-1 extreme value distribution, the probability of choosing choice *j* conditional on respondent *i* belonging to class *q* can be described by equation (25), where D_{it} refers to the choice set of respondent *i* at time period *t* and *h* denotes one specific element of the choice set D_{it}.

$$p_{it}(d_{it} = j |\, class\ q) = \frac{e^{v_{ijtq}(s_{it})}}{\sum_{h\epsilon D_{it}} e^{v_{ihtq}(s_{it})}} \tag{44}$$

Denote the probability that respondent *i* belongs to class q as $\pi_{i,q}$, then the probability of the alternative *j* being chosen for the respondent i at period *t* is:

$$p_{it}(d_{it} = j) = \sum_{q=1}^{Q} \pi_{i,q} \cdot \frac{e^{v_{ijtq}(s_{it})}}{\sum_{h\epsilon D_{it}} e^{v_{ihtq}(s_{it})}} \tag{45}$$

The population probability of class q, defined as the proportion of the individuals that belong to class q, is calcualted according to equation (46).

$$\pi_q = \frac{\sum_{i=1}^{N} \pi_{i,q}}{N} \tag{46}$$

The probability of respondent *i* being in class q ($\pi_{i,q}$) can then be calculated as the posterior probability based on the vehicle choice and charging decisions d_{it} see equation (47).

$$\pi_{iq} = \frac{\pi_q \times \left[\prod_{t=1}^{T} \prod_{j=1}^{J} (\Pr(d_{it} = j | class\ q))^{I(d_{it}=j)}\right]}{\sum_{q=1}^{Q} \pi_q \times \left[\prod_{j=1}^{J} \prod_{t=1}^{T} (\Pr(d_{it} = j | class\ q))^{I(d_{it}=j)}\right]} \tag{47}$$

The log-likelihood of the decisions of one individual *i* can be calculated according to equation (48).

$$ll_i(\theta) = \sum_{t=1}^{T_i} \sum_{j=1}^{J} \ln[p_{it}(d_{it} = j)]^{I(d_{it}=j)}$$

$$= \sum_{t=1}^{T_i} \sum_{j=1}^{J} \ln\left[\sum_{q=1}^{Q} \pi_{iq} \cdot \frac{e^{v_{ijtq}(s_{it})}}{\sum_{h \epsilon D} e^{v_{ihtq}(s_{it})}}\right]^{I(d_{it}=j)} \tag{48}$$

The log-likelihood of the sample then can be calculated according to equation (49).

$$LL_N(\theta) = \sum_{i=1}^{N} ll_i(\boldsymbol{\theta}) \tag{49}$$

4.3.3.4 Estimation of latent class DDCM

The estimation of DDCM is rather complicated compared with static discrete choice models, which remains a barrier of its broad adoption *(71)*. Rust first developed the Nested Fixed

Point Algorithm (NFPA) for the estimation of a single agent dynamic model *(71)*, which generates consistent estimates but suffers from a dimensionality curse: in general, DDCMs with high dimensions of state variables are usually intractable by NFPA, especially for DDCMs with infinite horizon *(50)*. The Two-Step method that came out later has relatively lower computation cost and eliminates the dimensionality curse because the value functions do not need to be calculated based on the state transition distributions, but rather can be simulated based on the conditional choice probabilities *(71)*.

I applied the finite mixture solution based on the EM algorithm *(72)* proposed by Arcidiacono and Jones to incorporate the heterogeneity of decision-making among BEV users *(71)* and the NFPA proposed by Rust *(50)* to calculate the value functions. Our application here is simpler in the sense that the problem has a finite horizon and four out of the six state variables are pre-determined, and for the two state variables that are uncertain (remaining range and availability of the chargers), their distributions are assumed to be known according to the questionnaire and the specifications of the experimental scenarios. On the other hand, our application is more complicated in the sense that state variables and transition functions of each respondent in each scenario is different from the rest. As such, the computation cost is higher for this problem.

The DDCM with heterogeneity can then be estimated following these six steps according to the EM algorithm *(28)*.

Step 1: Initialization of structural parameters

The first step is to make initial guesses of all the parameters to be estimated (θ^1, π^1).

Step 2: Update the Value Functions

In this step, for each class the value functions are updated based on the parameters and the class population probability. For finite horizon problem like this, the decision in the last period T is static, so the conditional value function at T is the utility function, which means:

$$v_{iTj}(s_{iT}, class\ q) = u_{iTj}(s_{iT}) \tag{50}$$

Then the value function of all the earlier periods can be obtained through backwards recursion. For example, the conditional value function at T – 1 is then:

$$v_{i,T-1,j}\left(s_{i,T-1}, q\right) = u_{i,T-1,j}(s_{i\tau}, q) + \beta \int ln \sum_{h\epsilon D_{iT}} \exp\{v_{iTj}(s_{iT}, q)\}\, dF_{is}\left(s_{iT} \middle| j, s_{i,T-1}\right) \tag{51}$$

Step 3: Update probability functions based on the new value functions

$$p_{it}(d_{it} = j) = \sum_{q=1}^{Q} \pi_{i,q} \cdot \frac{e^{v_{ijtq}(s_{it})}}{\sum_{h\epsilon D_{it}} e^{v_{ihtq}(s_{it})}} \tag{52}$$

Step 4: Update Posteriors of class probability

The posterior probability of respondent *i* in class *q* is calculated according to equation (53):

$$\pi_{iq} = \frac{\pi_q \left[\prod_{t=1}^{T_i} (\Pr(d_{it} = j | class\ q))^{I(d_{it}=j)}\right]}{\sum_{q=1}^{Q} \pi_q \left[\prod_{t=1}^{T_i} (\Pr(d_{it} = j | class\ q))^{I(d_{it}=j)}\right]} \tag{53}$$

Step 5: Update the population probabilities

The population probability of class *q* can be updated according to equation (54):

$$\pi_q = \frac{\sum_{i=1}^{N} \pi_{i,q}}{N} \tag{54}$$

Step 6: Maximization of the likelihood function

$$\theta = \underset{\theta}{\operatorname{argmax}} \sum_{i=1}^{N} \sum_{t=1}^{T_i} \sum_{q=1}^{Q} \pi_{iq} \cdot \ln \left[\frac{e^{v_{ijt}(s_{it},q)}}{\sum_{h \epsilon D_{it}} e^{v_{iht}(s_{it},q)}} \right]^{I(d_{it}=j)} \tag{55}$$

Step 7: Repeat step 2- step 6 until all the parameters converge.

Step 8: Procedures to ensure robustness

The standard errors based on the Hessian matrix of maximization function (equation 35) are biased downwards because the value functions are treated as known data in the maximization, but in fact they are calculated based on the values of the parameters *(30)*. Therefore, for the DDCMs used in this study, we used bootstrap with 250 simulated samples to calculate the standard errors. Each simulated sample is obtained by randomly selecting respondents from the dataset with replacement and the standard error of each parameter is the standard deviation of the sampling distribution.

When the optimization algorithm does not guarantee the global optimum, it is important to repeat the estimation steps with varied starting values and choose the one with the highest maximum likelihood.

5 Survey & Data for Home-Based Trip Tours

5.1 Survey design for home-based tours

This survey consisted of two parts: (1) a questionnaire on socio-demographic information and vehicle ownership; and (2) a travel day simulation section where the respondents were presented with travel days characterized by distance, charging opportunities and characteristics of charging opportunities such as charging price, level and availability of chargers. The scenarios of the travel day simulations are tailored to the respondents according the initial answers on the vehicle specification and socio-demographic information.

5.1.1 Background information

All the respondents of this survey were electric vehicle owners. The questionnaire asked them to report the following information: age, gender, education, household income, household size, home ZIP code, and the specific information of their vehicles in the household: the make, model, and year. For each of their electric vehicles, respondents were also asked for the maximum and minimum electric range on a full charge, in summer and in winter. Since this survey was conducted in summer, the average value of maximum summer range (r_{max}) and minimum summer range (r_{min}) is denoted as reported range ($r_{reported}$), which was used to assign the choice experiments to the respondents.

$$r_{reported} = \frac{1}{2}(r_{min} + r_{max}) \tag{56}$$

5.1.2 Travel day simulation

Each survey respondent was presented with eight scenarios featuring a tour characterized by the following variables: gasoline price, planned travel distances, planned stops, the dwell time at the planned stops, and the characteristics of the charging opportunities at the planned stops (including charging price, charging power, and the availability). The scenarios were pre-designed by the researchers and customized to the respondents according to the individuals' self-reported BEV ranges. For each scenario, the respondents were first asked to choose which vehicle to use, and if they chose a BEV, to make charging decisions at each planned stop. An interactive graphical interface and the experimental design of the scenarios are two key elements of the simulation design.

5.1.2.1 Display of the scenarios

In this section, each respondent was presented with 8 scenarios defined by me and customized according to the individuals' PEV ranges. Considering it is intractable to present the respondents with complex scenarios that are plausible to every one of them without collecting a large set of information on their daily travel, instead of asking the respondents to make decisions for themselves, we ask them to give advice for individuals that are very similar to them: with the same background information. Hsee and Weber *(74)* refer to this advisee as a "vivid other". Porman *(75)* found that when people are making decisions for others, they are more likely to "seek the ability to justify their choices", while when in their own decision-making process, "people usually exhibit higher degrees of attribute prominence". Therefore, at the beginning of the charging choice experiment part, the respondents will be first introduced to an imaginary individual - their vivid other (also called a digital avatar), as shown in FIGURE 6. The digital avatar is Jane if the respondent is female and John if the respondent is male. The digital avatars have similar socio-demographic information such as age, gender, income, and vehicle ownership.

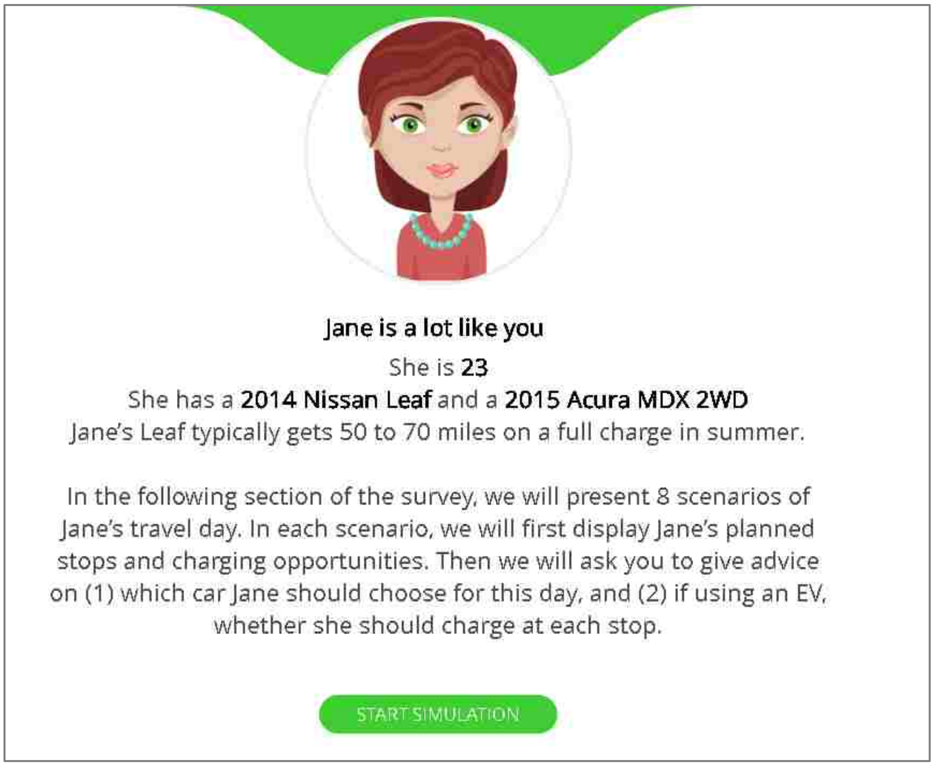


FIGURE 6 Introducing Jane

In each of the eight scenarios, the respondent was firstly presented with a specific home-based tour (Figure 7) and asked to recommend a specific vehicle for the tour (Figure 8). The choice set of vehicles was the list that the respondent had previously said they own. The relationship between the initial state of charge (100% in Figure 8) and the range available (60 miles) was based on the range reported by the respondent earlier in the questionnaire. If the respondent selected a BEV for the tour, they were then asked whether they would recommend charging at each stop with the tour progressed (Figures 9 – 11).

The presentation of information and solicitation of choices was designed to make the information tractable while reflecting the structure of the choice process in a real tour. The information in the graphical interface was displayed item by item using animation, which gives the respondents time to absorb the information. If the respondent chose to use a BEV for the presented tour, the survey tool stepped through stop by stop and asks the respondent to make charging decisions. As the tool stepped through the tour, additional information was revealed, namely the actual remaining range and whether there was a charger available upon arriving at each stop. In-use energy consumption on each individual trip was drawn from a distribution based on the respondent's reported maximum and minimum ranges. As such, the amount of range "consumed" on a given trip could be greater or less than the nominal length of that trip, and the respondent would not know for sure how much range would be consumed until the end of that trip. Similarly, the probability that at least one charger is available was displayed for all the following stations, but whether a plug was available for use at a given stop was not revealed until the respondent arrived at that stop in the simulation; plug availability was based on the probabilities shown to the respondents beforehand (e.g. "available on 3 out of 5 visits").

It was entirely possible in some cases for respondents to fail to complete a tour according to their original plan on this survey instrument. For example, if they selected a BEV for a tour with a trip length exceeding their BEV's range, or failed to charge when necessary, they received a message saying "There isn't enough electric range to get to the next charging station! Please continue with the next scenario!" and were taken to the next scenario. Not being able to finish a home-based trip tour according to the original plan could mean several possibilities: (1) Jane/Joe has to make a mid-trip stop specially for refueling the vehicle; (2) Jane/Joe can adjust their driving behavior to conserve energy to make it to the next stop; (3) Jane/Joe is stranded in the middle of the trip; etc. Without specifying this in the survey tool, we leave it to the respondents to interpret the situation and during the modeling process, we evaluate the negative utility of having to deviate from the original plan instead of being stranded in the middle of a trip.

Interested readers are welcomed to check out a demonstration of the SP scenario at this link: https://www.youtube.com/watch?v=JmALZPjUQ9U.

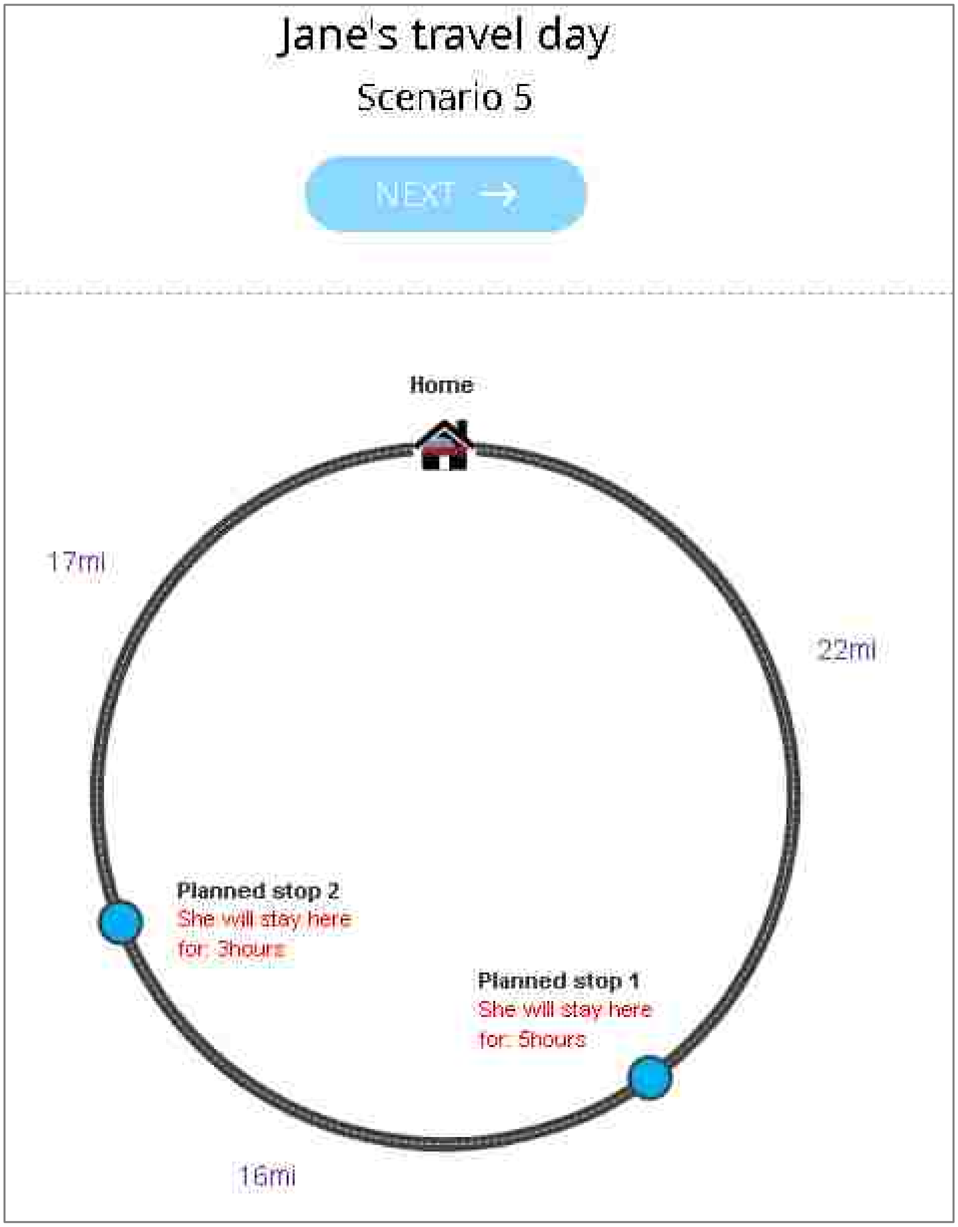


FIGURE 7 Screenshot 1 of the survey tool: Display of Jane’s travel day

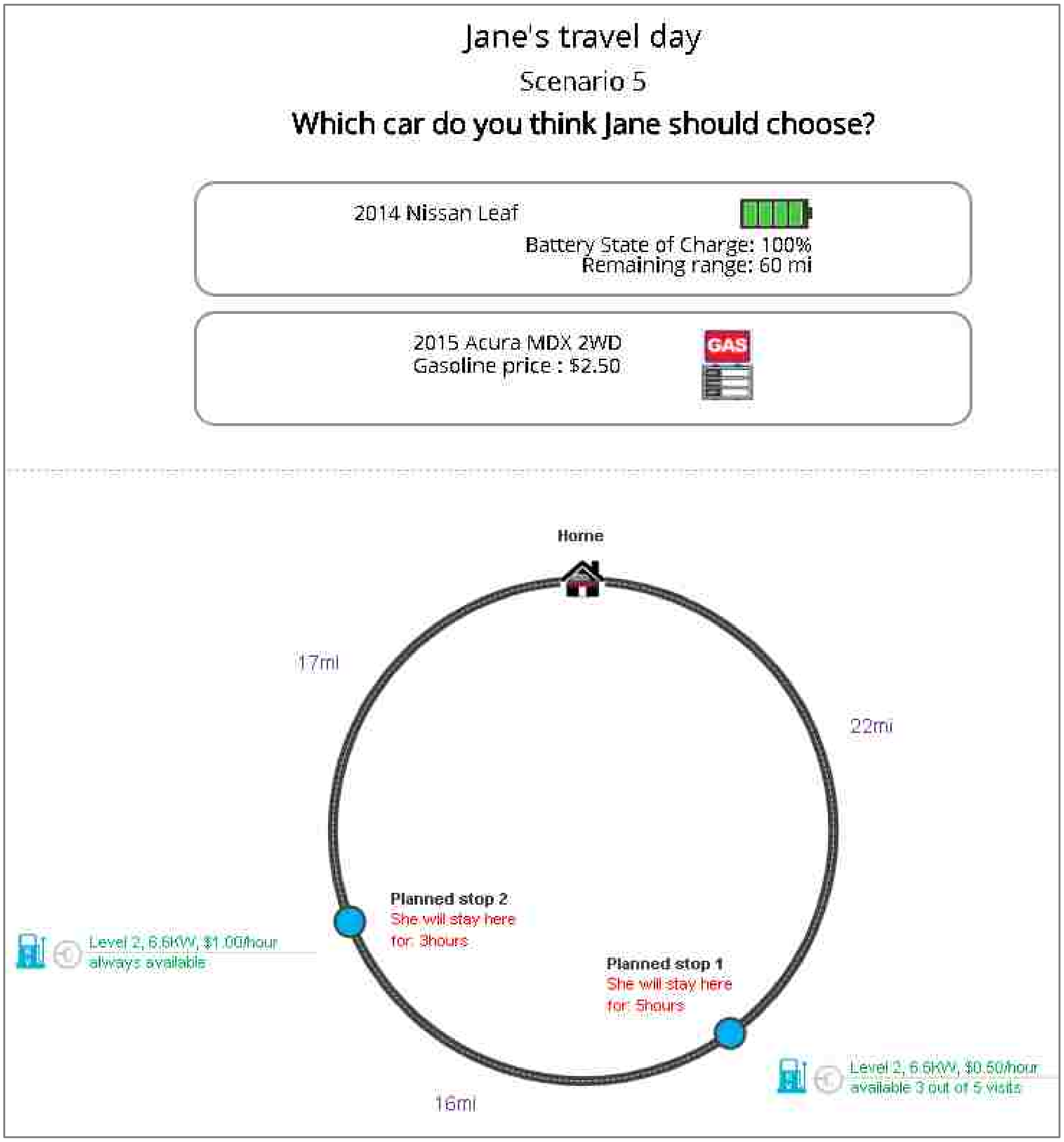


FIGURE 8 Screenshot 2 of the survey tool: vehicle choice for the travel day

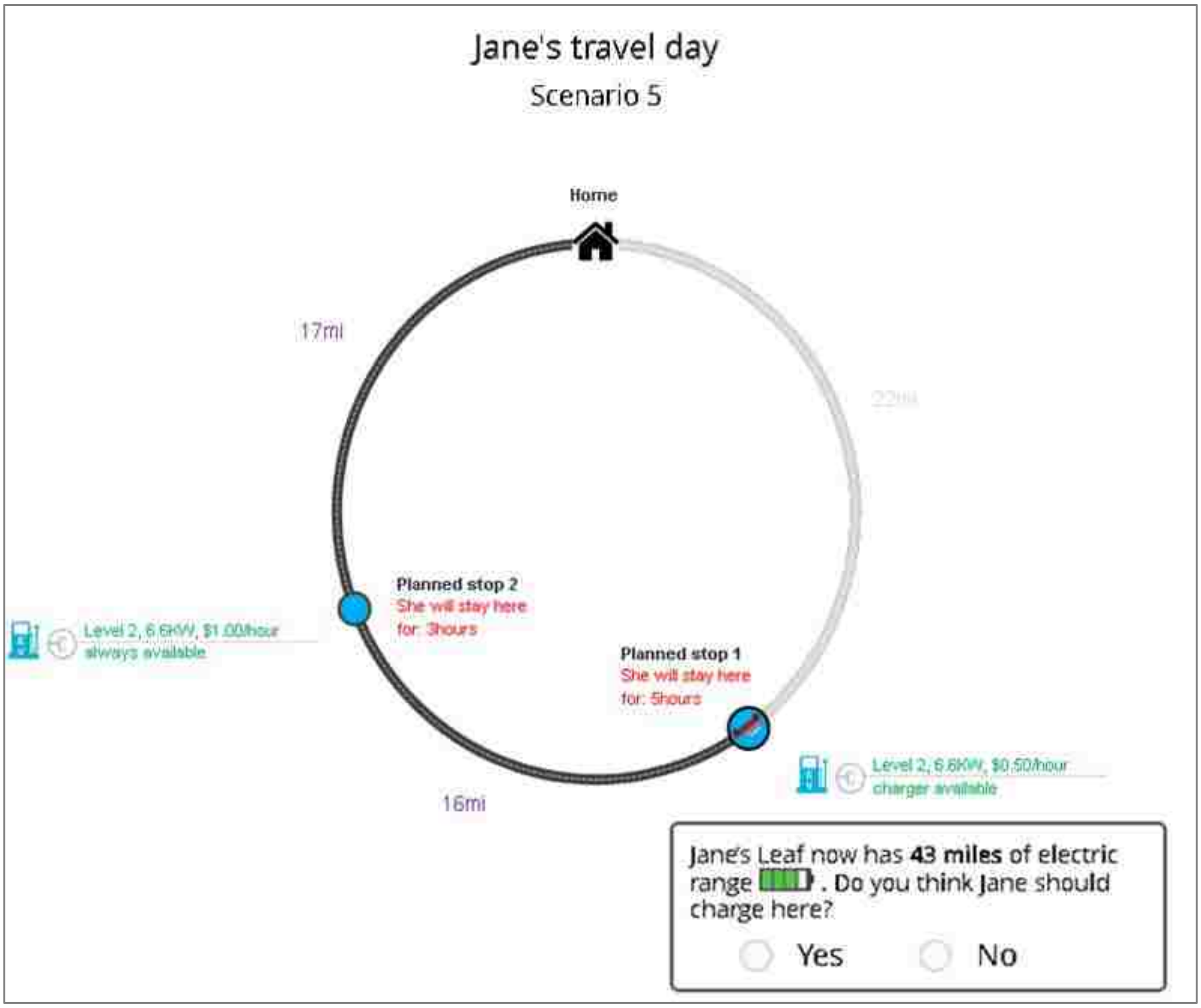


FIGURE 9 Screenshot 3 of the survey tool: Charging decision of the first stop

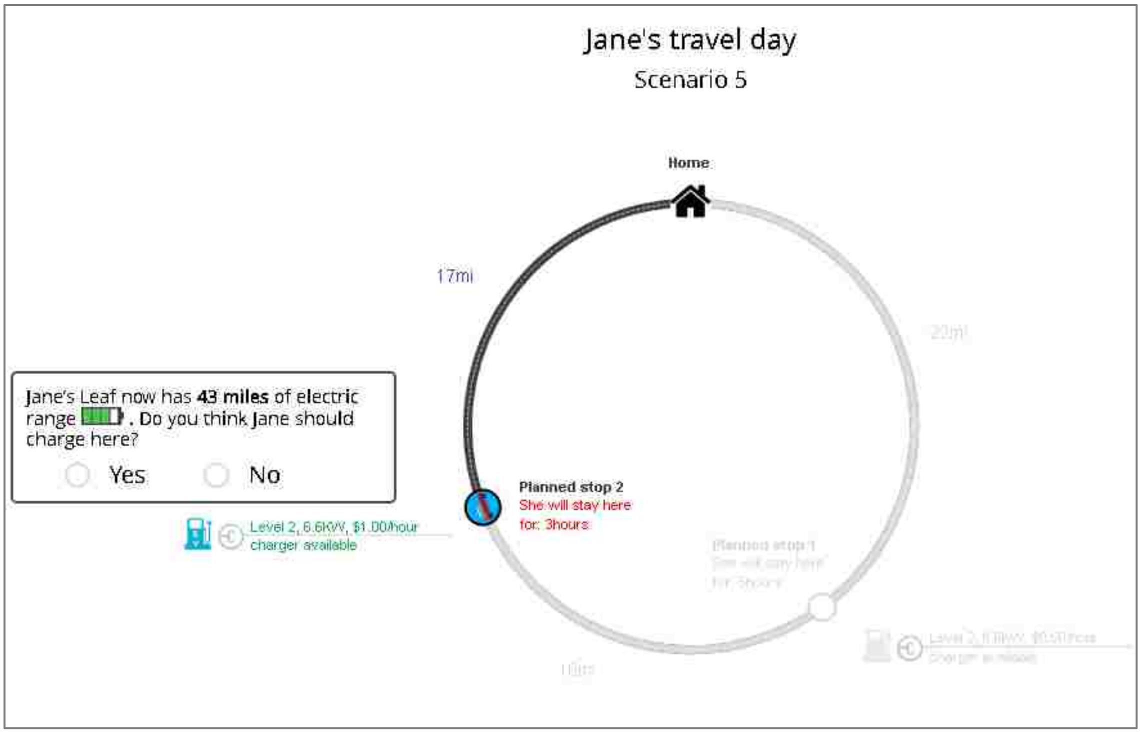


FIGURE 10 Screenshot 4 of the survey tool: Charging decision of the second stop

FIGURE 11 Screenshot 5 of the survey tool: Indicate Jane made it home

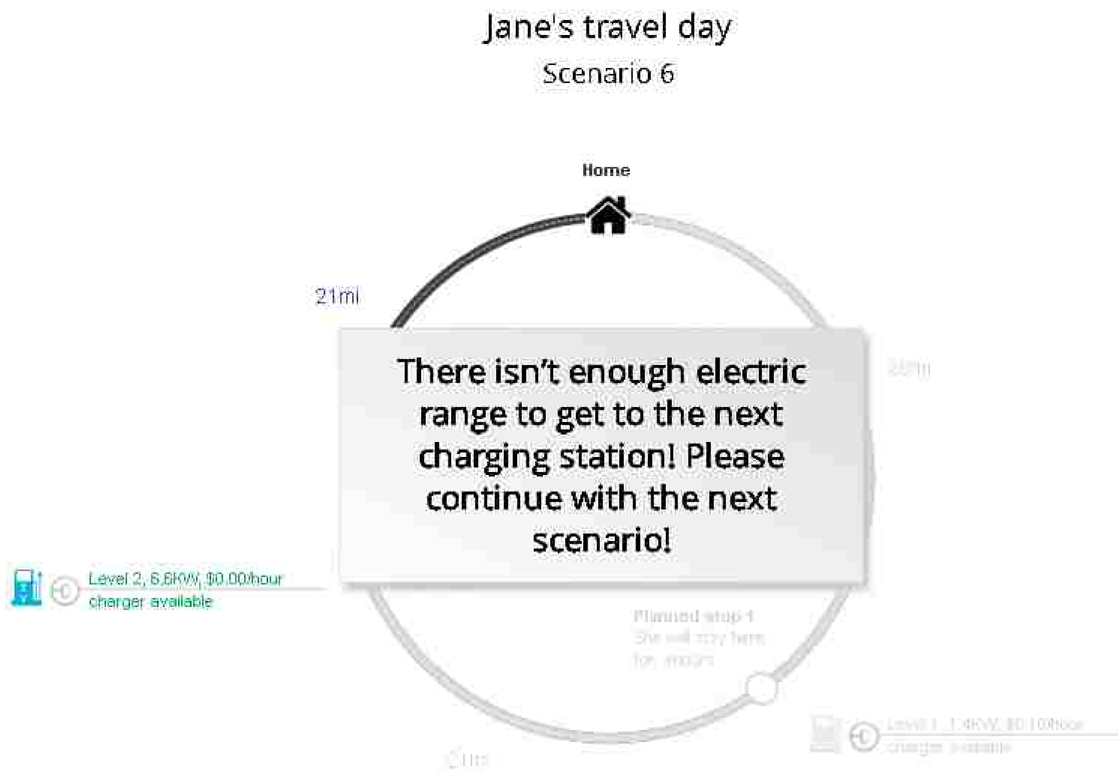


FIGURE 12 Screenshot 6 of the survey tool: When there is not enough electric range to get to the next charging station or home

When the remaining range of the vehicle is not enough for getting to the next station or home, the respondents are told that "There is not enough electric range to get to the next charging station" and then continue with the next scenario.

5.1.2.2 Design of the scenarios

(1) D-optimal design

The first step of the experiment design is to identify the factors that can influence the dependent variables interested. A factor is an experimentally adjustable variable. In this study, the factors include the gasoline price, the planned distance of the travel day, the charging price, charging power and availability of the chargers. Factors have levels, e.g. the levels of the gasoline price could be \$2.5, \$3.5 and \$4.5. The details of the factors are shown in the following subsections of this chapter.

In an experiment design, each factor usually has multiple levels. A treatment is made up of a combination of factors. A full factorial design with *r* replications consists of *N* factors: $x_n \in (x_1, \dots, x_N)$. If the number of levels of variable x_n is l_n, then the total number of treatments of the full factorial design with *r* replications is: $\prod_{i=1}^{N} l_n$. Compared to the simple method of changing one variable at a time, factorial design allows one to detect interactions between treatment factors and if there is no interaction, it allows one to efficiently use all experimental units to assess the effects of each individual factor *(76)*.

If there are many factors with multiple levels, the size of an experiment with factorial design grows rapidly. The practical solution is to include a proportion instead of all of the full factorial design scenarios. The goal of an experiment design is to identify the sources of variation of the vehicle choice decisions and charging decisions, which enables efficient estimates of the parameters for the later estimation of the models *(76)*. The efficiency of the estimates can be measured by the asymptotic variance-covariance matrix: the square roots of the diagonal values of the variance-covariance matrix are the standard errors of the estimates. The inverse of the Fisher's information matrix generates the estimators of the asymptotic variances, as shown by equation (57). Fisher information matrix is generated according to the second derivatives of the log-likelihood ($l(\theta)$).

$$Var(\hat{\theta}_{ML}) = \left[I(\hat{\theta}_{ML})\right]^{-1} \tag{57}$$

$$I(\theta) = -\frac{\partial^2}{\partial\theta_i \partial\theta_j} l(\theta) \tag{58}$$

D-optimal design uses the optimality criterion that results in minimizing the generalized variances of the parameters estimated by maximizing the determinant of the information matrix *(77)*. Fedorov *(76)* exchange algorithm offers the optimization algorithm to select the best subset of the full factorial scenarios. The basic idea of Fedorov exchange algorithm is to find the subset of scenarios that has the highest determinant of the population Fisher's information matrix. The algorithm starts with an initial optimal design, then for each iteration, choose a better one (higher determinant) from the candidate poll of the experiments. The goal of Fedorov exchange algorithm is to generate a list of experiments that will increase the determinant of the Fisher's information matrix then when the determinant stops increasing according to a pre-determined threshold, the design is chosen as the final list of experiments.

For this study, the experiment scenarios are generated based on the function optFederov in the R package AlgDesign *(78)*. The function takes the input of the full list of factorial experiments and the number of trials that need to be generated (nTrials). It generates a fixed number of scenarios (nTrials) that have the highest determinant of the Fisher's information matrix.

(2) Experimental design for home-based tour

Eight scenarios are customized to the respondents according to the range of the PEV they own: the planned distances of home-based tour scenarios are around the range of the PEVs, as shown in TABLE 3. When they have multiple PEVs, the scenarios are tailored according to the PEV with the largest electric range. In each scenario, the respondents choose from their own cars to drive for the travel day. When the respondent only owns PEVs, the choice of "rent a car" is included into the choice set. The survey respondents were instructed to assume other factors (such as the cost and availability of parking) are affected by the decision of whether or not to charge. The attributes and levels characterizing the choice situations are listed in TABLE 3. The scenarios generated from the design are randomly assigned to the respondents based on their range group.

TABLE 3 Attributes and Their Levels of the Experiments for home-based trips

Attributes	Variable	Description	Attribute levels
Charging price($/h)	$p_{charging}$	The recharging price at the station	Free, $0.50/h; $1.00/h; $1.50/h; $2.00/h; $5.00/h
Charging power(kW)	$Power$	The maximum charging speed at the station	1.9kW; 6.6kW
Dwell time(h)	t_{dwell}	The time duration for which the respondent will stay at this station	0.25h; 0.50h; 1h; 2h; 4h; 8h
Planned distance of the travel day (mi)	L	The distance of the whole travel day	Reported range - 40mi; Reported range - 20mi; Reported range - 10mi; Reported range - 5mi; Reported range; Reported range + 5mi; Reported range + 10mi; Reported range + 20mi; Reported range + 40mi.
Gasoline price ($)	p_{gas}	Gasoline price	$2.50/gallon; $3.00/gallon; $3.50/gallon; $4.00/gallon; $4.50/gallon
Availability	A%	The chance that there is a plug available at a charging station	20%, available 1 out of 5 visits; 40%, available 2 out of 5 visits; 60%, available 3 out of 5 visits; 80%, available 4 out of 5 visits; 100%, always available.

For each scenario, at the beginning of the travel day, the state of charge (SOC) is assumed to be 100%, which is justified because most people charge their EVs whenever they get home.

Remaining range refers to the amount of electric range left for the PEV when respondent *i* arrives at one station *t*. The survey tool measures the remaining range at each station by estimating the energy consumption of each trip based on the specific information of the vehicle reported by the respondents. In real life, the range consumed of a fixed distance of driving is uncertain due to driving habits, traffic condition and weather conditions, etc. This uncertainty of the range consumed ($r_{consumed}$) for distance l is considered by generating a random number according to the maximum and minimum range reported by the respondents, see equation (34).

$$r_{consumed} = l + l * \alpha * \rho_i \tag{59}$$

Random variable α is generated from a triangular distribution with maximum value of 1, minimum value of -1 and median value as 0. ρ_i is defined as the uncertainty factor based on the reported maximum (r_{max}) and minimum summer (r_{min}) full range, as shown by equation (35).

$$\rho_i = \frac{r_{max} - r_{min}}{r_{reported}} \tag{60}$$

When the respondents do not own any ICEV, the option “rent a car” is presented to for the scenarios. The rental cost (c_{rental}) is a randomly generated value from $30 to $100 from a uniform distribution.

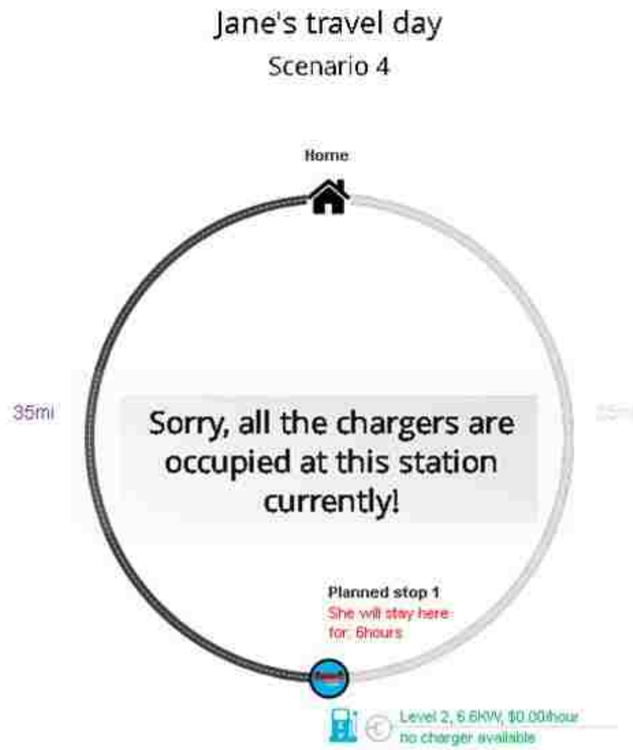


FIGURE 13 Screenshot 7 of the survey tool: No charger available at the current station

To account for the uncertainty of the availability of chargers at different stops, Bernoulli random numbers are generated according to the variable “Availability (A%)” in the experiment design. When there is no charger available according to the Bernoulli random number, the respondents are told all the chargers are occupied at this station currently, and then precedes to the next station.

5.2 Data for home-based tours

The survey on home-based tours was conducted during June to July 2016. The respondents were recruited mostly through the Electric Auto Association (EAA) and Plug-in America, whose members are usually enthusiastic about electric vehicle technology and related research, and willing to participate into the survey without any extrinsic incentives. There were in total 1014 PEV respondents, 916 of whom completed the full survey. The descriptive analysis of the sample is shown in Table 4. 81% of the respondents were male. The reported household income among the respondents is higher than average, with around 44% of respondents reporting a household income over $140,000. More than 50% of the survey respondents have at least Bachelor's degree. 878 of the respondents have BEVs and 276 own PHEVs. More than 54% of the respondents have BEV and ICEV, and 21% of the respondents just have BEV alone in their households, which shows that most BEV owners keep the choice of using an range unlimited alternative.

TABLE 4 Description of the Sample

Variable	Category	Sample Frequency	Sample Percentage	Variable	Category	Sample Frequency	Sample Percentage
Age	18-24	36	3%	Household Income	<$19,999	71	7%
	25-44	277	26%		$20,000-$39,999	72	7%
	45-55	314	29%		$40,000-$59,999	96	9%
	55-65	283	26%		$60,000-$79,999	77	7%
	65+	164	15%		$80,000-$99,999	109	10%
	Prefer not to answer	0	0%		$100,000-$119,999	93	9%
Gender	Male	867	81%		$120,000-$139,999	70	7%
	Female	190	18%		$140,000-$159,999	54	5%
	Prefer not to answer	17	2%		$160,000-$179,999	231	22%
Education	Less than High School	39	4%		$180,000-$199,999	45	4%
	High School / GED	35	3%		>$200,000	141	13%
	Some College	120	11%	Vehicle Ownership	BEV only	219	21%
	2-Year College Degree (Associates)	75	7%		PHEV only	68	6%
	4-Year College Degree (BA, BS)	410	38%		BEV & ICEV	570	54%
	Master's Degree	264	25%		BEV &PHEV	38	4%
	Doctoral Degree	126	12%		PHEV & ICEV	119	11%
	Professional Degree (MD, JD)	5	0%		BEV, PHEV & ICEV	51	5%

The distributions of the ranges of BEVs and PHEVs of the respondents are shown in Figure 14 and Figure 15 respectively. The most common BEV models are Nissan Leaf with rated range from 60 miles to 80 miles and Tesla models with range around 250 miles. The most common PHEV model among the respondents is Chevrolet Volt with range around 40 miles.

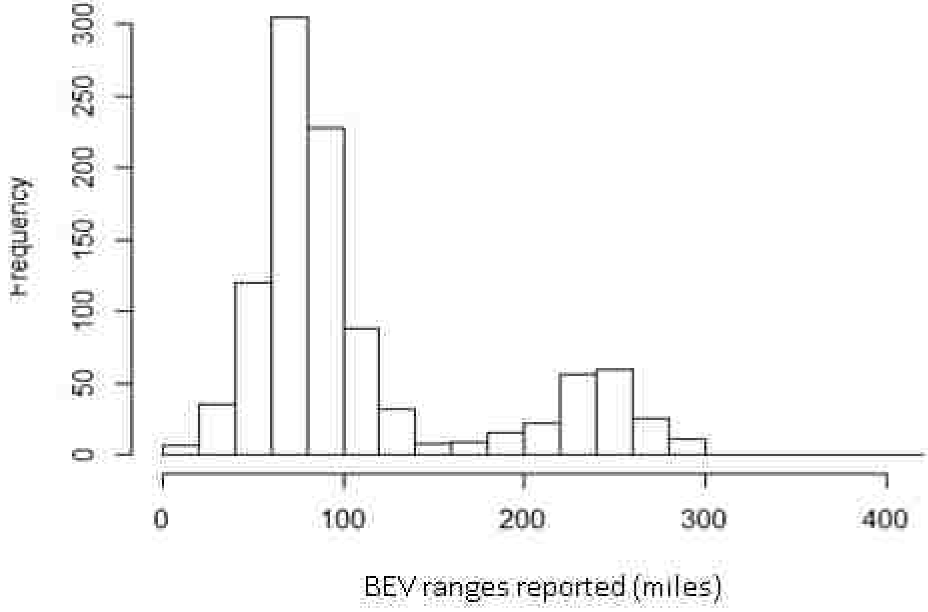


Figure 14: The distribution of ranges of the BEVs reported by the respondents

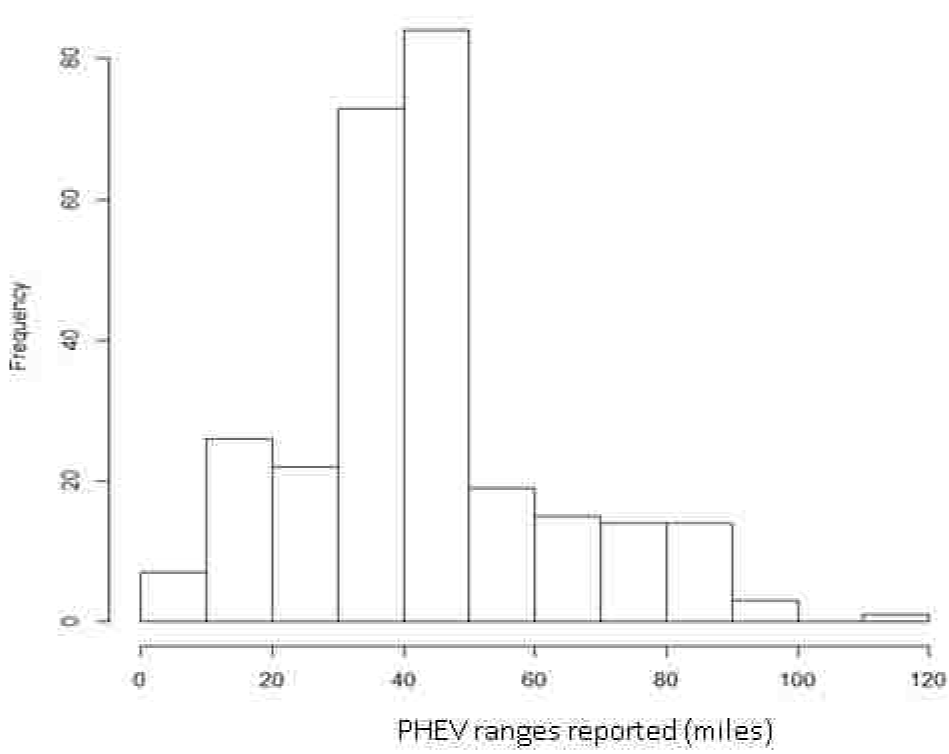


Figure 15: The distribution of ranges of the PHEVs reported by the respondents

Define the excess range as the value of reported range subtracted by the planned distance of the travel day. The distribution of the excess range is shown in the Figure 16.

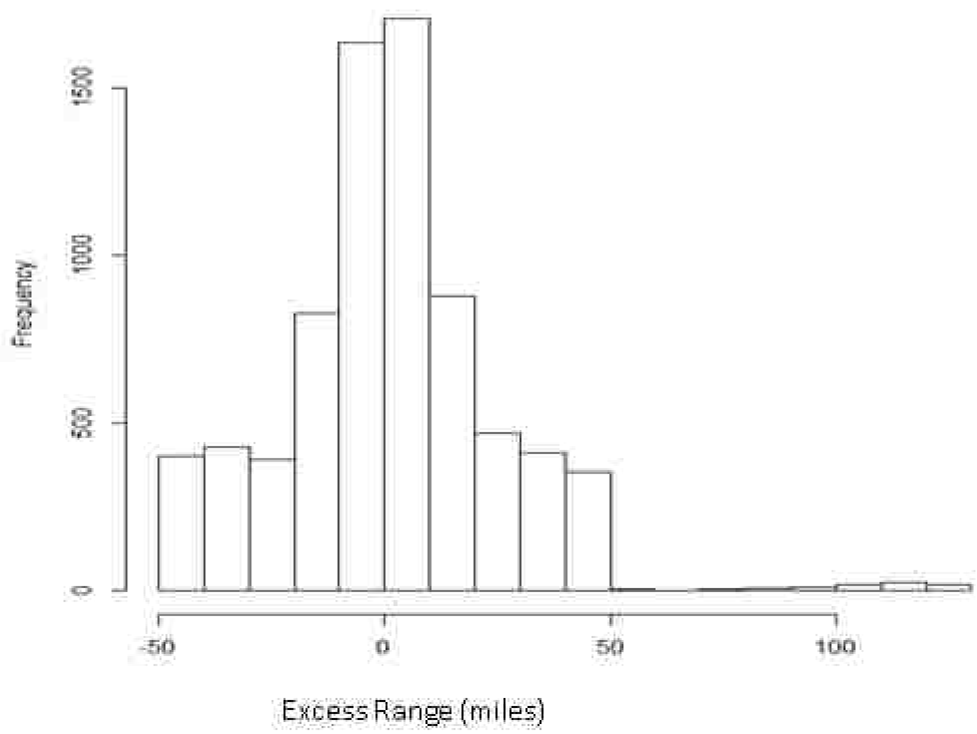


Figure 16: The distribution of the excess range

6 Analyses of Home-Based Trip Tours

6.1 Analysis 1: Modeling vehicle choices and charging behavior of BEV owners jointly using DDCMs

Summary

The net impacts of battery electric vehicles (BEVs) – including upstream emissions from electricity generation and the impact these vehicles place on the electricity grid – depend on both the amount of travel conducted by BEV and the times and locations that those BEVs are charged. It is therefore important to understand how BEV owners make decisions on which vehicle to use for a tour and when to charge. This paper presents a novel dynamic discrete choice model (DDCM) framework that jointly models the vehicle choice of BEV owners for a home-based travel tour and subsequent charging choices along the tour. The framework explicitly accounts for the stochastic nature of these decisions: earlier choices on vehicle use and charging influence the utility of the future choices; the expectation of the future options influences those earlier decisions; and choices are made under uncertainty about actual energy consumption and availability of chargers. This is a marked departure from prior work on charging behavior modeling, which has largely treated the sequential choices as independent. The model is fitted with data collected through an interactive web-based stated preference survey of BEV users. The final model identifies two decision-making patterns among BEV users: for Class 1, the respondents are willing to pay $10 in charging costs to avoid having to deviate from a planned tour (e.g, to make a mid-trip stop specially for refueling, slowing down to reduce energy consumption). Respondents in Class 2 are willing to pay $24. These results indicate for home-based trip tours, range anxiety – the fear of being stranded in the middle of a trip – is not a huge issue for BEV owners and encouraging BEV adoption is the key of infrastructure development.

This analysis was submitted to 2018 TRB annual meeting for presentation and the long abstract of it was included in the conference compendium.

6.1.1 Introduction

BEVs offer the potential to reduce gasoline consumption and local air pollution by replacing gasoline with electricity. The market share of BEVs has increased rapidly since the technology's mainstream debut in 2011, but range limitation remains a significant disadvantage. The BEV models available in the market offer a limited range compared with their gasoline counterparts; most BEV models have range significantly smaller than 300 miles. Range anxiety – BEV drivers' fear of being stranded in the middle of a trip before reaching the destination or a suitable charging point – is still an important barrier to the broader adoption of BEVs even though it can be mitigated with the increase of driving experience.

Public charging infrastructure, which helps increasing the operating radius of BEVs, is proved to be an important enabler of BEV adoption. The U.S. Department of Energy and a lot of state authorities have engaged a lot of effort on expanding public electric vehicle charging network. Understanding the charging decisions at the public charging stations and usage behavior of BEV owners is important for several reasons. First, the mix of generation sources supplied to the electric grid varies over time and space and depends on the time-varying electricity demand, so charging a BEV at different times or locations may result in different net emissions. Second, the degree of stress that BEVs place on electricity grid depends on whether they exacerbate existing demand peaks or fill in periods of lower demand. Third, the amount of petroleum demand displaced by a BEV and the corresponding emission and energy security effects depend on the number and length of trips for which the BEV displaces ICEV travel.

This paper focuses on two key types of decisions that a BEV owner must make for any given home-based trip tour with planned stops, as illustrated in Figure 1. First, they must decide whether to use their BEV or an alternative vehicle for the tour (stage 1 decision). If they elect to use their BEV, they must choose whether to charge the BEV at each opportunity as the travel day progresses (stage 2 decisions). The decisions of the two stages are inseparable intuitively: the vehicle choice influences whether they will need to charger their vehicles later, and the expectation of future charging needs and opportunities influences the vehicle choice. The charging decisions at the stops in the travel day are similarly connected: the charging decision at one earlier stop influences whether the vehicle needs to be charged at the following stops, and the expectation of future charging opportunities influences the charging decision at the current stop. This dependence between earlier decisions and later ones can be expressed in terms of utility theory: a decision at an earlier stop may affect not only the current utility but also the expected utility of the following stops; the value of the expected future utility may affect the decision at the current stop. The modeling method we use for this problem, dynamic discrete choice model (DDCM), intuitively can better describe these decisions based on intertemporal payoffs than traditional static discrete choice models.

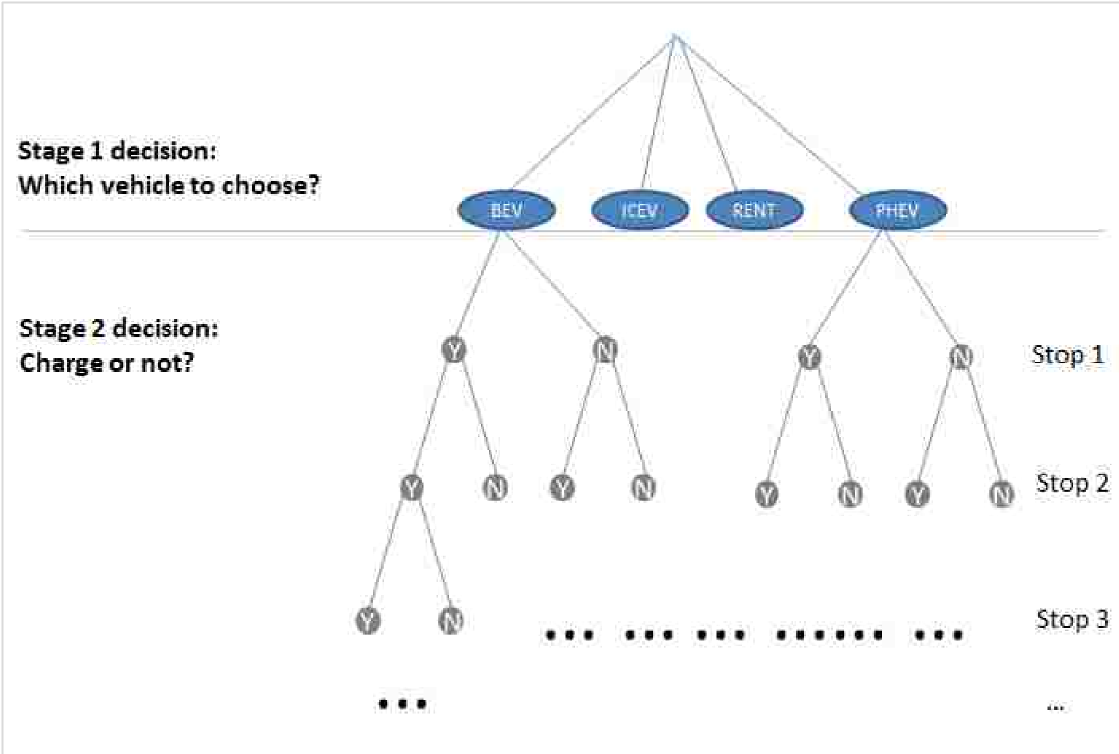


Figure 16: Decision process of BEV users

The analysis of this paper is based on data from a web-based interactive survey in which respondents were first asked about their socio-demographic information and the specific vehicles they own, then presented with home-based trip tour scenarios characterized by planned distances and stops, gasoline prices, and the characteristics of charging opportunities at the planned stops, including prices, charging levels (i.e. power), and reliability of plug availability. In each scenario, the respondents were asked whether they would choose to use their BEV for this travel day based on the charging opportunities and the gasoline price, then if so, whether to charge their BEV at each stop as the day progresses. Actual energy consumption and plug availability were revealed as the simulated tour proceeded.

6.1.2 DDCM model specification

6.1.2.1 Input Data of DDCM

The model incorporates the two decision stages in every scenario: vehicle choice (the stage 1 model) and then charging choices (the stage 2 model). The data can be expressed as equation (5), in which *i* denotes the respondents and *N* is the total number of respondents. The decision period *t* of individual *i* in this case represents the stops with "0" being the origin of the trip tour (home), "1" being the first stop, and T_i being the destination of the trip tour (also home). d_{it} is the decision of respondent *i* at decision period *t* (vehicle choice or charging decision at stop *i*).

$$Data = \{d_{it}, s_{it}, i{:}\, 1,2 \ldots N; t{:}\, 0,1, \ldots . T_i\} \tag{61}$$

At every period *t*, each individual chooses among *J* mutually exclusive alternatives to maximize the net utility, as in: $d_{it} = \{j{:}\, j \epsilon D_{it} = \{1,2, . . J\}\}$. The expression $d_{it} = j$ means that the respondent *i* chooses alternative *j* at period *t*. Denote the choice indicator I as equation (6):

$$\mathrm{I}(d_{it} = \mathrm{j}) = \begin{cases} 1, & if\ d_{it} = \mathrm{j} \\ 0, & if\ d_{it} \neq \mathrm{j} \end{cases} \tag{62}$$

For the stage 1 model, the choice set includes these three possible modes: BEV, ICEV, and RENT. The choice set is different for each respondent, depending on their self-reported vehicle holdings. For the stage 2 model, the choice set is the binary choice of charging or not. Denote $d_{it} = 1$ if the respondent chooses to charge, $d_{it} = 0$ if they choose not to charge.

6.1.2.2 State Variables

State variables refer to factors that can influence the value of utility, and thus influence the choices. The vector of state variables of decision period *t* of respondent *i* is denoted as s_{it}. The model here is specified as a DDCM of a forward-looking economic agent with six state variables. Four state variables are deterministic values of the characteristics of the future charging opportunities, including charging price, gasoline price, charging power, and dwell time at each stop. Two of the six state variables are non-deterministic, including the remaining range and the availability of the chargers. Conditional on the remaining range and the decision at the current stop *t*, the remaining range at the next stop *t+1* is can be uncertain due to the uncertainty of energy consumption for the fixed distance between stop *t* and *t+1*. This nuance can be captured by the transition function, $F(s_{i,t+1}|s_{it}, d_{it})$, the cumulative distribution function of state variable $s_{i,t+1}$ conditional on the current state $\mathrm{s_{it}}$ and the decision at the current stop d_{it}. The transition functions model the individuals' beliefs about the remaining range and the availability of chargers of the future stations. The following three sub-sections will explain the state variables and their transition functions in detail.

(1) State variable: remaining range (rr_{it})

The remaining range upon arriving at stop *t+1* ($rr_{i,t+1}$) equals the remaining range upon arriving at stop *t* (rr_{it}) plus the range obtained at the stop *t* ($r_{obtained_{it}}$), minus the range consumed on the way from stop *t* to stop *t+1* ($r_{consumed_{it}}$), as expressed by the following equation:

$$rr_{i,t+1} = rr_{i,t} + r_{obtained_{i,t}} - r_{consumed_{i,t}} \tag{63}$$

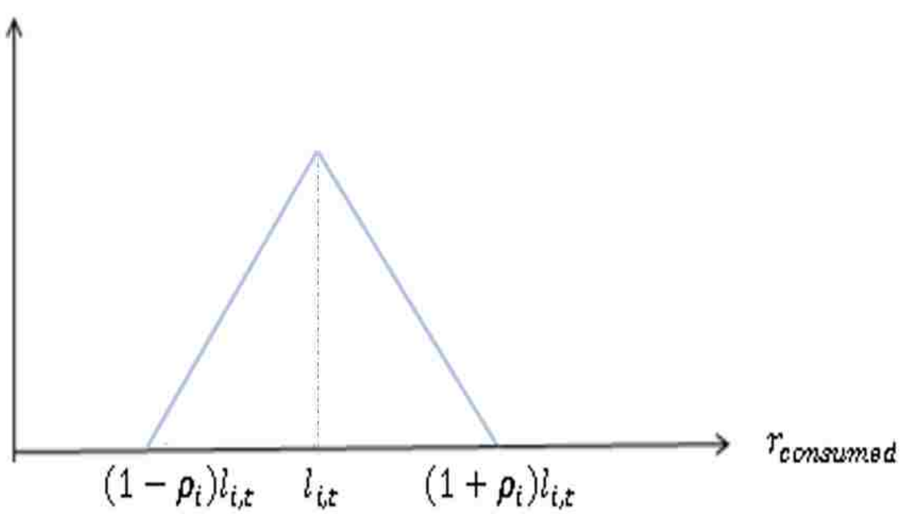
Range obtained ($r_{obtained}$) is the maximum electric range increase the BEV can get during the specified dwell time if the owner chooses to charge. It is zero if the owner chooses not to charge. If the dwell time (t_{dwell}) is sufficient for the BEV to reach a full charge (r_{full}), the range obtained is the difference between the full range and the remaining range ($r_{remaining}$).

Otherwise, the range obtained depends on the charging power ($Power$) and dwell time (t_{dwell}), see equation (64).

$$r_{obtained_{i,t}} = \begin{cases} Min\left\{\frac{Power*t_{dwell}}{ECR}, \quad r_{full} - rr_{i,t}\right\}, if\ d_{it} = 1 \\ 0, \qquad\qquad\qquad\qquad\qquad\quad if\ d_{it} = 0 \end{cases} \tag{64}$$

(ECR: Average electricity consumption rate in kWh / mile)

The range consumed ($r_{consumed_{i,t}}$) for a fixed distance is uncertain due to factors such as road and traffic conditions, which create variation in actual per-mile energy consumption. Variability in range consumed leads to uncertainty of the remaining range upon arriving at subsequent charging stations. The distribution $g(r_{consumed_{i,t}}|l_{i,t})$ models the BEV users' belief of range consumed for driving the distance from station *t* to station t+1: $l_{i,t}$. The triangular distribution density can be shown in the following graph:



Density of $g(r_{consumed_{i,t}}|l_{i,t})$

According to equations (63), the only uncertain component of the $rr_{i,t+1}$ is range consumed $r_{consumed_{it}}$. Thus, the density function of the state variable remaining range $rr_{i,t+1}$ is also a triangular distribution.

The probability density function $g(r_{consumed_{i,t}} | l_{i,t})$ can then be expressed as:

$$g\left(r_{consumed_{i,t}} \middle| l_{i,t}, \rho_i\right) = \begin{cases} 0, & r_{consumed_{i,t}} < (1-\rho_i) l_{i,t} \\ \dfrac{[r_{consumed_{i,t}} - l_{i,t}(1-\rho_i)]}{\rho_i{}^2 l_{i,t}{}^2}, & (1-\rho_i) l_{i,t} < r_{consumed_{i,t}} < l_{i,t} \\ \dfrac{1}{\rho_i l_{i,t}}, & r_{consumed_{i,t}} = l_{i,t} \\ \dfrac{2[l_{i,t}(1+\rho_i) - r_{consumed_{i,t}}]}{\rho_i{}^2 l_{i,t}{}^2}, & l_{i,t} < r_{consumed_{i,t}} < l_{i,t}(1+\rho_i) \\ 0, & r_{consumed_{i,t}} > (1+\rho_i) l_{i,t} \end{cases} \tag{65}$$

According to equations (63), the only uncertain component of the $rr_{i,t+1}$ is range consumed $r_{consumed_{i,t}}$. Therefore, the density function of the state variable remaining range $rr_{i,t+1}$ is also a triangular distribution with the density function as shown by equation (65):

$$f\left(rr_{i,t+1} \middle| \mathrm{d_{i,t}}, \mathrm{s_{i,t}}, l_{i,t}, \rho_i\right) =$$

$$\begin{cases} 0, & rr_{t+1} < rr_t + r_o - l(1+\rho_i) \\ \dfrac{[rr_{t+1} - rr_t - r_o + l(1+\rho_i)]}{\rho_i{}^2 l^2}, & rr_t + r_o - l(1+\rho_i) < rr_{t+1} < rr_t + r_o - l \\ \dfrac{1}{\rho_i l}, & rr_{t+1} = rr_t + r_o - l \\ \dfrac{[rr_t + r_o - l(1-\rho_i) - rr_{t+1}]}{\rho_i{}^2 l^2}, & rr_t + r_o - l < rr_{t+1} < rr_t + r_o - l(1-\rho_i) \\ 0, & rr_{t+1} > rr_t + r_o - l(1-\rho_i) \end{cases} \tag{65}$$

(Note that some subscripts are deleted to simplify the equation. rr_{t+1} is $rr_{i,t+1}$; rr_t is $rr_{i,t}$; r_o is $r_{obtained_{i,t}}$; l is $l_{i,t}$.)

(2) State variable: Charger availability ($a_{i,t}$)

The availability variable has five levels in the scenarios *A%= {20%, 40%, 60%, 80%, 100%}*. The distribution of the availability of the chargers at stop *t* for respondent *i* is assumed to follow a Bernoulli distribution with the success probability of $A\%_{it}$. So the probability mass function for availability at stop *t* is:

$$k(a_{i,t}) = \begin{cases} A\%_{it}, & a_{it} = 1 \\ 1 - A\%_{it}, & a_{it} = 0 \end{cases} \tag{66}$$

The availability of chargers between the stations is assumed to be independent, which means the value of $a_{i,t+1}$ is independent of a_{it}. Then the transition function of availability could be expressed as equation (67).

$$k(a_{i,t+1}|a_{it}) = k(a_{i,t+1}) = \begin{cases} A\%_{i,t+1}, & a_{i,t+1} = 1 \\ 1 - A\%_{i,t+1}, & a_{i,t+1} = 0 \end{cases} \tag{67}$$

(3) Deterministic state variables

The four deterministic state variables are charging price, dwell time, gasoline price and charging power. They are used to derive the following variables nnstead being included directly in the utility functions,: a continuous variable on charging cost $c_{charging}$; a dummy variable called deviation (DEV) that represents whether the traveler can get to the next stop or has to deviate from the original tour plan ($DEV = 0$ when the agent can get to the next station with the remaining range and $DEV = 1$ when the agent needs to deviate from the plan and find charging stations other than those at planned stops on the tour).

The gasoline costs of the ICEVs ($gas\ cost_{i,icev}$) are also calculated according to the fuel economy of the car and the planned travel distance of the tour and are assumed to be deterministic in the present model.

Charging cost

Plug time (t_{plug}) is the time duration which the BEV stays plugged in to the charger. We assume that once a BEV is plugged in, it will remain plugged until it is fully charged, or it is time for the driver to depart. If the car cannot reach a full battery during the dwell time, plug time will be equal to the dwell time. Otherwise, plug time is equal to the time needed for the BEV to become fully charged. It is calculated as equation (68).

$$t_{plug_{it}} = Min\left\{t_{dwell_{it}}, \frac{(r_{reported} - rr_{it}) \times ECR}{Power}\right\} \tag{68}$$

Charging cost ($c_{charging_{it}}$) is calcualated according to the plug time:

$$c_{charging_{it}} = p_{charging} \times \ t_{plug_{it}} \tag{69}$$

Deviation (DEV)

DEV is a dummy variable showing whether the driver has to deviate from the original trip plan (e.g, make a mid-trip stop specially for refueling the vehicle) to get to the next planned stop with a charging opportunity. Note that not being able to reach the next planned stop with the remaining range does not necessarily mean the traveler will be stranded in the middle of the trip, but he/she has to deviate from the original travel plan, for example by finding chargers out of the planned stops or driving with a lower speed to conserve energy.

DEV can be calculated according to equation (70). This value varies according to the charging decision. If the respondents choose to charge, it is written as $\mathrm{DEV}_{\mathrm{charge,i,t}}$. If the respondents choose not to charge, it is written as $\mathrm{DEV}_{\mathrm{not\ charge,i,t}}$.

$$DEV_{it} = \begin{cases} 1, & if\ rr_{i,t+1} < 0 \\ 0, & if\ rr_{i,t+1} \geq 0 \end{cases} \tag{70}$$

Gasoline cost of ICEV

For the ICEVs, the gasoline cost is calculated according to the fuel economy (mpg) of the respondent's gasoline car, the gasoline price (p_{gas}) provided by the scenario, and the planned distance (L) of the travel day.

$$gas\ cost_{i,icev} = \frac{L}{mpg} * p_{gas} \tag{71}$$

6.1.2.3 Flow utility

The flow utilities of the two-stage decisons are defined separately.

Stage 1 model (vehicle choice):

The utility of ICEVs is defined as equation (72); for the choice of "rent a car", the coefficients of rental cost and gasoline cost are estimated, as shown in equation (73); for BEV, the alternative specific constant (ASC_{bev}) is estimated, as shown in equation (74).

$$u_{icev_i} = \theta_1 * gas\ cost_{i,icev} + \varepsilon_{icev_i} \tag{72}$$

$$u_{rent_i} = \theta_2 * C_{rental_i} + \theta_3 * L * p_{gas_i} + \varepsilon_{rent_i} \tag{73}$$

$$u_{bev_i} = ASC_{bev} + \varepsilon_{bev_i} \tag{74}$$

The flow utility of BEV at this stage only includes an alternative specific constant, which might appear odd to some readers. However, this is a reasonable specification because when the respondents decide whether to use their BEV for the travel day, they also consider the expected utility of charging at future stops, which will be reflected by the specification of the stage 2 model. Since gasoline and rental costs are treated as deterministic, they are treated as though they are all incurred at the time of the first stage decision.

Stage 2 model (charging choices):

For the charging choices of BEV drivers, the coefficients of charging cost and deviation are estimated, as shown by equation (75) and equation (76). The utility of the charging choice depends on the financial cost of charging (zero when drivers choose not to charge) and the cost of having to deviate from the planned travel itinerary. The alternative specific constant for charging captures the general inconvenience of charging, such as the effort of plugging in the car. A DDCM considering the charging cost at home of BEVs was also estimated, but the results showed that the charging cost at home is not a statistically significant predicter of the vehicle and charging choices and deleting it does not cause significant change of the other estimates. Therefore, we decided on the more parsimonious model specification, as shown here.

$$U_{bev\ charge_{i,t}} = \theta_4 * C_{charging_{i,bev,t}} + \theta_5 * DEV_{charge,i,t} + ASC_{bev_{charge}} + \varepsilon_{bev\ charge_{it}} \quad (75)$$

$$u_{bev,not\ charge_{i,t}} = \theta_5 * DEV_{not\ charge,i,t} + \varepsilon_{bev,not\ charge_{it}} \quad (76)$$

6.1.3 Results

6.1.3.1 Model results

Models with different number of classes and different model specifications were tested and the model with the smallest BIC value was chosen, as shown in Table 5

TABLE 5: Results of the DDCM for vehicle choice and charging choice

	Class 1		Class 2	
	Coefficient	p-value	Coefficient	p-value
ASC-BEV	1.6526	<0.01	1.5145	0.25
θ_1 (gas cost-ICEV)($)	-0.0017	0.82	-0.0066	<0.01
θ_2 (rental cost-RENT) ($)	-0.0195	<0.01	-0.0213	0.36
θ_3 (gas price*distance-RENT)($*mile)	0.0002	0.77	-0.0005	<0.01
θ_4 (charging cost-BEV)($)	-0.1376	<0.01	-0.1178	<0.01
θ_5 (Deviation - BEV) (0,1)	-1.4140	<0.01	-2.7855	<0.01
Membership Probability	42.7%		57.3%	
Years of using an EV	3.1		2.2	
Environmental concern	0.31		0.21	
Performance preference	0.09		0.05	
Total log-likelihood (LL_{DDCM})	-5937.34			
stage 1 log-likelihood ($LL_{DDCM-stage\ 1}$)	-1753.32			
Stage 2 log-likelihood ($LL_{DDCM-stage\ 2}$)	-4184.02			

Two classes of decision-making patterns are found. The alternative specific constants (ASC-BEV) show that for the respondents in both classes, BEV is the default choice when charging costs are zero and there is no risk of having to deviate from the planned tour. The probability of choosing BEV is negatively correlated with charging cost and the possibility of deviation from the original plan in the middle of the travel tour. The probability of choosing ICEV is negatively correlated with gasoline cost though it is not statistically significant for class

1. The probability of choosing RENT is negatively associated with the rental price though it is not statistically significant for class 2.

Comparing the relationship between the coefficients of the variable deviation (DEV, θ_5) and BEV charging cost (θ_4), those in class 1 are willing to pay about \$10 to charge the vehicle to avoid having to deviate from the planned tour, while those in class 2 are willing to pay about \$24. This shows the negative utility of having to deviate from the original plan is respectively \$10 and \$24 for class 1 and class 2. One might expect the negative utility of being stranded to be a lot larger than the negative utility of deviation, since getting stranded in the middle of a trip is very expensive in terms of cost, time, convenience, and reliability. This could mean that the survey respondents are confident that they can find mid-trip chargers away from their planned stops when it is necessary, and the negative utility of stopping specially for charging in the middle of the trip is respectively \$10 and \$24. It is also possible that experienced BEV users might be able to reduce their energy consumption rate by adjusting their driving behavior, thus extend their remaining range to get to the next stop with charging opportunities. Comparing the social demographic information of the two classes, class 1 on average has longer history of using BEVs compared with class 2, and a higher percentage of the respondents in class 1 stated that their motivation for purchasing/leasing a BEV included concerns about the environment and a preference for BEVs' performance characteristics. This could mean that for earlier BEV users with more driving experience, the negative utility of deviation is a lot smaller than relatively newer adopters because they are more familiar with the charging network and more confident about the vehicle performance. Hence, more driving experience will help relieve range anxiety and the relatively more recent BEV users are likely to change their preference with the gain of more experience with driving BEV. However, it is also possible that the earlier BEV adopters are inherently different from the relatively recent BEV adopters: they might be more tolerant and more optimistic about electric vehicles, so even when the recent BEV adopters gain more driving experience, their preference will not change greatly.

6.1.3.2 Sensitivity Analysis

The final model shows that one of the major considerations of BEV users when they make decisions on the vehicle to use and the charging choices for a home-based trip tour is whether they can get to the next stop without having to deviate from the planned route (e.g, having to make a mid-trip stop for refueling), which can be influenced by both the reliability of the chargers (indicated by the availability of chargers specified in the experiment design) and the energy consumption from the current stop to the next. The availability of the chargers is included in the model as a state variable with known Bernoulli distribution with the parameter as presented in the scenarios. Its influence on vehicle choice and charging decisions does not show directly in the model results because it is not estimated as a structural parameter, but its effects can be calculated based on the model. For the current sample, with other variables being fixed, the increase of the availability of all the chargers from 20% to 100% results in an increase of more than 12% in BEV use and an 11% increase in VMT that is driven by BEVs instead of ICEVs (Figure 17).

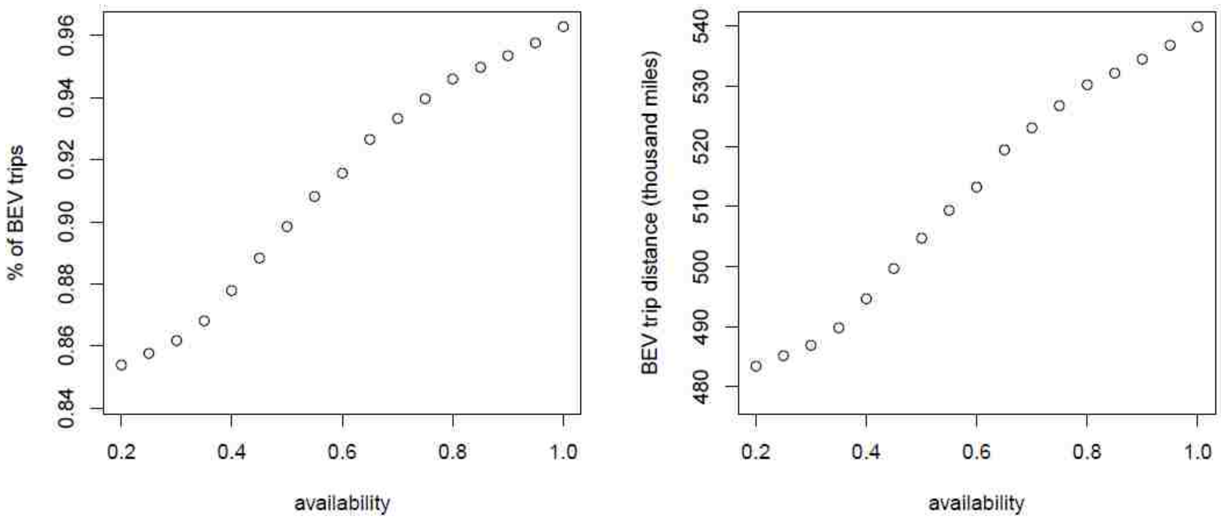


Figure 17 Sensitivity of the availability of the chargers (0-100%)

Based on the current sample and the travel day scenarios presented to the respondents, when the charging price at all the stations increases from zero to five dollars per hour while other characteristics of the scenarios stay the same, the number of BEV trips drops by about 17 percent and the VMT displacement by BEVs drops by about 21 percent (Figure 18).

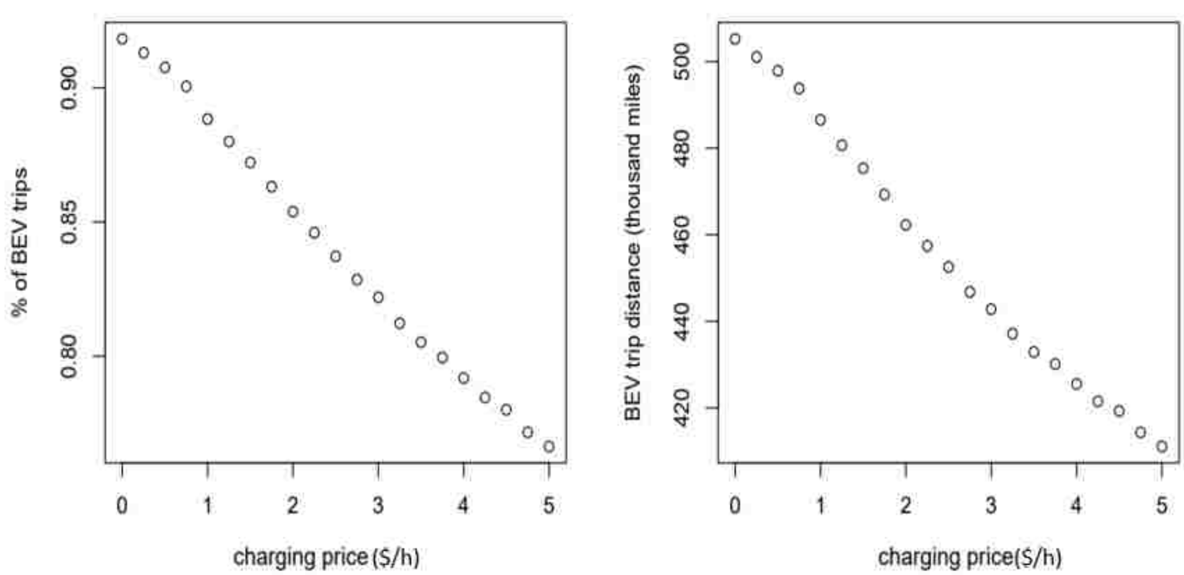


Figure 18 Sensitivity of charging price

Even though charging cost and the variable deviation are statistically significant predictors of the vehicle choice and charging decisions of BEV owners, the size of the effects appears to be limited when it comes the change of number of BEV trips and BEV trip distance. This could mean that for this sample, the BEV users are not particularly sensitive to charging price and the availability of the chargers for home-based tours. The possible explanations are: (1) finding mid-trip chargers is inconvenient, but not very costly; (2) Experienced BEV drivers can gain extra mileage by adjusting their driving techniques (hypermiling) and the cost (the negative utility) of doing so is not high; (3) when there is no charger available at a stop when they arrive, BEV users are willing to wait for the chargers to be available; (4) BEV users are not sensitive to the charging cost of one trip because in the long run, BEVs help save fuel cost from using gasoline; (5) we cannot exclude the possibility of hypothetical bias, especially respondents' usual tours are significantly shorter than the range of their vehicles; (6) the BEV owners in this sample were self-selected into participation in this survey. They could be more optimistic and enthusiastic about EV technology than general public or the population of BEV owners, therefore favor BEVs when facing the scenarios.

6.1.4 Conclusions

This paper applied DDCM with a finite horizon to model vehicle choice and charging decisions for a home-based trip tour jointly with the consideration of heterogeneity. It accounts for the dependence between an earlier decision and a later one: a decision at an earlier stop may affect not only the current utility but also the expected utility of the following stops, and the value of the expected future utility may affect the decision at the current stop. The final model highlights the heterogeneity among BEV users when it comes to vehicle choice and charging decisions for a home-based travel day. BEV owners who have a longer history of using an EV are willing to pay about $10 to avoid having to deviate from their original plan (e.g, make mid-trip stops specially for refueling), whereas the relatively newer adopters are willing to pay $24. Even though charging cost and deviation from the original plan are significant predictors of the vehicle choice and charging decisions, the analysis shows that the BEV owners in this sample are not very sensitive to charging price and the availability of the chargers: increasing the availability of chargers from 20% to 100% only attracts 12% more of BEV use, and a price drop from $5/h to free only increase BEV trips by 17%. We speculate that for BEV owners, range anxiety is not a serious issue, and it is also possible that more driving experience helps relieve range anxiety. Therefore, the design of EV charging facilities should try to relieve "range anxiety anxiety" (the fear of potential BEV adopters for having range anxiety if they own a BEV) among potential BEV adopters. BEV owners are not particularly sensitive to the fuel cost at a public charging station of one trip because BEVs help save fuel cost in the long run since most charging happens at home. Although, we are aware that this analysis can potentially suffer from self-selection bias and hypothetical bias. A similar analysis based on reveal-preference data from a more representative sample will help confirm these conclusions.

6.2 Analysis 2: Modeling PHEV charging choices using DDCMs

Summary

Having both an internal combustion engine and an electric powertrain, PHEVs are supposed to be less dependent on public charging opportunities than BEVs. However, evidences show that PHEVs plug in more often thanks BEVs. This phenomenon is described as "gas anxiety" of PHEV users by the media, meaning a strong desire to avoid using gasoline. An earlier research effort of mine investigated the existence of gas anxiety among PHEV owners empirically and found that PHEV owners who are earlier adopters and whose motivation of

owning an EV is not primarily financial value gasoline cost much more heavily than charging cost *(45)*. This study aims to test empirically whether "gas anxiety" exits among PHEV owners and its role on charging decision-making for home-based tours using DDCM. The modeling results are mostly consistent with my previous study on the influence of gas anxiety on the charging choices of PHEV users based on a survey conducted in 2013 *(45)*, however, the proportion of the gas anxiety group decreased. This could be an indication that earlier adopters might have certain qualities, e.g. strong environmental values, that make them try to avoid using gasoline. With the market moving forward, the proportions of earlier adopters become smaller, and a bigger proportion of PHEV users make their charging decisions with the goal of minimizing the total cost. Thus, the future public chargers might need to be priced competitively with the gasoline on per mile basis in order to encourage the usage of public charging. This analysis was submitted to 2017 TRB annual meeting for presentation and the long abstract of it was included in the conference compendium.

6.2.1 Introduction

Vehicle electrification has potential to reduce oil dependence and environmental impacts of automobiles. The major barriers of BEV adoption include the high cost of batteries which transfers to high initial cost and its range limitation compared to its petroleum-powered counterparts. PHEVs offer the potential to overcome these barriers by combining an internal combustion engine, an electric powertrain and onboard charging equipment. They offer to reduce gasoline use and GHG emissions while retaining the ability to travel long distances and refuel quickly and conveniently. PHEVs users are not likely to have range anxiety[2] since PHEVs are

[2] Range anxiety: the fear of being stranded in the middle of a trip because the battery is depleted *(7)*.

inherently less dependent on recharging infrastructure. However, data shows that PHEV drivers for whom plugging in is optional recharge more often than BEV drivers for whom plugging in is mandatory *(23).* This surprising result has led to the popular concept in the media among PHEV owners , “gas anxiety” , which describes the apparent desire of PHEV drivers to avoid using gasoline *(45).*

In an earlier research project done by the authors, based on a web-based stated preference survey conducted in 2013, we tested empirical evidence of gas anxiety using a latent class logit model. The results reveal two classes of decision making patterns among the survey respondents: (1) those who are more recent adopters and whose primary motivation of owning an EV is financial savings tend to make decisions that minimizes the cost (2) those who are relatively earlier adopters and whose motivation of EV usages is not only financial tend to value gasoline cost much more heavily than recharging cost, which is consistent with the concept of "gas anxiety". The allocation model results show that, class 2 is a big portion of the PHEV drivers surveyed (66%). However, our data cannot answer which one of these two groups is more representative of the future PHEV users. *(45).*

This study serves as a continuum of the research on the role of gas anxiety on charging decision making of PHEV drivers. The new survey collect data from choice ea home-based trip tour instead of one individual trip. The choice experiment in the survey that (46) is based on asked the respondents to make charging choices based on the characteristics of one charging station presented in the scenario. One comment we got a lot from the last survey is that PHEV users’ charging choices will not solely depend on the characteristics of one station as presented, but also on the following charging opportunities.

In the new choice experiment for this study, instead of asking the respondents to make their charging choices based on the specific information at one station, the respondents will be firstly presented with a travel day and then the respondents will be asked whether they choose to use their PEV on this particular travel day in certain scenarios, and if so, whether to charge their PHEVs at each stop of the travel day as the day progresses. The graphic display and the step-by-step appearance of information is also expected to reduce the hypothetical bias resulted from comprehension burden.

This study uses DDCM framework to analyze the charging choices of PHEV users. DDCMs assume that choices made in earlier periods affect the potential payoffs of the following decision periods, and the earlier choices are assumed to be made based on the expected future utility. This approach could potentially better represent the decision processes of PHEV drivers, who are likely to consider the future charging opportunities in a travel day when deciding whether to drive or charge a PHEV earlier.

6.2.2 DDCM model specification

(1) Derivation of the variables

I derived variables that represent the amount of energy obtained (how much energy can be attained at this station) and the costs (including the gasoline costs and electricity costs) based on the characteristics of the scenarios characterized by variables including charging price, charging power, gas price, remaining range and distance to destination. In this section, I explain how the following four variables were derived: percentage of range obtained ($r_{obtained}(\%)$), charging cost at the stop ($c_{charging}$), electricity cost at home (c_{home}), and gasoline cost to finish the trip (c_{gas}). Table 3 defines the variables we use in our analysis.

Percentage of potential range obtained

The energy that can potentially be obtained from recharging is measured as the range obtained at the station ($r_{obtained}$). If the dwell time (t_{dwell}) is sufficient for the PHEV to reach a full charge (r_{full}), the range obtained is the difference between the full range and the remaining range ($r_{remaining}$). Otherwise, the range obtained is a function of the charging power (P) and dwell time (t_{dwell}):

$$r_{obtained} = Min\left\{\frac{P * t_{dwell}}{ECR}, r_{full} - r_{remaining}\right\} \tag{77}$$

(ECR: Electricity consumption rate)

$$r_{obtained}(\%) = \frac{r_{obtained}}{r_{full}} \times 100\% \tag{78}$$

Costs

When a PHEV driver decides to recharge, we hypothesize that three costs could enter consideration: (1) the cost of charging at this stop: $c_{charging}$; (2) the cost of charging at home at the end of the travel day, c_{home_charge}; and (3) the cost of gasoline if the battery of the PHEV is depleted before arriving home, c_{gas}. The calculations of these variables are listed below.

(1) Charging cost at this stop ($c_{charging}$)

Plug time (t_{plug}) is the time duration that the PHEV stays plugged on the charger. We assume that once a PHEV is plugged in, it will remain plugged till it is fully charged or it is time for the driver to depart. Therefore, if the car cannot reach a full battery during the dwell time, plug time is equal to the dwell time. Otherwise plug time is equal to the time needed for the PHEV to become fully charged. It is calculated as equation (79).

$$t_{plug} = Min\left\{t_{dwell}, \frac{(r_{full} - r_{remaining}) \times ECR}{P}\right\} \quad (79)$$

Plug time is used to calculate the charging cost at the stop, which is the charging cost if the PHEV driver chooses to charge at a charging station:

$$c_{charging} = p_{charging} \times \ t_{plug} \quad (80)$$

(2) Electricity cost at home (c_{home})

c_{home} is the amount of money that will be paid to get the PHEV back to a fully charged state after the travel day. It depends on PHEV driver's decision of whether to charge at this station or not. Based on the charging decision, the remaining range when the driver leaves the station ($r_{after\ stop}$) can be calculated as:

$$r_{after\ stop} = \begin{cases} r_{remaining} + r_{obtained} & if\ charge \\ r_{remaining} & if\ not\ charge \end{cases} \quad (81)$$

If the electric range after a stop is less than the distance to home, the remaining electric range of the PHEV when it gets home (r_{home}) will be zero. Otherwise, if the electric range after a stop (r_{after_stop}) is enough for the driver to get home using electricity, the range remaining when the driver arrives home r_{home}can be calculated as range after stop minus the distance to home (d_{home}).

$$r_{home} = max(0, r_{after\ stop} - d_{home}) \quad (82)$$

Then the electricity cost at home (c_{home}) can be calculated as:

$$c_{home} = (r_{full} - \ r_{home}) \times \ ECR \ \times p_{electricity} \quad (83)$$

(ECR: Electricity consumption rate)

Electricity cost at home (c_{home}) depends on the charging decisions at the stop. If the respondents choose to charge, it is denoted as c_{home_charge}. For the choice of not to charge, the electricity cost at home can be written as $c_{home\_not\ charge}$.

(3) Gasoline cost (c_{gas})

The gasoline cost is:

$$c_{gas} = max(0, \frac{d_{home} - r_{after\ stop}}{mpg} \times p_{gas}) \tag{84}$$

Gasoline cost depends on the respondents' charging decisions at the stop. If a PHEV driver chooses to charge, it can be written as c_{gas_charge}. If the PHEV driver chooses not to charge, it can be written as $c_{gas\_\ not\ charge}$.

(2) State variable: the remaining range

The remaining range upon arriving at stop *t+1* ($rr_{i,t+1}$) equals the remaining range upon arriving at stop *t* (rr_{it}) plus the range obtained at the stop *t* ($r_{obtained_{it}}$), minus the range consumed on the way from stop *t* to stop *t+1* ($r_{consumed_{it}}$), as expressed by the following equation:

$$rr_{i,t+1} = rr_{i,t} + r_{obtained_{i,t}} - r_{consumed_{i,t}} \tag{85}$$

Range obtained ($r_{obtained}$) is the maximum electric range increase the PHEV can get during the specified dwell time if the owner chooses to charge. It is zero if the owner chooses not to charge. If the dwell time (t_{dwell}) is sufficient for the PHEV to reach a full charge (r_{full}), the range obtained is the difference between the full range and the remaining range ($r_{remaining}$).

Otherwise, the range obtained depends on the charging power (*Power*) and dwell time (t_{dwell}), see equation (86).

$$r_{obtained_{i,t}} = \begin{cases} Min\left\{\frac{Power*t_{dwell}}{ECR}, \quad r_{full} - rr_{i,t}\right\}, if\ d_{it} = 1 \\ 0, \qquad\qquad\qquad\qquad\qquad\qquad\quad if\ d_{it} = 0 \end{cases} \tag{86}$$

(ECR: Average electricity consumption rate in kWh / mile)

The range consumed ($r_{consumed_{i,t}}$) for a certain distance is uncertain due to factors such as road and traffic conditions, which create variation in actual per-mile energy consumption. Variability in range consumed leads to uncertainty of the remaining range upon arriving at subsequent charging stations. The distribution $g(r_{consumed_{i,t}}|l_{i,t})$ models the PHEV users' belief of range consumed for driving the distance from station *t* to station *t+1*: $l_{i,t}$. According to equations (85), the only uncertain component of the $rr_{i,t+1}$ is range consumed $r_{consumed_{it}}$. Thus, the density function of the state variable remaining range $rr_{i,t+1}$ is also a triangular distribution. According to equations (85), the only uncertain component of the $rr_{i,t+1}$ is range consumed $r_{consumed_{i,t}}$.

(3) State variable: Charger availability ($a_{i,t}$)

There are five levels of the availability variables in the scenarios *A%= {20%, 40%, 60%, 80%, 100%}*. The distribution of the availability of the chargers at stop *t* for respondent *i* is assumed to be Bernoulli distribution with the success probability of $A\%_{it}$. So the probability mass function for availability at stop *t* is:

$$k(a_{i,t}) = \begin{cases} A\%_{it}, & a_{it} = 1 \\ 1 - A\%_{it}, & a_{it} = 0 \end{cases} \tag{86}$$

Charger availability between the stations is assumed to be independent, which means the value of $a_{i,t+1}$ is independent from a_{it}. The transition function of availability could be expressed as equation (87).

$$k(a_{i,t+1}|a_{it}) = k(a_{i,t+1}) = \begin{cases} A\%_{i,t+1}, & a_{i,t+1} = 1 \\ 1 - A\%_{i,t+1}, & a_{i,t+1} = 0 \end{cases} \quad (87)$$

(4) Utility functions

In the chosen model, four variables were used to predict class membership: gender, income, the years of owing an EV (continuous), and whether the respondent identified financial benefits as their only motivation for buying a PHEV (yes or no). The first three variables were from the questionnaire and the last was derived from an open-ended question on the motivation of the respondents choosing to use electric vehicles. The utility functions of the class allocation model are as following:

Utility of the class allocation model for Class 1:

$$U_{class\ 1,i} = \gamma_0 + \gamma_1 \cdot Male_i + \gamma_2 \cdot HighIncome_i + \gamma_3 \cdot Years\ of\ EV\ ownership_i + \gamma_4 \cdot Financial\ benefits_i + \varepsilon_{1i} \quad (88)$$

Utility of the class allocation model for Class 2:

$$U_{class\ 2} = \varepsilon_{2i}$$

Within class 1, the utility of charging at the given station conditional on respondent *i* being in Class 1 for is:

$$U_{charge,it} \mid class\ 1 = \theta_{0,class\ 1} + \theta_{1,class\ 1} \cdot r_{obtained,it}(\%) + \theta_{2,class\ 1} \cdot C_{charging,it} + \theta_{3,class\ 1} \cdot C_{home_{charge},it} + \theta_{4,class\ 1} \cdot C_{gas_{charge},it} + \theta_{5,class\ 1} \cdot Availability_{it} + \varepsilon_{charge,i,class1} \quad (89)$$

Within class 1, the utility of not charging at this station for respondent *i* is:

$$U_{not\ charge,i} | \ class\ 1 = \theta_{3,class\ 1} \cdot C_{home_{not}charge,it} + \theta_{4,class\ 1} \cdot C_{gas_{not}charge,it} + \varepsilon_{not\ charge,i,class\ 1} \quad (90)$$

Within class 2, the conditional utility of charging at this station for respondent *i*:

$$U_{charge,i} \mid class\ 2 = \theta_{0,class\ 2} + \theta_{1,class\ 2} \cdot r_{obtained,it}(\%) + \theta_{2,class\ 2} \cdot C_{charging,it} + \theta_{3,class\ 2} \cdot C_{home_{charge},it} + \theta_{4,class\ 2} \cdot C_{gas_{charge},it} + \theta_{5,class\ 2} \cdot Availability_{it} + \varepsilon_{charge,i,class\ 2} \quad (91)$$

Within class 2, the conditional utility of not charging at this station for respondent *i*:

$$U_{not\ charge,i} | \ class\ 2 = \theta_{3,class\ 2} \cdot C_{home_{not}charge,it} + \theta_{4,class\ 2} \cdot C_{gas_{not}charge,it} + \varepsilon_{not\ charge,i,class\ 2} \quad (92)$$

6.2.3 Results

The results of the DDCM for PHEV charging choices are listed in TABLE 6.

TABLE6 Results of the DDCMs of PHEV charging behavior

DDCM ($\beta = 0$)	Class 1				Class 2			
	Est.	Std. err	t-test	p-value	Est.	Std. err	t-test	p-value
Intercept	0.30	0.9	0.33	0.74	0.22	0.07	3.14	<0.01
percentage of range obtained	2.65	0.69	3.84	<0.01	3.06	1.22	2.51	0.01
charging cost at this stop	-0.96	0.36	-2.67	<0.01	-0.82	0.31	-2.65	<0.01
electricity cost at home	-0.67	0.33	-2.03	0.04	-0.92	0.38	-2.42	0.02
gasoline cost	-1.05	0.41	-2.56	0.01	-1.86	0.55	-3.38	<0.01
availability	0.35	0.22	1.59	0.11	0.41	0.25	1.64	0.10
	Class 1				Class 2			
Class allocation model	Est.	Std. err	t-test	p-value	Est.	Std. err	t-test	p-value
Intercept	0.66	0.21	3.14	<0.01	-	-	-	-
Male	0.21	0.39	0.54	0.59	-	-	-	-
High income	-0.62	0.35	-1.77	0.08	-	-	-	-
Years of owning/leasing EV	-0.85	0.31	-2.74	<0.01	-	-	-	-
Financial benefits as the motivation	0.86	0.51	1.69	0.09	-	-	-	-
membership probability	0.46				0.54			
Log-likelihood	-3665.68							
DDCM ($\beta = 0.99$)	Class 1				Class 2			
	Est.	Std. err	t-test	p-value	Est.	Std. err	t-test	p-value
Intercept	-0.21	0.35	-0.60	0.55	0.21	0.06	3.50	<0.01
percentage of range obtained	1.25	0.6	2.08	0.04	2.69	1.31	2.05	0.04
charging cost at this stop	-0.66	0.29	-2.28	0.02	-0.66	0.26	-2.54	0.01
electricity cost at home	-0.81	0.36	-2.25	0.02	-0.73	0.36	-2.03	0.04
gasoline cost	-0.82	0.43	-1.91	0.06	-1.12	0.49	-2.29	0.02
availability	1.32	0.35	3.77	<0.01	1.09	0.31	3.52	<0.01
Class allocation model	Class 1				Class 2			

	Est.	Std. err	t-test	p-value	Est.	Std. err	t-test	p-value
Intercept	1.21	0.35	3.46	<0.01	-	-	-	-
Male	0.43	0.34	1.26	0.22	-	-	-	-
High income	-0.32	0.26	-1.23	0.22	-	-	-	-
Years of owning/leasing EV	-0.56	0.29	-1.93	0.06	-	-	-	-
Financial benefits as the motivation	0.67	0.51	1.31	0.19	-	-	-	-
membership probability	0.39				0.66			
Log-likelihood	-3628.31							

The DDCM was estimated twice with two different β values: $\beta = 0$ and $\beta = 0.99$. When $\beta = 0$ the DDCM degraded to static discrete choice model, as in the charging decision is made only based on the characteristics of the current stations. The results show that when $\beta = 0$, the model generates two classes of respondents: those with lower income and shorter EV ownership tend to evaluate the gasoline cost and charging cost similarly (class 1, the cost-minimizing group) and those with relatively higher income and longer EV ownership tend to weight gasoline cost more heavily (the gas anxiety group). This result is consistent with the conclusions of my earlier study *(23)*. When $\beta = 0.99$, in the class allocation model, only the variable “years of owning/leasing EV” is borderline significant with p-value of 0.06. Those with longer EV usages still show heavier evaluation of the gasoline cost than charging cost (about 1.7 times), but respondents with relatively shorter EV ownership (class 1) also weigh the gasoline cost more heavily than charging cost (about 1.2 times). With the increase of availability, the probability of charging at the station increases.

Comparing the DDCM ($\beta = 0$) based on the survey conducted in 2016 with the latent class model results based on the survey conducted in 2013*(23)*, the proportion of class 1 increases by 12% whereas the group with gas anxiety (class 2) drops. This could mean that with the market moving forward, the proportion of those with gas anxiety decreases because the proportion of earlier adopters with higher environment values drops. This could mean that future public chargers need to be priced competitively with the gasoline on per mile basis to encourage the usage of public charging.

6.2.4 Conclusions

An earlier research paper that I worked on indicated two classes of decision-making patterns among PHEV users *(23)*: (1) a cost- minimizing group who value gasoline cost and recharging cost approximately equally, and (2) a gas anxiety group who value gasoline cost much more heavily than recharging cost. Respondents in Class 2 (gas anxiety group) expressed a willingness to recharge, even if using gasoline would cost approximately four times as much as the cost of the gasoline avoided. While Class 2 (gas anxiety group) represents the majority of our sample, more recent PHEV adopters are more likely to be in Class 1 (cost-minimizing group). This work serve as a continuation of the earlier study *(23)*. Here I used the dynamic discrete choice modeling to capture PHEV charging choice decision pattern based on the data collected from the choice experiment on the home-based tours. The results of the DDCM show great consistency with *(23)*: relatively earlier adopters value (class 2) gasoline cost a lot more heavily than charging cost whereas relatively more recent adopters (class 1) tend to arbitrage the cost. My results also suggest the proportion of the PHEV users who make decision to minimize the costs is bigger than the sample collected for the earlier study (23), which could be a sign that in the future, public charging should be priced competitively with gasoline cost on a per-mile basis in order to attract PHEV users.

6.3 Analysis 3: Calculated choices or quick decisions? Comparison of DDCMs with SDCMs

based on simple heuristics

Summary

The impact of PEVs on the electricity grid and gasoline displacement depends on the distance of the trips that can be covered by electricity. It is therefore important to understand how PEV owners make decisions on which vehicles to use and when to charge, which can be influenced by multiple factors including the characteristics of the trips and charging opportunities. Complicating such analyses is the intertemporal dependence of choices: when using a PEV, decisions about charging depend on both prior choices and expectations about the future charging opportunities; and decisions on which vehicle to use depend on opportunities for charging. Based on the data from the stated preference survey among PEV owners described in Chapter 5, this paper compares two approaches to modeling PEV owners' choices of vehicle choice for a home-based tour and charging choices at the subsequent stops: static discrete choice modeling which treats all choices as independent; and dynamic discrete choice modeling (DDCM) which explicitly accounts for the intertemporal payoffs associated with vehicle use and charging choices under uncertainty. The results indicate both models can help to understand how PEV users make decisions about which vehicle to use for a travel day and can inform charging demand forecasting of PEV users. The DDCM based on the intertemporal payoffs offers slightly better correct prediction rate. However, this improved predictive power comes at the cost of considerably higher computational time and a much more involved process for model development and estimation that may be substantially less accessible to many potential users. This analysis was submitted to 2019 TRB annual meeting for presentation and the long abstract of it was included in the conference compendium.

6.3.1 Introduction

Plug-in electric vehicles (PEVs), including battery electric vehicles (BEVs) that only run on electricity and plug-in hybrid electric vehicles (PHEVs) that combine an internal combustion engine and an electric powertrain, offer the potential to reduce gasoline consumption and local air pollution by replacing gasoline with electricity. Public charging infrastructure, which can help increase the operating radius of PEVs, is proved to be an important enabler of electric vehicle adoption. Understanding the charging and use pattern of PEV owners is important for several reasons. First, the amount of petroleum demand displaced by a PEV, and the corresponding emission and energy security effects, depend on the number and length of trips for which the PEV displaces internal combustion engine vehicle (ICEV) travel. Second, the mix of generation sources supplied to the electric grid varies over time and space and depends on the time-varying electricity demand, so charging a PEV at different times or locations may result in different net emissions impacts. Third, the degree of stress that PEVs place on electricity grid depends on whether they exacerbate existing demand peaks or fill in periods of lower demand.

This paper focuses on two key types of decisions that a PEV owner must make for any home-based trip tour with planned natural stops (for example workplace, grocery store, etc.). First, they must decide whether to use their PEV or an alternative for the tour (stage 1 decision). If they elect to use their PEV, they must choose whether or not to charge the PEV at each opportunity as the travel day progresses (stage 2 decisions). The decisions of the two stages are inseparable intuitively: the vehicle choice influences whether they will face the charging decisions later, and the expectation of future charging needs and opportunities influences the vehicle choice. The charging decisions at any two stops in the travel day are similarly connected: the charging decision at one stop influences whether the vehicle needs to be charged at the following stops, and the expectation of future charging opportunities influences the charging decision at the current stop. This dependence between earlier decisions and later ones can be expressed in terms of utility theory: a decision at an earlier stop may affect not only the current utility but also the utility of the following stops; the value of the expected future utility may affect the decision at the current stop.

A dynamic discrete choice model (DDCM) explicitly accounts for these intertemporal payoffs under the assumption that the choice decision maximizes the expected net-utility, instead of the single utility at the current period, making it fundamentally different from a static discrete choice model (SDCM). The authors have applied DDCM to the modeling of vehicle use and charging choices of PEV in an earlier study and presented the detailed model specification and estimation of DDCM with the consideration of heterogeneity *(2)*. In this article, we compare the results of these DDCMs with those of SDCMs based on several much simpler decision heuristics to test whether the vehicle use and charging choices of PEV users are better described by the DDCMs than the SDCMs; in short, do respondents appear to make calculated choices based on the expected net-utility, or quick decisions based on much simpler heuristics?

The literature shows that multiple factors influence the charging decisions of PEV owners and that derived variables based on SOC, such as potential range obtained at a station might be a better predictor of charging choices than SOC itself. The literature stresses the heterogeneity of decision-making among PEV users and latent class logit models perform better than mixed logit models. Since the goal of this paper is to compare two different modeling approaches based on different hypotheses, to make it easier to display the results and convey the message, we assume homogeneity.

For the decisions on vehicle use (stage 1 decision), we compare the SDCMs based on four simple heuristics (Heuristic 1-4) and two DDCMs with different model specifications. For the charging choices (stage 2 decisions), we compare the SDCMs based on two simple heuristics (Heuristic 5-6) with the two DDCMs, (see Table 7). The model specification of the DDCMs and the simple heuristics on charging decisions (Heuristic 5-6) are informed by earlier studies on charging behavior modeling of BEVs and PHEVs *(43-45,47)*. The goodness of fit and the correct prediction rates of these models are compared.

TABLE 7 Description and specification of the models

Model	Dependent Variable	Systematic Component of the Utility functions
Heuristic 1: BEV is chosen if the travel day can be completed without public charging.	Stage 1: vehicle choice	$u_{icev_i} = \theta_1 * gas\ cost_{i,icev};$ $u_{rent_i} = \theta_2 * C_{rental_i} + \theta_3 * L * p_{gas_i}$ $u_{bev_i} = \theta_4 * Complete_{bev,i} + ASC_{bev}$ $u_{phev_i} = \theta_{12} * r_{excess_{phev,i}} + ASC_{phev}$
Heuristic 2: BEV is chosen if the travel day can be completed with 100% certainty.	Stage 1: vehicle choice	$u_{icev_i} = \theta_1 * gas\ cost_{i,icev};$ $u_{rent_i} = \theta_2 * C_{rental_i} + \theta_3 * L * p_{gas_i}$ $u_{bev_i} = \theta_5 * Complete\%_{bev,i} + ASC_{bev}$ $u_{phev_i} = \theta_{12} * r_{excess_{phev,i}} + ASC_{phev}$
Heuristic 3: BEV is chosen if the travel day can be completed with 100% certainty with a reasonable cost.	Stage 1: vehicle choice	$u_{icev_i} = \theta_1 * gas\ cost_{i,icev};$ $u_{rent_i} = \theta_2 * C_{rental_i} + \theta_3 * L * p_{gas_i}$ $u_{bev_i} = \theta_5 * Complete\%_{bev,i} + \theta_6 * C_{charging,bev,100\%,i} + ASC_{bev}$ $u_{phev_i} = \theta_{12} * r_{excess_{phev,i}} + ASC_{phev}$
Heuristic 4: BEV is chosen according to the expected probability of getting stranded based on the uncertainty of the energy consumption and the availability of the chargers.	Stage 1: vehicle choice	$u_{icev_i} = \theta_1 * gas\ cost_{i,icev};$ $u_{rent_i} = \theta_2 * C_{rental_i} + \theta_3 * L * p_{gas_i}$ $u_{bev_i} = \theta_7 * Risk_{bev,i} + \theta_8 * p_{charging,bev,mn,i} + ASC_{bev}$ $u_{phev_i} = \theta_{12} * r_{excess_{phev,i}} + ASC_{phev}$
Heuristic 5: charging decision depends on the current charging cost, gasoline cost (for PHEV only), and whether the car can get to the next charging opportunity without deviation from the original stop plan, i.e. one does not have to make stops specifically for charging the vehicle.	Stage 2： charging choice	$u_{bev\ charge_{i,t}} = \theta_9 * C_{charging_{i,bev,t}} + \theta_{10} * DEV_{charge,i,t} + ASC_{bev\_charge}$ $u_{bev,not\ charge_{i,t}} = \theta_{10} * DEV_{not\ charge,i,t}$ $u_{phev,charge_{i,t}} = \theta_{13} * C_{charging_{i,phev,t}} + \theta_{14} * c_{gas_{charge,i,t}} + ASC_{PHEV\_charge}$ $u_{phev,not\ charge_{i,t}} = \theta_{14} * c_{gas_{not\ charge,i,t}}$
Heuristic 6: on top of the variables included in heuristic 5, the potential electric range	Stage 2: charging choice	$u_{bev\ charge_{i,t}} = \theta_9 * C_{charging_{i,bev,t}} + \theta_{10} * DEV_{charge,i,t} + \theta_{11} * r_{obtained_{i,t}} + ASC_{bev\_charge}$ $u_{bev,not\ charge_{i,t}} = \theta_{10} * DEV_{not\ charge,i,t}$

can be obtained at a station also influences charging choices.		$u_{phev,charge_{i,t}} = \theta_{13} * C_{charging_{i,phev,t}} + \theta_{14} * c_{gas_{charge,i,t}} + \theta_{15} * r_{obtained_{i,t}} + ASC_{PHEV\_charge}$ $u_{phev,not\ charge_{i,t}} = \theta_{14} * c_{gas_{not\ charge,i,t}}$
DDCM 1 For stage 1 decision, decision of whether to use PEV depends on the expected net-utility of the future periods. For stage 2 decision, charging choices depend on the current costs plus the expected net-utility of the future charging opportunities.	Stage 1 & stage 2 jointly	**Stage 1:** $u_{icev_i} = \theta_1 * gas\ cost_{i,icev};$ $u_{rent_i} = \theta_2 * C_{rental_i} + \theta_3 * L * p_{gas_i}$ $u_{bev_i} = ASC_{bev}$ $u_{phev_i} = ASC_{phev}$ **Stage 2:** $u_{bev\ charge_{i,t}} = \theta_9 * C_{charging_{i,bev,t}} + \theta_{10} * DEV_{charge,i,t} + ASC_{bev\_charge}$ $u_{bev,not\ charge_{i,t}} = \theta_{10} * DEV_{not\ charge,i,t}$ $u_{phev,charge_{i,t}} = \theta_{13} * C_{charging_{i,phev,t}} + \theta_{14} * c_{gas_{charge,i,t}} + ASC_{PHEV\_charge}$ $u_{phev,not\ charge_{i,t}} = \theta_{14} * c_{gas_{not\ charge,i,t}}$
DDCM 2 On top of the variables included in DDCM 1, the vehicle choice and charging decisions are also influenced by the potential electric range can be obtained at each charging opportunity.	Stage 1 & stage 2 jointly	**Stage 1:** $u_{icev_i} = \theta_1 * gas\ cost_{i,icev};$ $u_{rent_i} = \theta_2 * C_{rental_i} + \theta_3 * L * p_{gas_i}$ $u_{bev_i} = ASC_{bev}$ $u_{phev_i} = ASC_{phev}$ **Stage 2:** $u_{bev\ charge_{i,t}} = \theta_9 * C_{charging_{i,bev,t}} + \theta_{10} * DEV_{charge,i,t} + \theta_{11} * r_{obtained_{i,t}} + ASC_{bev\_charge}$ $u_{bev,not\ charge_{i,t}} = \theta_{10} * DEV_{not\ charge,i,t}$ $u_{phev,charge_{i,t}} = \theta_{13} * C_{charging_{i,phev,t}} + \theta_{14} * c_{gas_{charge,i,t}} + \theta_{15} * r_{obtained_{i,t}} + ASC_{PHEV\_charge}$ $u_{phev,not\ charge_{i,t}} = \theta_{14} * c_{gas_{not\ charge,i,t}}$

6.3.2 Specifications of the models

6.3.2.1 Specifications of the DDCMs

(1) State variables ($s_{i,t}$) and transition functions (F_{is})

DDCM 1 assumes a forward-looking economic agent with six state variables, two among which model the individuals' beliefs about the remaining range (*remaining range* ($rr_{i,t}$)) and the availability of chargers of the future stations (*charger availability* ($a_{i,t}$)), and the rest four are deterministic state variables.

Remaining range ($rr_{i,t}$)

The remaining range upon arriving at station *t+1* ($rr_{i,t+1}$) equals the remaining range at station *t* ($rr_{i,t}$) plus the range obtained at the station *t* ($r_{obtained_{i,t}}$), minus the range consumed on the way from station *t* to station *t+1* ($r_{consumed_{i,t}}$), as expressed by the following equation:

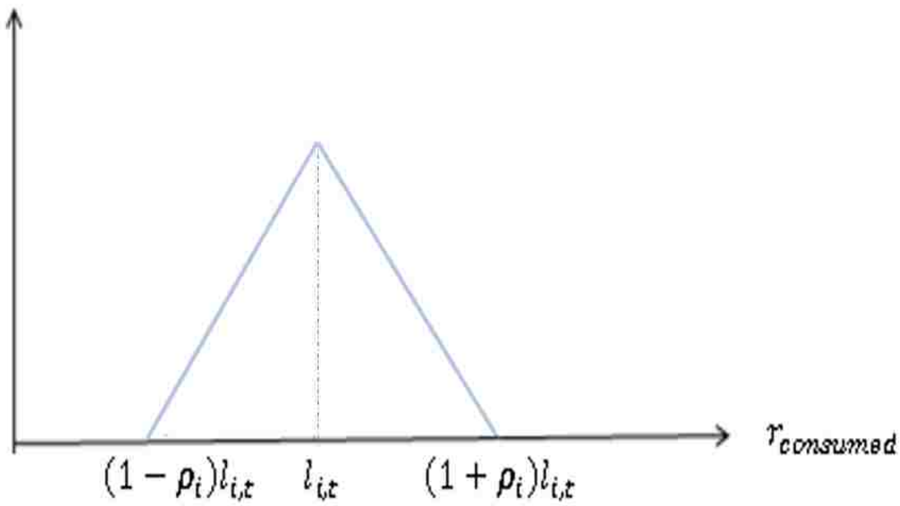
$$rr_{i,t+1} = rr_{i,t} + r_{obtained_{i,t}} - r_{consumed_{i,t}} \tag{93}$$

Range obtained ($r_{obtained}$) is the maximum electric range increase the PEV can get at the station during the specified dwell time if the owner chooses to charge. It is zero if the owner chooses not to charge. If the dwell time (t_{dwell}) is sufficient for the PEV to reach a full charge (r_{full}), the range obtained is the difference between the full range and the remaining range ($r_{remaining}$). Otherwise, the range obtained depends on the charging power (*Power*) and dwell time (t_{dwell}), see equation (94).

$$r_{obtained_{i,t}} = \begin{cases} Min\left\{\frac{Power * t_{dwell}}{ECR}, \quad r_{full} - rr_{i,t}\right\}, & if\ d_{it} = 1 \\ 0, & if\ d_{it} = 0 \end{cases} \tag{94}$$

(ECR: Average electricity consumption rate in kWh / mile)

The distribution of range consumed ($r_{consumed_{i,t}}$) for driving the distance from station *t* to station *t+1*: $l_{i,t}$ is assumed to be a triangular distribution ($g(r_{consumed_{i,t}} | l_{i,t})$) based on the uncertainty factor ρ_i) described in the following graph:



Density of $g(r_{consumed_{i,t}}|l_{i,t})$

According to equation (93), the only uncertain component of $rr_{i,t+1}$ is $r_{consumed_{i,t}}$. So the distribution of the state variable remaining range $rr_{i,t+1}$ conditional on $rr_{i,t}$ and d_{it} is also a triangular distribution.

Charger availability ($a_{i,t}$)

There are five levels of the availability variables in the scenarios *A%= {20%, 40%, 60%, 80%, 100%}*, as shown in Table 3. The distribution of the availability of the chargers at station *t* for respondent *i* is assumed to be Bernoulli distribution with the success probability of $A\%_{i,t}$. So the probability mass function for availability at station *t* is:

$$k(a_{i,t}) = \begin{cases} A\%_{i,t}, & a_{i,t} = 1 \\ 1 - A\%_{i,t}, & a_{i,t} = 0 \end{cases} \tag{95}$$

Charger availability between the stations is assumed to be independent from each other, which means the value of $a_{i,t+1}$ is independent of $a_{i,t}$. Then the transition function of availability could be expressed as equation (96).

$$k\left(a_{i,t+1}|a_{i,t}\right) = k\left(a_{i,t+1}\right) = \begin{cases} A\%_{i,t+1}\,, & a_{i,t+1} = 1 \\ 1 - A\%_{i,t+1}\,, & a_{i,t+1} = 0 \end{cases} \quad (96)$$

Deterministic state variables

The four deterministic state variables are the charging price, the dwell time, the gasoline price and the charging power. Instead of using these state variables directly in the utility functions, they are used to derive the following variables: continuous variables on charging cost $c_{charging}$, gasoline cost of PHEVs $c_{gas,phev_{i,t}}$, gasoline cost of ICEVs $c_{gas,icev_{i}}$); and a dummy variable called deviation (DEV) that represents whether the BEV can get to the next stop or has to deviate from the original tour plan ($DEV = 0$ when the BEV can get to the next station with the remaining range and $DEV = 1$ when the BEV driver needs to deviate from the plan and find charging stations other than those at planned stops on the tour).

Charging cost of PEV ($c_{charging_{i,t}}$)

Plug time (t_{plug}) is the time duration that the PEV stays plugged in to the charger. We assume that once a PEV is plugged in, it will remain plugged until it is fully charged or it is time for the driver to depart. So, if the car cannot reach a full battery during the dwell time, plug time will be equal to the dwell time. Otherwise plug time is equal to the time needed for the PEV to become fully charged. It is calculated as equation (97).

$$t_{plug_{i,t}} = Min\left\{t_{dwell_{i,t}}, \frac{(r_{reported} - rr_{i,t}) \times ECR}{Power}\right\} \quad (97)$$

Plug time is used to measure the charging cost at the stop, which is defined as the total charging cost if an individual chooses to charge at station *t*:

$$c_{charging_{i,t}} = p_{charging} \times t_{plug_{i,t}} \quad (98)$$

Deviation of BEV (DEV)

DEV is a dummy variable showing whether the driver can get to the next stop (i.e. the next charging opportunity) with the remaining range. Note that the being unable to reach the next planned stop does not necessarily mean the traveler will be stranded in the middle of the trip, but she will have to deviate from the original travel plan, for example by finding chargers out of the planned tour or driving with a lower speed to conserve energy.

DEV can be calculated according to equation (99). This value varies according to the charging decision. If the respondents choose to charge, it can be written as $\mathrm{DEV}_{\mathrm{charge,i,t}}$. If the respondents choose not to charge, it can be written as $\mathrm{DEV}_{\mathrm{not\ charge,i,t}}$.

$$DEV_{i,t} = \begin{cases} 1, & if\ rr_{i,t+1} < 0 \\ 0, & if\ rr_{i,t+1} \geq 0 \end{cases} \tag{99}$$

Gasoline cost of PHEV ($c_{gas,phev_{i,t}}$)

The gasoline cost is calculated based on the remaining range and also the distance to travel to the next station, see equation (100).

$$c_{gas,phev_{i,t}} = max(0,\ \frac{l_{i,t} - \left(rr_{i,t} + r_{obtained_{i,t}}\right)}{mpg} \times p_{gas}) \tag{100}$$

The gasoline cost of the PHEV here is denoted as $c_{\mathrm{gas\_charge}}$ when the respondent chooses to charge. For the choice of not to charge, the gasoline cost of the PHEV can be written as $c_{\mathrm{gas\_\ not\ charge}}$.

Gasoline cost of ICEV ($c_{gas,icev_i}$)

For ICEVs, the gasoline cost is calculated based on the fuel economy (mpg) of the gasoline car, the gasoline price (p_{gas}) of the scenario, and the planned distance (L) of the travel day.

$$c_{gas,icev_i} = \frac{L}{mpg} * p_{gas} \tag{101}$$

(2) Model specification of the DDCM 1and DDCM 2

The flow utilities of the two stages of DDCMs are defined independently, see Table (1). For both DDCM1 and DDCM 2, the utility functions of ICEV and RENT consider the gasoline cost and rental cost. For DDCM 1, For BEVs, the charging cost and DEV are included and for PHEVs, the charging cost and gasoline cost are included. DDCM2 adds in one more variable range obtained ($r_{obtained}$) .

6.3.2.2 Specifications of the SDCMs

The systematic components of the utility functions of all the SDCMs are listed in Table 1. For the four heuristics on stage 1 decision on vehicle choice, the utility functions for ICEV, RENT, and PHEV stay the same: for ICEVs, we consider the gasoline cost ($c_{gas,icev_i}$); for RENT, we consider the rental cost and the indicator of gasoline cost (planned distance L multiplied by gasoline price p_{gas_i}); and for PHEV, we consider the excess range ($r_{excess_{phev,i}}$), as in the difference between the range of the vehicle and the planned tour length (equation 102).

$$r_{excess_{phev,i}} = r_{reported} - L \tag{102}$$

For heuristics 1-4, the utility functions of the BEV change according to the hypotheses of the models. For heuristic 1, the hypothesis is that the BEVs will be chosen if the travel day can be completed without public charging, so the variable $Complete_{bev,i}$ is used as a predictor.

$$Complete_{bev,i} = \begin{cases} 1, & if\ r_{reported} \geq L \\ 0, & if\ r_{reported} < L \end{cases} \tag{103}$$

For heuristic 2, the hypothesis is that the BEVs will be chosen if the travel day can be completed with 100% certainty (variable $Complete\%_{bev,i}$), which means either the range of the vehicle is large enough to cover the planned distance of the travel day ($Complete_{bev,i} = 1$) or the potential range gained at a stop where there is always a charger available is enough for the BEV to finish the trip tour. For heuristic 3, we added the charging price at the stop where there is always a charger available.

For heuristic 4, the hypothesis is that BEV is chosen according to the expected probability of getting stranded ($Risk_{bev,i}$) based on the distribution of the energy consumption and the availability of the chargers. The assumptions on the distributions of the energy consumption and the availability of chargers are previously specified in section 5.1.2.

For the two heuristics on stage 2 decisions about charging choices, heuristic 5 assumes the charging decisions of BEV users depend on the charging cost and whether the driver needs to deviate from the originally planned tour to get to the next stop; and charging decisions of PHEV users depend on the charging and gasoline costs to get to the next stop. Heuristic 6 hypothesizes that the potential range obtained at the charging stations also influences the charging decisions. The utility functions can be found in the Table 7.

6.3.3 Results

To compare the models and avoid overfitting, 60% of the respondents are grouped into a training set for estimating the models, and 40% of the respondents are grouped into a test set for model evaluation. All the models involved in this research paper are trained based on the same training set and evaluated based on the same test set.

The results on the stage1 decisions (shown in TABLE 8) consistently indicate that the gasoline cost of ICEV and RENT do not have a significant influence on the vehicle choice for the home-based tours. The probability of choosing rental car is significantly negatively associated with the rental cost. All the costs are significantly negatively correlated with the probability of the relative mode and the potential range obtained at a station is positively correlated with the choice of using a BEV or PHEV. The ability to complete the tour without public charging or complete the tour with 100% certainty is positively correlated with the probability of choosing BEV. All these results are consistent with intuition and the estimates tend to be robust across different models. These results based on the training set (60% of the whole sample) are consistent with the estimates of the model based on the whole dataset.

TABLE 8 Models results of vehicle choice (stage 1)

Mode	Variables	NULL	Heuristic 1	Heuristic 2	Heuristic 3	Heuristic 4	DDCM 1	DDCM 2
ICEV	Gasoline cost ($gas\ cost_{i,icev}$, θ_1)		-0.001	0.001	-0.001	-0.001	-0.008	0.002
RENT	Rental cost (C_{rental}, θ_2)		-0.028***	-0.025***	-0.025***	-0.026***	-0.026***	-0.026***
	Gasoline cost ($L * p_{gas}$, θ_3)		0.516	0.377	0.291	0.246	0.451	0.398
BEV	Complete ($Complete_{bev}$, θ_4)		2.089***					
	Complete100% ($Complete\%_{bev}$, θ_5)			1.966***	2.062***			
	Charging price at 100% station ($p_{charging,bev,100\%}$, θ_6)				-0.045***			
	Risk of getting stranded-C ($Risk_{bev}$, θ_7)					-3.555***		
	Minimum charging price ($C_{charging,bev,min}$, θ_8)					-0.174***		
	Deviation (DEV, θ_9)						-3.419***	-3.250***
	Charging cost ($C_{charging_{bev}}$, θ_{10})						-0.061***	-0.121***

	Range obtained ($r_{obtained_{bev}}$, θ_{11})							0.025***
PHEV	Excess range ($r_{excess_{phev,i}}$, θ_{12})		0.012***	0.010***	0.010***	0.012***		
	Charging cost ($C_{charging_{pjev}}$, θ_{13})						-0.124***	-0.200***
	Gasoline cost ($C_{gas_{phev}}$, θ_{14})						-0.247***	-0.211***
	Range obtained ($r_{obtained_{phev}}$, θ_{15})							0.040***
	ASC_{BEV}	1.803***	2.901***	0.320***	0.286***	2.434***	2.073***	2.120***
	ASC_{PHEV}	1.897***	2.068***	2.053***	2.042***	2.034***	1.839***	1.788***
	ASC_{BEV_charge}						-0.306***	-0.826***
	ASC_{PHEV_charge}						-0.247***	-0.857***
N		4298	4298	4298	4298	4298	4298	4298
Log-Likelihood of Mode Choices		-1870	-1651	-1612	-1609	-1556	-1508	-1503
Correct Prediction Rate		81.2%	85.8%	86.6%	86.7%	87.0%	87.1%	86.8%
AUC (BEV)		0.546	0.739	0.764	0.760	0.802	0.817	0.813

* p-value <0.1; ** p-value<0.05; *** p-value<0.01

These models are evaluated according to their prediction accuracy of the test set. When the vehicle that was chosen has the highest predicted probability in the model, we count that as a correct prediction. The correct prediction rate of each model is listed in TABLE 8. Comparing the goodness of fit of the simple heuristics and the dynamic models, the DDCMs offer higher log-likelihood and slightly better correct prediction rates. However, the improvement seems trivial considering the static models all have high correct prediction rate. The plot of the predicted probability of choosing BEV and the actual frequency (Figure 19) and the receiver operating characteristic (ROC) curve (Figure 20) show that heuristic 4 provides very similar prediction accuracy to DDCM 1. A ROC curve shows the relationship between the sensitivity (true positive rate) and the specificity (true negative rate) based on different discrimination threshold of a prediction model. Every point on the graph represents the corresponding true positive rate and true negative rate based on one threshold point between zero and one. Therefore, when the area under the curve is larger, as in when the curve is closer to the upper left corner of the graph, it means the model offers better prediction power.

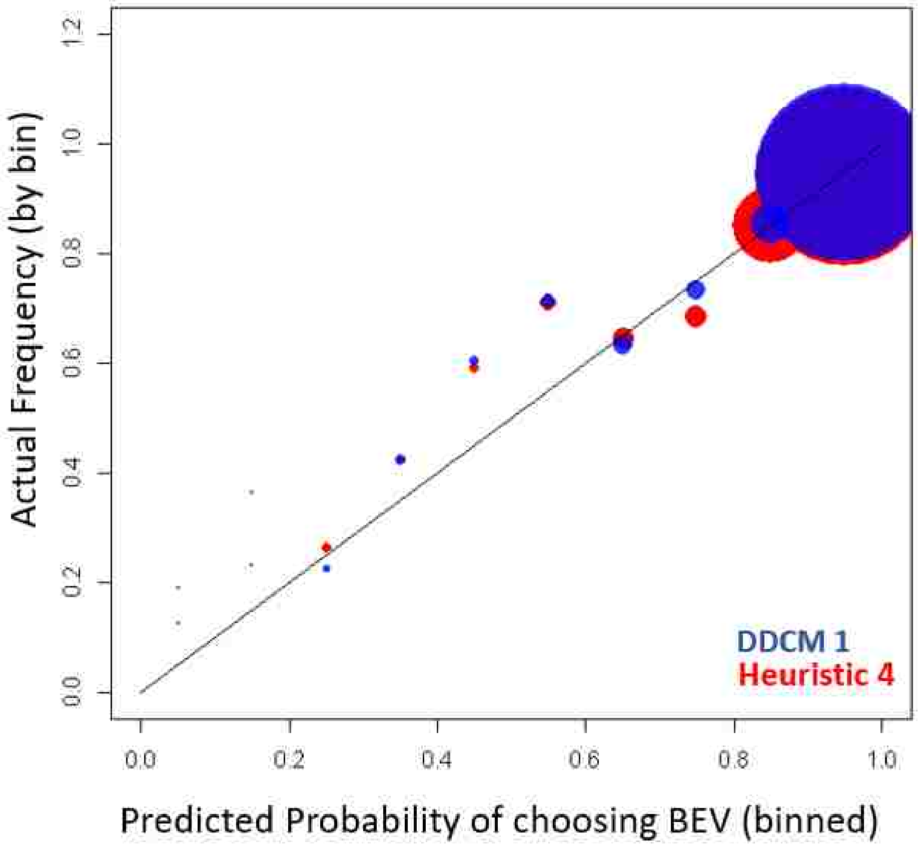


FIGURE 19 Predicted probability and actual frequency of choosing BEV
(note that the size of the circles means the number of observations in that bin)

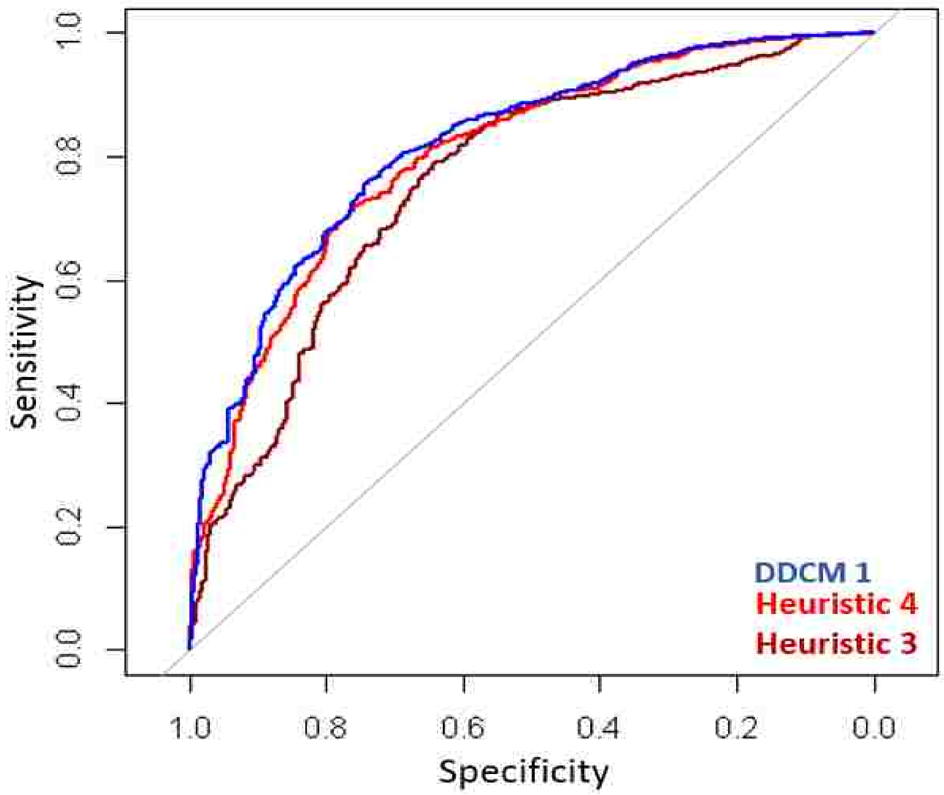


FIGURE 20 Comparison of the Roc curves of choosing to charge

The results of the models on charging choices (shown in TABLE 9) consistently show that for BEVs, the respondents express a willingness to pay extra (more than $20) to avoid having to deviate from their original plan based on the relative sizes of the coefficients on the charging cost and deviation variables. The estimates are consistent for both the DDCMs and SDCMs. For PHEVs, gasoline cost is valued more heavily than charging cost (1.1 to 2.8 times) according to the estimates of the coefficients. This is consistent with the results of our earlier study *(23)*.

TABLE 9 Model results of charging choices (stage 2 decisions)

Mode	Variables	NULL	Heuristic 5	DDCM 1	Heuristic 6	DDCM 2
BEV	Deviation (DEV, θ_9)		2.769***	-3.419***	2.619***	-3.250***
	Charging cost ($C_{charging_{bev}}, \theta_{10}$)		-0.016**	-0.061***	-0.131***	-0.121***
	Range obtained ($r_{obtained_{bev}}, \theta_{11}$)				0.037***	0.025***
PHEV	Charging cost ($C_{charging_{phev}}, \theta_{13}$)		-0.343***	-0.124***	-0.445***	-0.200***
	Gasoline cost ($C_{gas_{phev}}, \theta_{14}$)		-0.947***	-0.247***	-0.793***	-0.211***
	Range obtained ($r_{obtained_{phev}}, \theta_{15}$)				0.038***	0.040***
	ASC_{BEV_charge}	0.244***	-0.064	-0.306***	-0.897***	-0.826***
	ASC_{PHEV_charge}	-0.344***	-0.238*	-0.247**	-0.779***	-0.857***
N		6447	6447	6447	6447	6447
Log-Likelihood of Mode Choices		-2848	-2542	-2388	-2402	-2330
Correct Prediction Rate		56.6%	62.4%	69.2%	70.6%	72.3%
AUC		0.551	0.712	0.766	0.787	0.793

* p-value <0.1; ** p-value<0.05; *** p-value<0.01

To assess the rate of correct predictions, we define that the predicted choice is to charge when the probability of charging according to the model is greater than 0.5; otherwise the predicted choice is not to charge. According to this criterion, the correct prediction rate of each model for the test set is listed in Table 9. The results show that the correct prediction rate of DDCM is only slightly better. The comparison plots (Figure 21) and the ROC curves (Figure 22) show that the DDCMs based on expected net-utility produce a lot fewer predicted probabilities close to 0.5.

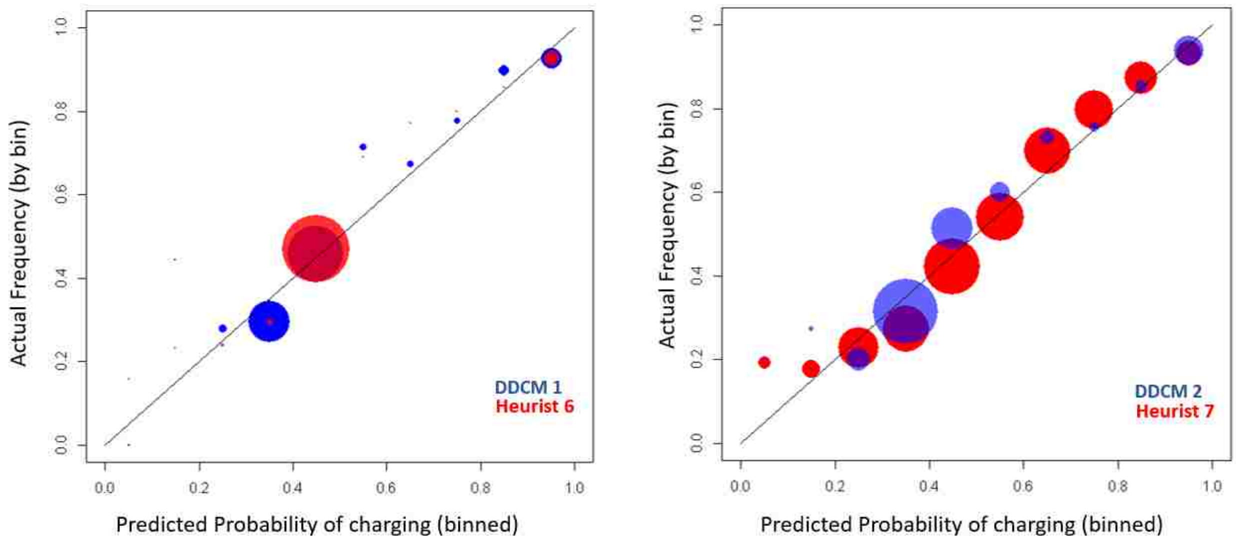


FIGURE 21: Predicted probability and actual frequency of charging
(note that the size of the circles means the number of observations in that bin)

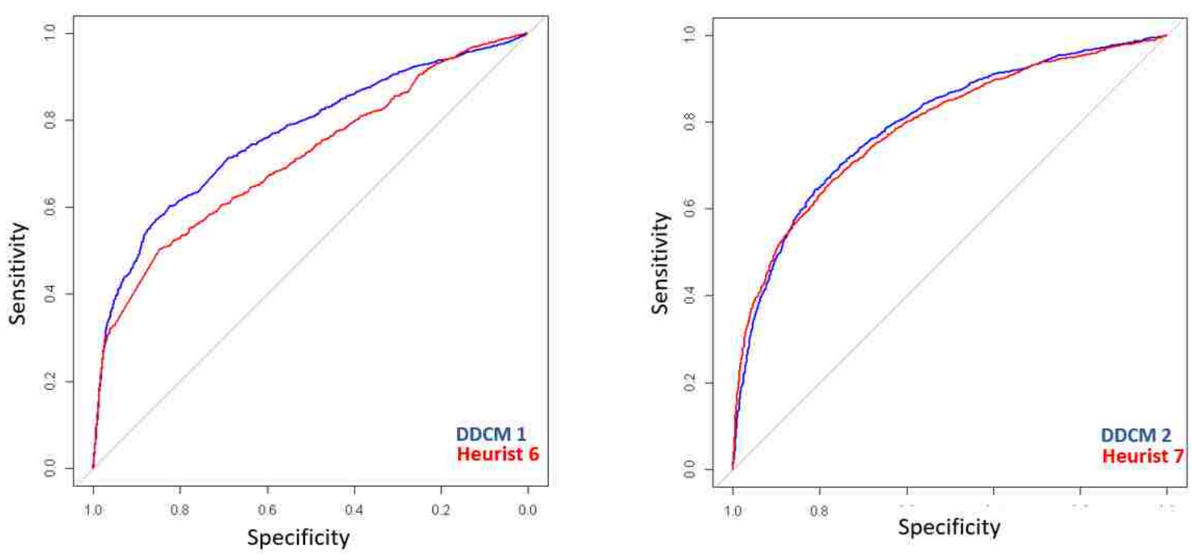


FIGURE 22: Comparison of the ROC curves of choosing to charge

6.3.4 Conclusions

Previously published approaches to modeling the charging behavior of PEV drivers include various versions of static conditional logit models and a new addition – DDCMs. This study compares the two: static discrete choice models based on simple decision heuristics and dynamic discrete choice models based on intertemporal payoffs, to find out for home-based trip tours whether the decisions of vehicle use and charging choices of PEVs are quick decisions or relatively calculated choices. The model results show that the DDCMs offer slightly better goodness of fit and higher within-sample prediction accuracy, but this improved predictive power comes at a significant cost. For one, the computational time to estimate a DDCM is considerably higher than that needed to estimate a static model: The DDCMs each takes approximately 5 hours to converge under parallel computing on a computer with eight cores, whereas each SDCM takes a few seconds. Second, the process for model development and estimation of a DDCM is considerably more involved, requiring customized coding to implement the intertemporal payoffs, and efficient parameter estimation. Third, the DDCM entails a complicated theoretical model that may be substantially less accessible to many potential users.

7 Survey & Data for Long-Distance Trips

7.1 Focus group discussion on the use of BEV for long-distance trips

To inform the design of the survey on long-distance trips by BEVs and the modeling strategies, a focus group discussion was conducted among ten BEV owners that were recruited though online forums. The goal of this discussion was to understand first what factors BEV owners consider when they make the decisions on which vehicle to use for a long-distance trip, then how they make the decisions on where to charge their cars on a long-distance trip using BEVs. The guiding questions to elicit these included the following five: (1) What do you consider when you decide on the vehicle to use for a long-distance travel day; (2) Do you plan your charging stops before a long-distance trip using a BEV? If so, how? (3) Do you use any EV trip planners or apps to plan your charging stops? And if so, how would you describe your experience with them? (4) What are the biggest concerns that you have for driving your BEV for long-distance trips? (5) What is the most important enabler for long-distance trips by BEVs: bigger battery packs, more reliable charging stations, higher charging power, or charging stations in more places?

Nine of these ten respondents owned either a Tesla or Chevrolet Bolt EV – both with range over 200 miles. One respondent owned a Nissan Leaf with the range of around 80 miles. The interview took the form of a one-hour online video interview, where the respondents called in to a Zoom conference from their personal device. These respondents were from different states: Washington, California and Florida and nine of them have experience of using their BEVs for long-distance trips. Since these respondents were self-selected into this focus group and most of them are quite active on the online forums as observed by the author, they are likely to be EV enthusiasts and take pride of owning BEV and using BEV instead of gasoline cars, their results of this discussion probably does not generalize well to the broader population of BEV users. Even though these respondents are more likely to use BEV for long-distance trips than the population, the goal of this focus group discussion is on the decision processes that will inform the model specification instead of the generalization of the user preferences. The model parameters, which eventually represent the preference, will be estimated later by the discrete choice models based on the survey data. We were able to gain the following insights that inform the design of the survey and the choice experiments.

(1) Considerations of vehicle choice for long-distance trips

The first consideration of whether to choose a BEV for long-distance trips is to see whether the trip distance is significantly longer than the vehicle range, and if so whether there are enough chargers along the route, which both directly reflect whether one will run into the problem of battery deprivation. Time constraint also plays a role: whether there is enough time during the day for both driving and charging can influence the decision on vehicle choice. The possibility of combining charging with other activities (such as lunch and rest) is likely to make BEVs more attractive for long-distance trips. It is important to incorporate other necessary activities during refueling so there is no need to stop specifically for other purposes such as using the restroom and having lunch. If the charging rate matches the time they want to stay at a station, they are more likely to use BEVs for the trip. Some respondents mentioned that the destination chargers are important for long-distance BEV trips. When asked about the concerns of using BEV for long-distance trips, they also mentioned that the reliability of the information on the online charging networks (such as PlugShare) is important as wrong information on the condition of the chargers could lead to a huge delay and uncertainty. Since none of the respondents mentioned the availability of the chargers at a station and the charging price, I asked the following two subsequent questions: (1) How often do you run into a situation where the chargers are all being used, and you have to wait? And (2) Is charging price an important consideration when it comes to vehicle choice? Interestingly, I was told that the currently, these two are not important factors as they seldom need wait at charging stations. The cost is not a big issue because in the long run, using BEVs shows less cost than gasoline cars on an annual basis and Tesla users can use the Super chargers for free.

To sum it up, when deciding whether to use BEVs for a long-distance trip, BEV owners currently consider the distance of the trip relative to the vehicle range, whether there are enough chargers along the trip, whether there are facilities at the charging stations, and whether there are chargers at the destinations.

(2) When and where to charge on a long-distance BEV trip?

All the respondents mentioned that they plan their long-distance trips based on mid-trip chargers, meal plans and destinations chargers. The most common platform for trip planning is PlugShare in combination with Google Maps, and Tesla users have their own trip planning application based on the Supercharger network. They do not always stick to their plan with charging as the energy consumption is uncertain, but they can often reduce range consumption rate by changing their driving behavior, such as slowing down, or turning off the heater, etc. The fact that they plan their charging locations beforehand indicates that the decision of whether to charge at a particular location can also be correlated with the characteristics of the other stations.

This focus group discussion shows that the following characteristics of long-distance trips needs to be considered for the choice experiment: distance from original to destination, spacings between stations, number of charging stations, destination charging facilities, and the characteristics of each charging station, including time to access, charging price, power and the amenities at the stations (whether restaurants, restroom, and WiFi are available at the stations.).

7.2 Survey design for long-distance tours

The survey on using BEV for long-distance trips took the form of an online survey administrated through a custom-built web-based survey tool. It included three sections: (1) one questionnaire section on the socio-demographic information about the subjects and the detailed vehicle information of the vehicles owned by the respondents; (2) another questionnaire section on the risk-taking propensity and environmental values of the subjects; (3) a stated choice experiment section where the respondents were first presented with long-distance trip scenarios characterized by planned travel distance and characteristics of charging stations along the way including charging price, charger level, the time that it takes to access the charging station, and the facilities near the charging station. Then they were asked to give advice on the vehicle to drive for each scenario and whether to charge at each station in each scenario.

7.2.1 Background information

All the respondents of this survey were reported being electric vehicle owners. The questionnaire asked them to report the following information: age, gender, education, household income, household size, home ZIP code, and the specific information of their vehicles in the household: the make, model, and year. For each of their electric vehicles, respondents were also asked for the maximum and minimum electric range on a full charge, in summer and in winter. Since this survey was conducted in summer, the average value of maximum summer range (r_{max}) and minimum summer range (r_{min}) is denoted as reported range ($r_{reported}$), which was used to assign the choice experiments to the respondents.

$$r_{reported} = \frac{1}{2}(r_{min} + r_{max}) \tag{104}$$

To capture the risk-taking propensity and environmental values of the respondents when it comes to transportation, ten Likert-scale questions on respondents' attitude towards taking risks and ten Likert-scale questions on the respondents' environmental values were included in the questionnaire. The questions were selected according to the literature *(80)*. The ten 6-level Likert-scale questions on risk-taking propensity are: (1) I don't mind taking the latest possible public transport connection to the airport; (2) I would go on a two-week vacation in a foreign country without booking ahead; (3) I would drive my EV without planning out the charging on the way; (4) I start earlier if I assume that there will be congestion on my route; (5) If I don't know the way I just start into the general direction and search my way step by step; (6) I start earlier if I have to drive an unfamiliar route; (7) I try to be at the airport at the latest possible time; (8) Reoccurring rituals give me a feeling of control and security; (9) I prefer to organize my holidays spontaneously; (10) I prefer a clearly structured, repetitive daily schedule. The ten 6-level Likert-scale questions on environmental values are: (1) I worry about environment problems; (2) Too much attention is paid to environmental problems; (3) Environmental problems are exaggerated; (4) The risk of the greenhouse effect is exaggerated; (5) I am optimistic regarding the state and future of our environment; (6) Environmental pollution affects my health; (7) Environmental problems have consequences for my life; (8) I can see with my own eyes that the environment is deteriorating; (9) Environmental problems are a risk for the future of our children; (10) Environmental protection costs too much.

7.2.2 Travel day simulation

Each respondent was presented with eight scenarios featuring a trip characterized by the following variables: gasoline price, planned travel distances, charging stations along the trip, the characteristics of the charger at the destination, and the characteristics of the charging stations long the trip including charging price, charging power, how long it takes to drive to the charging station from the highway, and what facilities are available at this charging station. The scenarios were defined by the researchers and customized to the respondents according to the individuals' self-reported BEV ranges and the design of the scenarios are described in detail in section 7.2.2.1 and 7.2.2.2. For each scenario, the respondents were asked to choose which vehicle to use, and if they chose a BEV, to make charging decisions at each charging station.

The reported range was used later in the survey to distribute the scenarios: when the report range is over 200 miles, then the scenarios customized to the respondents were based on their own BEV, however, when the range of the BEV is lower than 200 miles, the respondents were randomly assigned an imaginary BEV with a range from 250 miles to 400 miles and they were asked to make decisions based on this imaginary vehicle instead of their own BEV. The reasoning of doing this is to avoid asking the respondents to make decisions based on their own BEVs that are not practical for long-distance trips. The choice set of vehicles for respondents who had a BEV with range over 200 miles included all their own vehicles, and if they did not own a gasoline alternative, a rental car option with the rental price being specified in the scenario was provided. For respondents who did not own a BEV with range over 200 miles, the choice set of vehicles included an imaginary long-range vehicle with range being specified in the scenario and the other vehicles they own, and if they do not have a gasoline alternative, a rental car option was also included.

An interactive graphical interface and the experimental design of the scenarios are two key elements of the simulation design, which are described in the following two sections respectively.

7.2.2.1 Display of the scenarios

In this section, each respondent was presented with 8 scenarios pre-designed and customized according to the individuals' PEV ranges. Considering it is intractable to present the respondents with complex scenarios that are plausible to every one of them without collecting a large set of information on their daily travel, instead of asking the respondents to make decisions for themselves, we ask them to give advice for individuals that are very similar to them: with the same background information. The reasoning is the same as described in section 5.1.2.1.

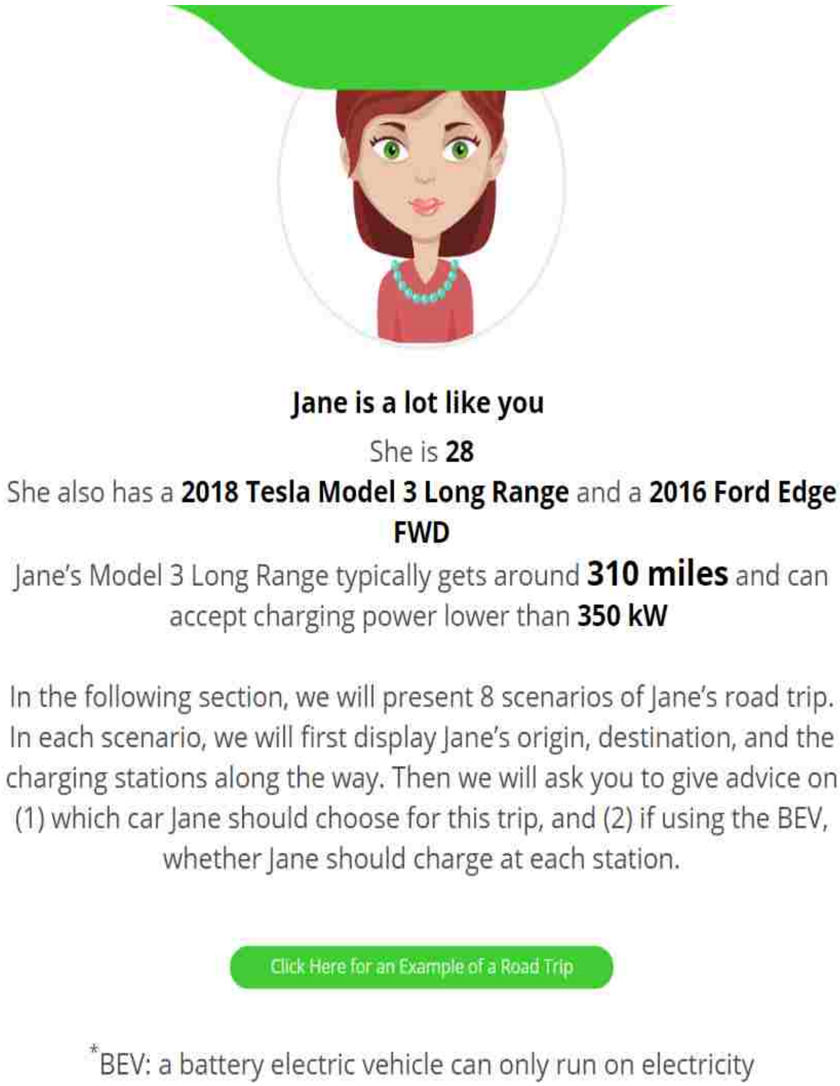


FIGURE 23 Introducing Jane

Before starting the choice experiment, the respondents were shown an example of the long-distance trip that shows the key elements of the display of a scenario, as shown in FIGURE 24. The items of information were displayed one by one in order to give the respondents time to absorb the information. Then the respondents could start the choice experiments by clicking the button 'Ready for Simulation'.

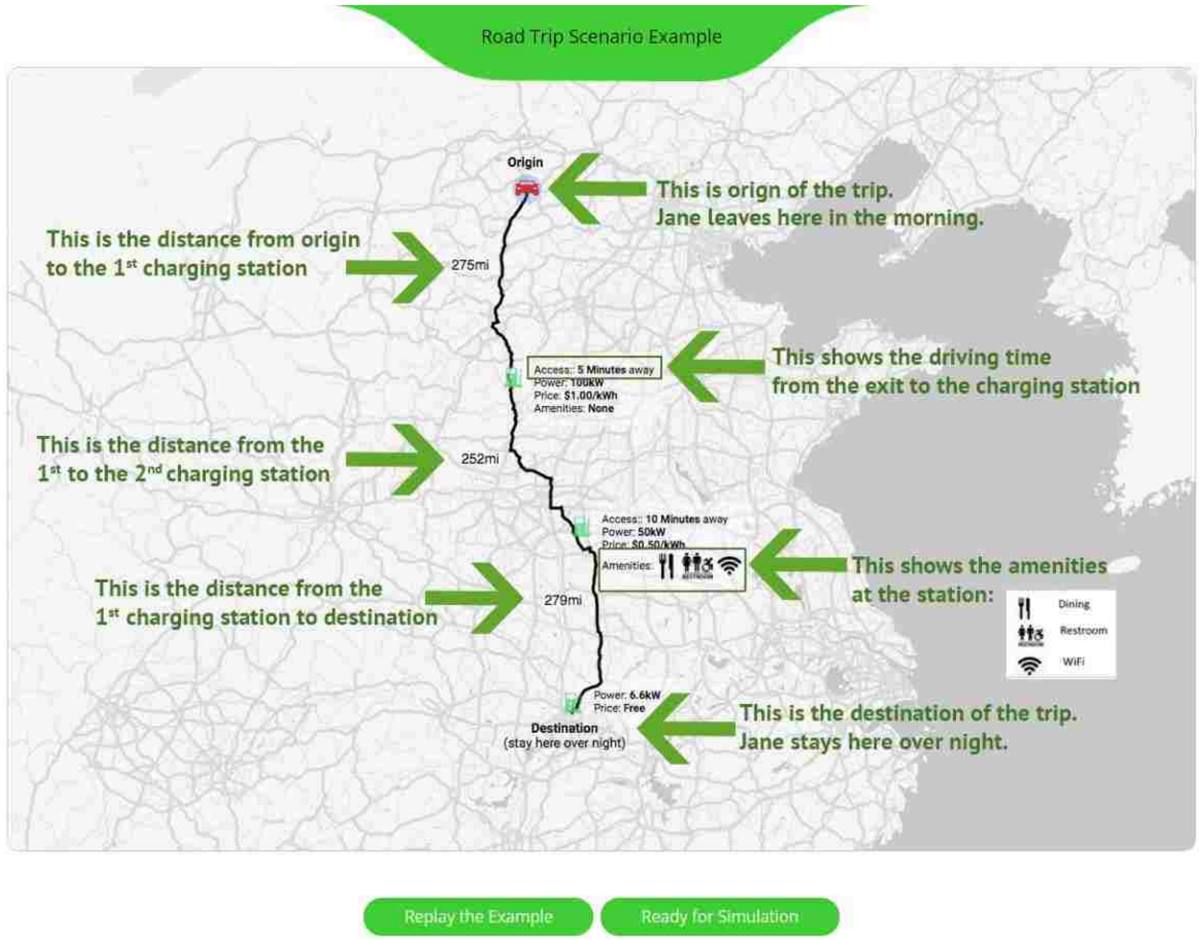


FIGURE 24 Long-distance trip scenario example

In each of the eight scenarios, the respondent was firstly presented with a specific long-distance trip and asked to recommend a specific vehicle for the tour (Figure 25). The choice set of vehicles was the list that the respondent had previously said they own if one of their cars was a BEV with range over 200 miles. Otherwise, the low-range BEV was replaced with an imaginary BEV with the range of a random number between 250 to 400 miles specified in the scenario by the researchers. If the respondent selected a BEV for this long-distance trip scenario, they were then asked whether they would recommend charging at each station with the tour progressed (Figures 26) and if so, how much range they want to get from the station (Figure 27).

The presentation of information and solicitation of choices was designed to make the information tractable while reflecting the structure of the choice process in a real tour. If the respondent chose to use a BEV for the presented long-distance trip scenario, the survey tool stepped through station by station and asks the respondent to make charging decisions. As the tool stepped through the tour, additional information on the actual remaining range was revealed. In-use energy consumption on each individual trip was drawn from a distribution based on the respondent's reported maximum and minimum ranges. As such, the amount of range "consumed" on a given trip could be greater or less than the nominal length of that trip, and the respondent would not know for sure how much range would be consumed until the end of that trip.

FIGURE 25 Vehicle choice

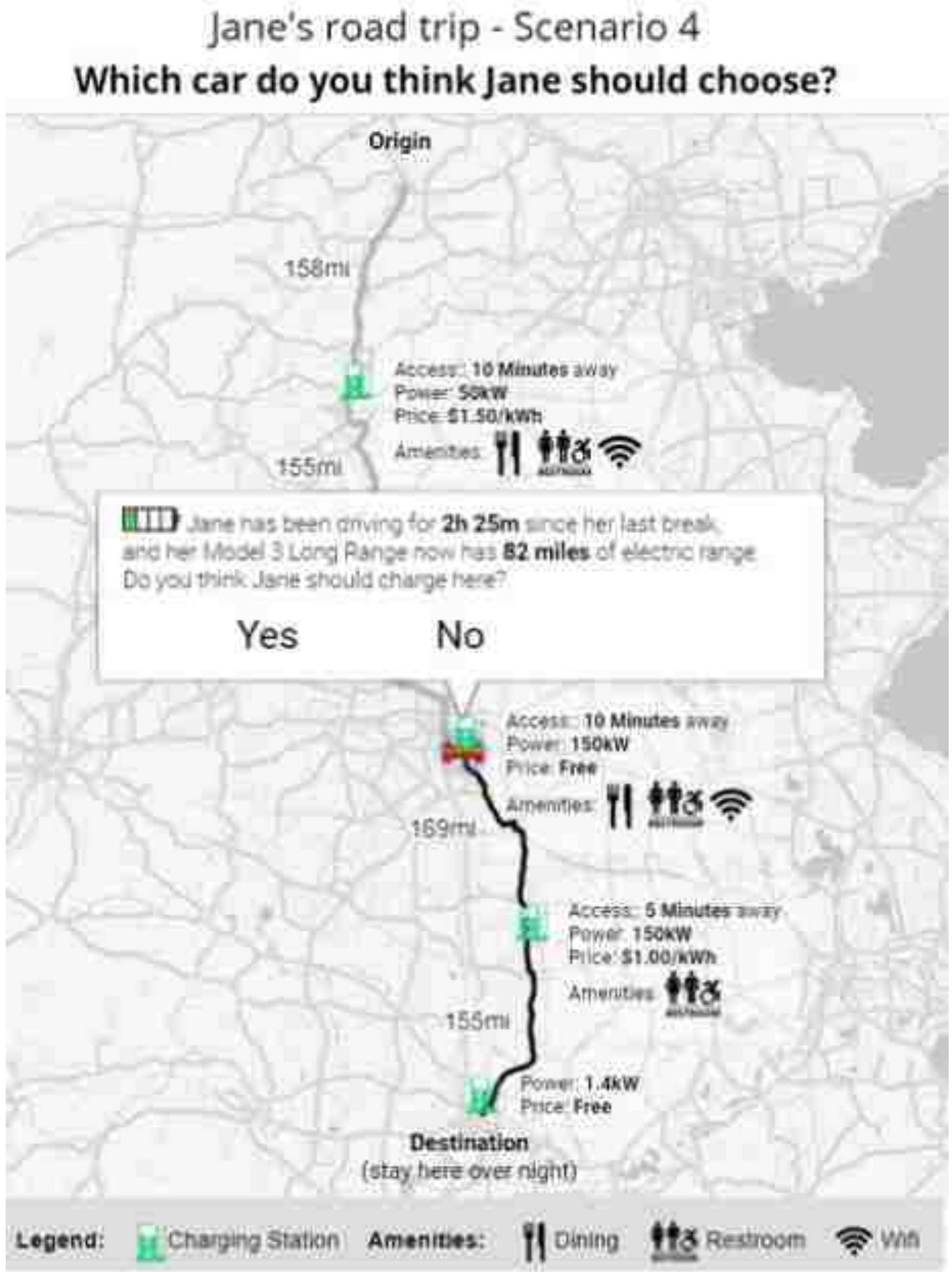


FIGURE 26 Charging choice

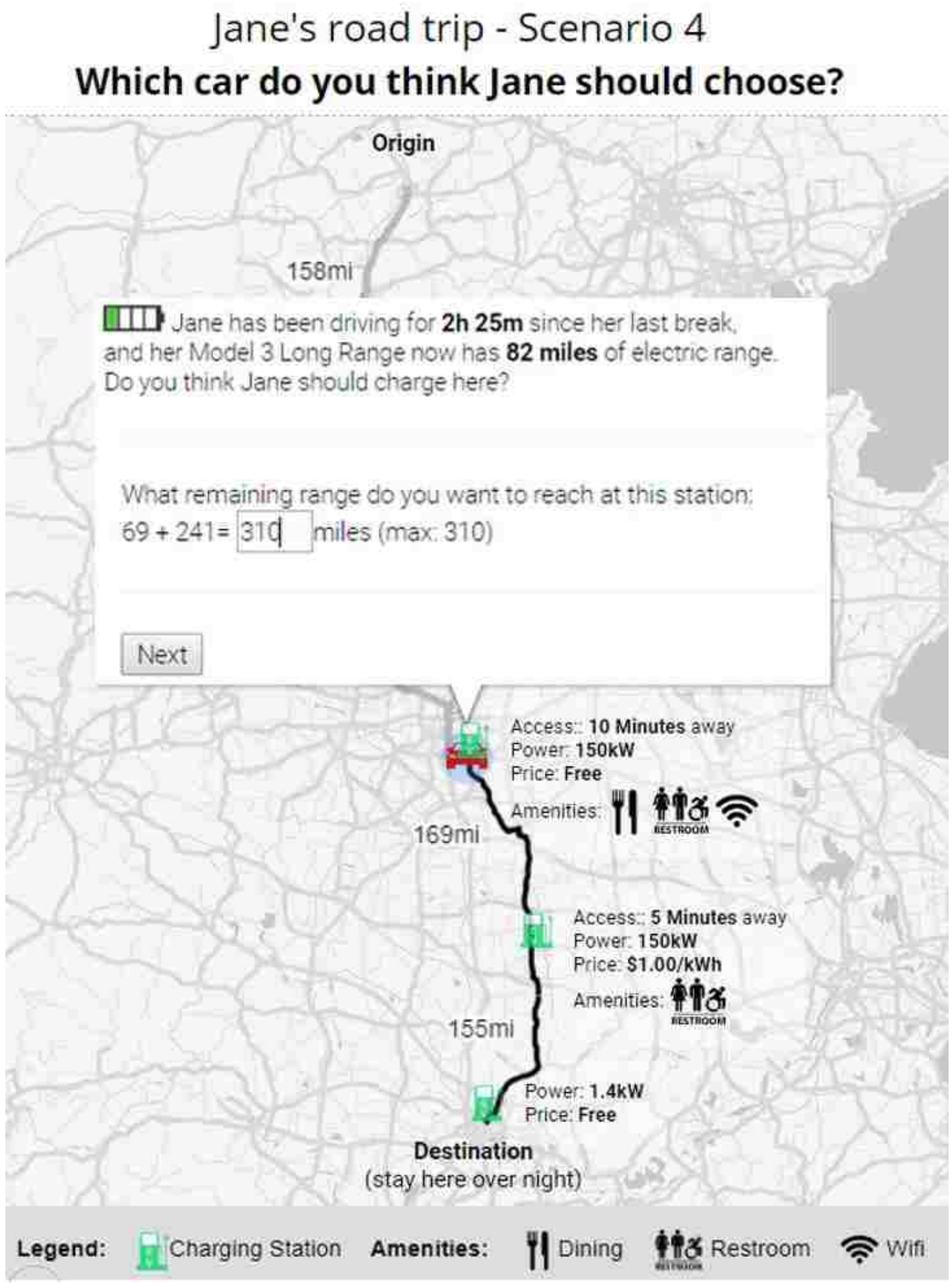


FIGURE 27: The remaining range after charging

FIGURE 28 Screenshot 5 of the survey tool: Indicate Jane made it to her destination

Similar to the home-based tours, it was entirely possible in some cases for respondents to fail to complete a long-distance trip scenario according to their original plan on this survey instrument. For example, if they selected not to charge at the station when the remaining range of the BEV was 100 miles and the distance until the next charging station was 98 miles, because of the uncertainty of energy consumption, the actual range consumed for the 98 miles drive could be more than 100 miles. This in real life, could be due to the change of driving behavior, weather conditions, traffic situation, or topography, etc. In the survey tool, this translates into a randomly generated number from a triangular distribution based on the maximum and minimum range of the BEVs provided by the respondents: if the full range of the vehicle is relatively stable, for example always is 300 miles, then the range consumed for a 98 miles drive is 98 miles; if the maximum and minimum range differ by a lot (250 miles and 300 miles), then the range consumed for a trip of fixed distance could vary greatly. Therefore, an uncertainty factor was constructed, as previously described in section 5.1.2.2 ($\rho_i = \frac{r_{max} - r_{min}}{2 \times r_{reported}}$). If the remaining range is lower than the distance to the next station or the trip destination (adjust according to the uncertainty factor), received a message saying "There isn't enough electric range to get to the next charging station! Please continue with the next scenario!" and were taken to the next scenario. Not being able to reach the next station does not mean that one is stranded in real life, but there could be a few possibilities: (1) One has to make a mid-trip stop specially for refueling the vehicle; (2) One can adjust their driving behavior to conserve energy to make it to the next stop; (3) One has to turn down the heater/air conditioner to conserve energy; etc. Without specifying this in the survey tool, we leave it to the respondents to interpret the situation and during the modeling process, we evaluate the negative utility of having to deviate from the original plan instead of being stranded in the middle of a trip.

Interested readers are welcomed to check out a demonstration of the SP scenario at this link: http://ec2-34-216-252-211.us-west-2.compute.amazonaws.com/.

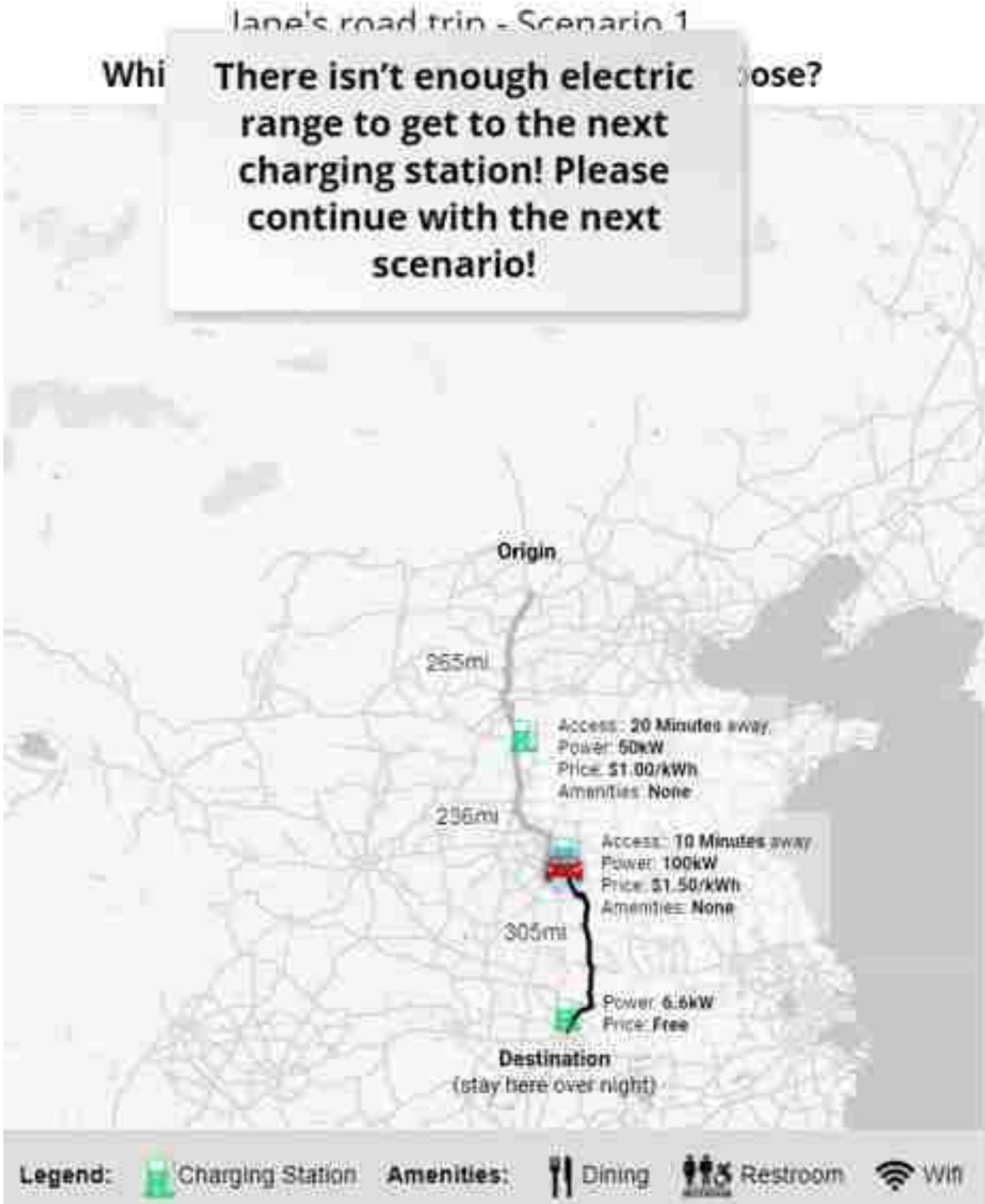


FIGURE 29 Screenshot 6 of the survey tool: When there is not enough electric range to get to the next charging station or home

7.2.2.2 Experimental design for long-distance tours

The first step of the experiment design is to identify the factors that can influence the dependent variables of interest. The focus group discussion shows that the following factors are important variables that influence BEV owners' choice of whether to use their BEVs for a long-distance trip and where to charge the vehicles: the vehicle range, the distance of the long-distance trip, the number of charging stations and the spacings between the stations, the chargers at the destinations, and the characteristics of the charging stations long the trip: charging price, charging power, and the time it takes to access the charging station. The full list of attributes and levels are listed in Table 10.

TABLE 10 Attributes and Their Levels of the Experiments for long distance trips

Attributes	**Variable**	**Description**	**Attribute levels**
Number of charging stations	$N_{chargers}$	The number of accessible charging stations on the way from the origin to the destination	2; 4; 6; 8.
Gasoline price ($)	p_{gas}	Gasoline price	$2.50/gallon; $3.50/gallon; $4.50/gallon
Charging price($/h)	$p_{charging}$	The recharging price at the station	Free; $0.5/kWh; $1.00/kWh;
Charging power(kW)	$Power$	The maximum charging speed at the station	50 kW; 100 kW; 150 kW; 300kW
Access time of the charging station (min)	t_{access}	How many minutes of extra driving it takes to get to the charging station	5 minutes; 15 minutes; 30 minutes
Amenities	A	The amenities available at the station	3 levels: (1) No amenities (2) Restroom only (3) Cafeteria/restaurants, WiFi and restroom
Destination chargers		The level of chargers at the destination	3 levels: Level 1; Level 2; DCFC;

The levels of gasoline price, charging price and level of destination chargers are based on the distribution or the possible range of these variables in real life. Because of the limitations of the experiment tool and in order to reduce the response burden, I applied two simplifications: the distance of the long-distance trip is assumed to be fixed as 800 miles, the number of charging stations are of four levels: 2, 4, 6, and 8. The spacings between the stations are relatively even but are perturbed by a random number from -20% to 20%. For example, the example shown in Figure 29 of section 7.2.2.1, has two charging stations and the distances of each trip leg are respectively 265, 236 and 305 miles. Chargers with the power of 150 kW is not available in the market right now but will be deployed in some places in the US in the near future. Chargers with 300kW are to be development in the future but it is included in the experiment to even though it could be far away from reality. I choose to use the access time instead of the distance to the chargers to avoid confusion related to the travel time due to the different of traffic situations in different areas.

Similar to the experiment design of the home-based tours described in section 5.1.2.2, I used D-optimal design to select the best subset of the scenarios. For this study, the experiment scenarios are generated based on the function optFederov in the R package AlgDesign *(78)*. The function takes the input of the full list of factorial experiments and the number of trials that need to be generated (nTrials). It generates a fixed number of scenarios (nTrials) that have the highest determinant of the Fisher's information matrix. The design is blocked according to the high vehicle range group (for respondents with BEVs with range over 200 miles) and low vehicle range group. For the respondents who do not own a high range vehicle (low vehicle range group), instead of asking them to make suggestions based on their own vehicles, I provided a hypothetical BEV with range being a random number from 200 miles to 400 miles to replace the original vehicle.

For each scenario, at the beginning of the travel day, the state of charge (SOC) is assumed to be 100%, which is justified because most people charge their EVs whenever they get home. Remaining range is the amount of electric range left for the PEV when respondent *i* arrives at one station *t*. The survey tool calculates the remaining range at each station by estimating the energy consumption of each trip based on the vehicle specific information reported by the respondents. In real life, the range consumed of a certain distance of driving is uncertain due to driving habits, traffic condition and weather conditions, etc. This uncertainty of the range consumed ($r_{consumed}$) for distance *l* is considered by generating a random number according to the maximum and minimum range reported by the respondents, see equation (105).

$$r_{consumed} = l + l * \alpha * \rho_i \tag{105}$$

Random variable α is generated based on triangular distribution with maximum value of 1, minimum value of -1 and median value as 0. ρ_i is defined as the uncertainty factor based on the reported maximum (r_{max}) and minimum summer (r_{min}) full range, as shown by equation (106).

$$\rho_i = \frac{r_{max} - r_{min}}{2 \times r_{reported}} \tag{106}$$

When the respondents do not own an ICEV, the option “rent a car” is presented to for the scenarios. The rental cost (c_{rental}) is a random value from \$30 to \$100.

7.3 Data for long-distance trips

The survey on long-distance tours was conducted during September to October 2018. The respondents were recruited mostly through the Electric Auto Association (EAA) and Plug-in America, whose members are generally enthusiastic about electric vehicle technology and related research, and willing to participate into the survey without any extrinsic incentives. There were in total 309 PEV respondents, 267 of whom completed the full survey. A descriptive analysis of the sample is shown in Table 2. 80% of the respondents were male. The reported household income among the respondents is higher than average, with around 39% of respondents reporting a household income over $140,000. More than 69% of the respondents have at least Bachelor's degree. Among the respondents who completed the survey, 117 of the respondents own high range BEVs (BEVs with more than 200 miles of range) and 150 of the respondents do not own high range vehicles. The respondents were from different regions in the US with majority from the east and west coasts, which reflects the distribution of the PEV owners in the country.

TABLE 11 Description of the Sample

Variable	Category	Sample Frequency	Sample Percentage	Variable	Category	Sample Frequency	Sample Percentage
Age	18-24	6	2%	Household Income	<$19,999	15	5%
	25-44	72	24%		$20,000-$39,999	18	6%
	45-55	85	28%		$40,000-$59,999	33	11%
	55-65	88	29%		$60,000-$79,999	30	10%
	65+	51	17%		$80,000-$99,999	27	9%
	Male	242	80%		$100,000-$119,999	27	9%
Gender	Female	60	20%		$120,000-$139,999	18	6%
Education	High School or less	18	6%		$140,000-$159,999	24	8%
	Some College	40	13%		$160,000-$179,999	63	21%
	2-Year College Degree (Associates)	37	12%		$180,000-$199,999	18	6%
	4-Year College Degree (BA, BS)	96	31%		>$200,000	27	9%
	Master's Degree	80	26%	PEV ownership	High range (>=200 mi)	117	44%
	Doctoral Degree	37	12%		Low range (<200 mi)	150	56%

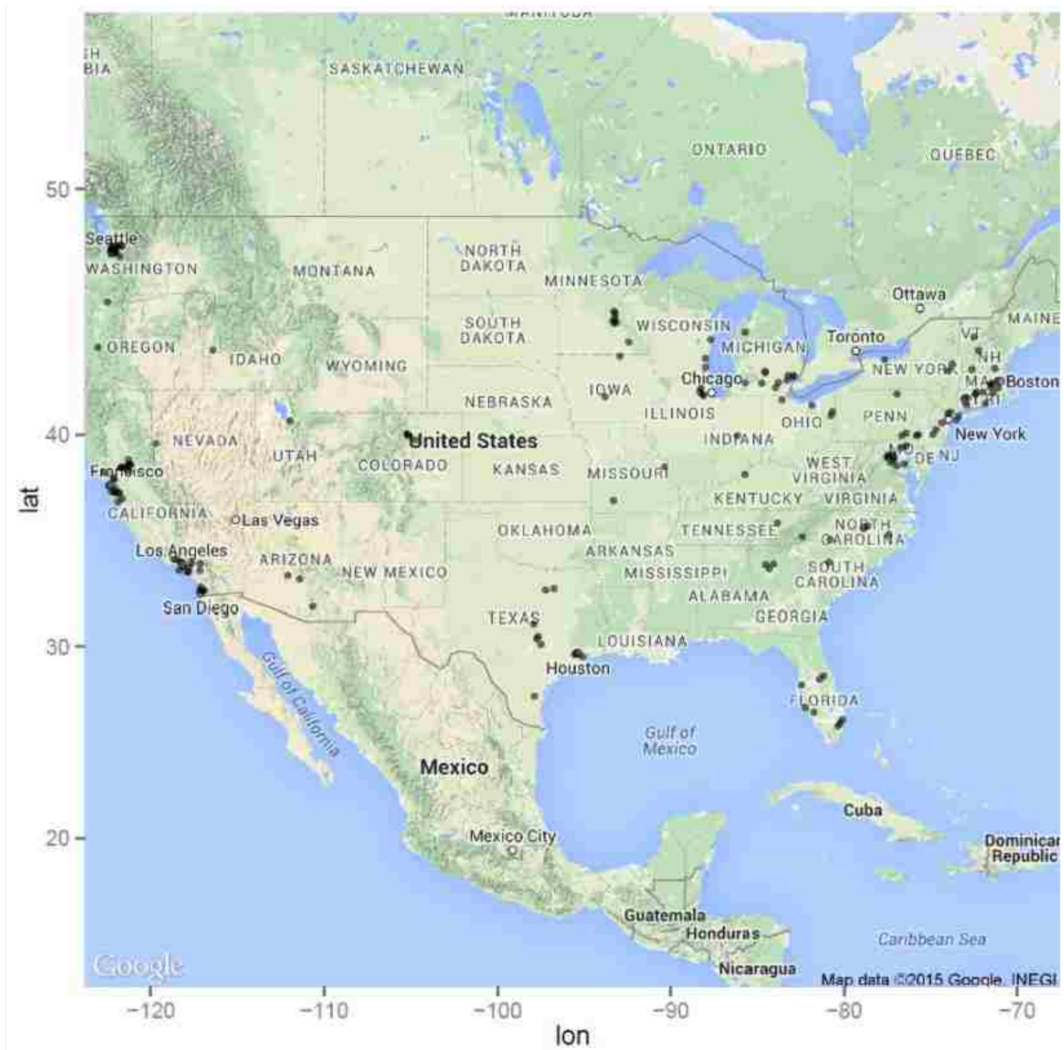


Figure 30 Geographic distribution of the respondents

The attitudinal variables, particularly those on the environmental values and risk-taking propensity are likely to be significant predictors of whether to use BEVs for long-distance trips and whether to charge at the charging stations. Ten Likert-scale questions are included in the questionnaire section on social demographic information to capture the environmental values and risk-taking propensity respectively. It is not practical to include the results of each question in the models. Therefore, I used factor analysis to reduce the dimensionality and extract the latent factors to use for the models. The factor analysis was conducted in R, using the fa function from psych package. To increase the robustness, I explored the data with multiple factor analysis models using different rotation and factor extraction methods. The scree plots indicate that the number of latent factors should be between 2-4. I chose the model with 2 latent factors as the questions are essentially of two dimensions: the environmental values and the risk-taking propensity score. The loadings of the questions on the two factors are shown in TABLE 12. The cumulative variance explained by the two factors is 0.34.

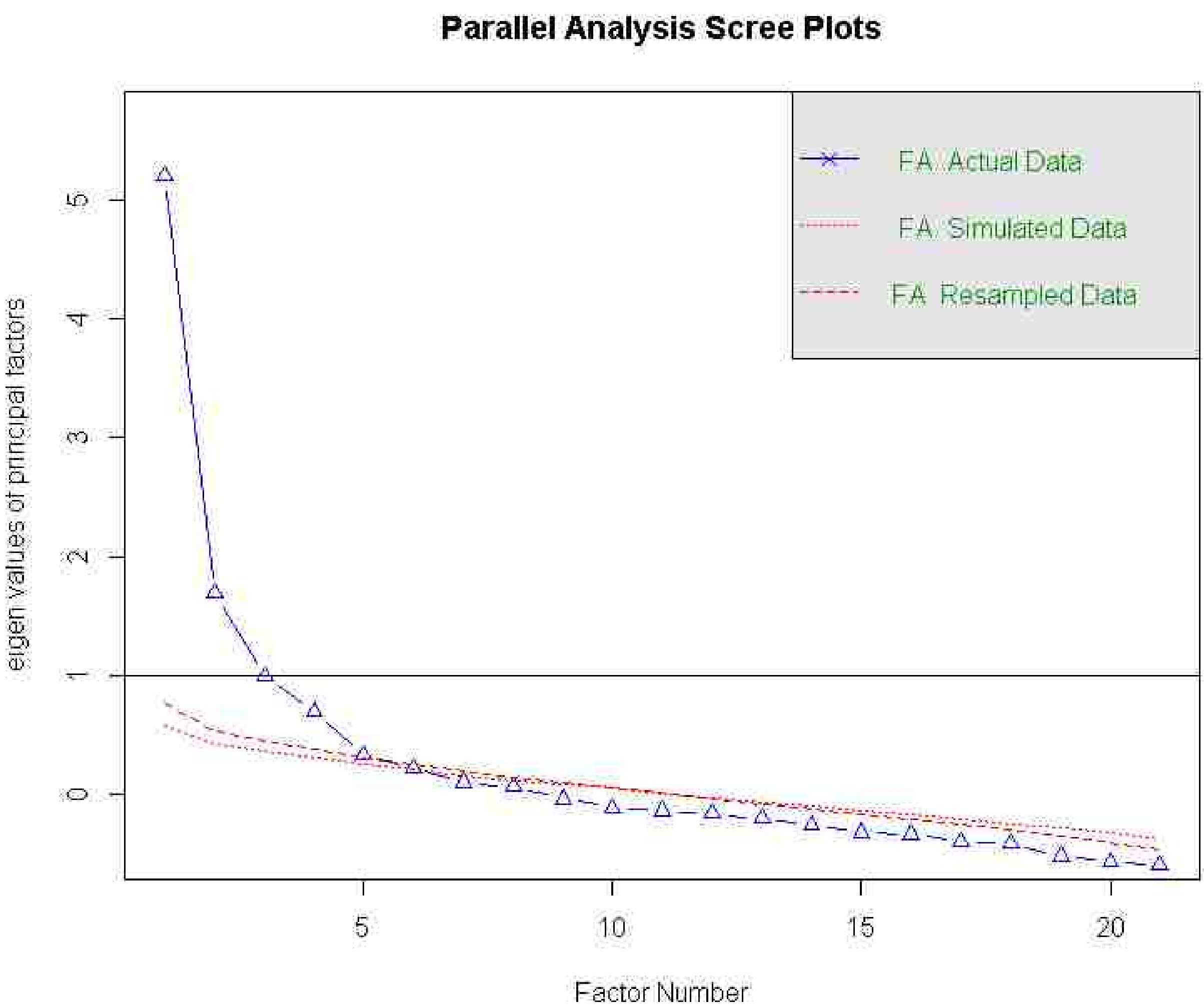


Figure 31 Number of factors for the attitudinal variables

TABLE 12 The loadings of the factors

Questions	Factor 1 - environmental values	Factor 2 - risk-taking propensity
(1) I don’t mind taking the latest possible public transport connection to the airport;	-0.174	0.193
(2) I would go on a two-week vacation in a foreign country without booking ahead;	-0.113	0.486
(3) I would drive my EV without planning out the charging on the way;	0.042	0.226
(4) I start earlier if I assume that there will be congestion on my route;	-0.132	-0.416
(5) If I don't know the way I just start into the general direction and search my way step by step;	0.062	0.484
(6) I start earlier if I have to drive an unfamiliar route;	-0.074	-0.522
(7) I try to be at the airport at the latest possible time;	0.094	0.461
(8) Reoccurring rituals give me a feeling of control and security;	0.042	-0.336
(9) I prefer to organize my holidays spontaneously;	-0.084	0.546
(10) I prefer a clearly structured, repetitive daily schedule	0.074	-0.452
(1) I worry about environment problems;	0.557	0.025
(2) Too much attention is paid to environmental problems;	-0.841	-0.007
(3) Environmental problems are exaggerated;	-0.807	0.130
(4) The risk of the greenhouse effect is exaggerated;	-0.783	0.168
(5) I am optimistic regarding the state and future of our environment;	-0.479	-0.012
(6) Environmental pollution affects my health;	0.342	0.131
(7) Environmental problems have consequences for my life;	0.502	0.101
(8) I can see with my own eyes that the environment is deteriorating;	0.743	0.051
(9) Environmental problems are a risk for the future of our children;	0.844	-0.013
(10) Environmental protection costs too much	-0.777	-0.001

8 Analyses of Long-Distance BEV Trips

8.1 Analysis 4: Vehicle choices for long-distance trips

Summary

Enabling BEV for long-distance trips is not only important for improving the mobility quality of current BEV owners, but also essential for boosting mainstream adoption of BEVs as DCFCs allow BEVs to be used for nearly all trips, catapulting the BEV from commuter-car status to the primary household vehicle. Therefore, it is important to study how BEV users make decisions on whether to choose their BEVs for a long-distance trip. The data for this paper are from a stated choice experiment where the respondents were first presented with long-distance trip scenarios characterized by planned distances, gasoline price, number of charging stations, and the characteristics of each charging stations, and then asked to give advice on vehicle choices and if a BEV was chosen, whether to choose to charge at each station as the trip progressed. The results of the latent class regression model on the vehicle choices for long-distance trips show that gasoline cost of the ICEVs, the relative distance of the trip compared to the range, the relative maximum spacing compared to the vehicle range, and the destination chargers are all important enablers of long-distance BEV trips. Both increasing vehicle range and the density of the charging network are important for encouraging BEV owners to use their BEVs for long-distance trips – one does not substitute another.

8.1.1 Introduction

Even though BEV stock has been increasing rapidly in the US, it still takes only a small proportion of the vehicle ownership. Using BEV for long-distance is still a rare case among the BEV users and this topic has not been studied empirically – the only few “case studies” that are available now are some unofficial blog posts by some dedicated BEV enthusiast who have one or a few experiences of using BEVs for road trips. However, with more high range BEV models entering the market and more DCFCs being deployed nationwide, this is likely to change. Enabling BEV for long-distance trips is not only important for improving the mobility quality of the current BEV owners, but also essential for boosting mainstream adoption of BEVs *(81, 82)*. The National Research Council and Transportation Research Board *(83)* see DCFC on long-distance travel corridors as occupying a small but important niche, serving relatively few charging events but being critical in those cases. By enabling rapidly recharging in the middle of a trip, DCFCs are essential for the transition of BEVs from commuter-cars to primary household vehicles by allowing BEVs to be used for nearly all trips *(83)*. The design of DCFC charging network is intrinsically tied to the behaviors and choices of individual vehicle owners since a system cannot be optimized effectively without a clear understanding of the users' preferences, and "an understanding of fast charging station choice behavior is of paramount important in knowing how EV users trade off the relevant fast charging infrastructure to accelerate EV market growth" *(83)*. The two important questions about the users' preferences when it comes to using BEV for long-distance trips are (1) Will someone use their BEV or an alternative vehicle for a long-distance trip, given charging opportunities along the way? (2) When using their BEV, when and where do they choose to charge? In this section, I aim to answer the first question.

The only research work on BEV for long-distance trip *(84)* reported four focus group discussions. The respondents of these discussions were mostly not EV owners. It was found that the following aspects might be relevant to BEV use for long-distance trips: (1) the range of the vehicle; (2) the density of the charging stations grid, and (3) the attractiveness of the places where the charging stations are located: a service area and a simple parking lot off the highway could be significantly different. The focus group discussion among BEV owners I conducted also shows that when deciding whether to use BEVs for a long-distance trip, BEV owners currently consider the distance of the trip relative to the vehicle range, whether there are enough chargers along the trip, whether there are facilities at the charging stations, and also whether there are chargers at the destinations, as described in detail in section 7.1.

For home-based trip tours, the vehicle choice decisions and charging choices are estimated jointly (see section 6.1). However, for long-distance trips, according to the focus group discussion, the decision processes are different for the two stages: the vehicle choice decisions mainly depend on the trip level characteristics, such as the distance of the trip relative to the vehicle range, and the distances between charging stations relative to the vehicle range. The detailed characteristics of the charging stations are only considered for charging choices, but not for the vehicle choice decisions. In this section, based on the data collected from the choice experiment on long-distance BEV trips, I built latent class logistic regression models to understand how BEV owners make decisions on which vehicle to use for a long-distance trip given trip characteristics, vehicle specifications, and the characteristics of the charging stations along the trip.

8.1.2 Variables and model specification

Latent class logistic regression model is used for this analysis. The model framework is described in detail in section 4.3.2.

8.1.2.1 Variables for the main model

The focus group discussion shows that when deciding whether to use a BEV for a long-distance trip, BEV owners currently consider the distance of the trip relative to the vehicle range, whether there are enough chargers along the trip, and whether there are chargers at the destinations. Therefore, the following factors of the BEVs and the trips are considered for the model:

(1) the relative distance of the trip (L/r_{full}): the distance of the long-distance trip (L) divided by the full range of the BEV (r_{full});

(2) the relative size of the biggest station spacing (Max_Spacing$/r_{full}$): the largest distance from one station to the following station (Max_Spacing) divided by the full range of the BEV (r_{full});

(3) the furthest restroom break ($l_{restrooms}$): the largest distance from one station with restroom to the next on the trip route;

(4) whether there will be restaurants near the stations ($Restaurants$): it is a dummy variable with 1 representing there are restaurants near the stations, and 0 otherwise;

(5) the type of the destination chargers ($Des_{charger}$): there are three different destination charger types: L1 (1.4 kW), L2 (6.6kW), and DCFC (50 kW).

For ICEVs and RENT options, the gasoline cost is calculated according to the fuel economy (mpg) of the respondent's gasoline car (average fuel economy as 25 mpg for the rental cars), the gasoline price (p_{gas}) specified in choice experiment scenario, and the planned distance (L) of the travel day.

$$gas\ cost_{i,icev} = \frac{L}{mpg} * p_{gas} \tag{107}$$

8.1.2.2 Variables for class allocation model

The variables included in the class allocation model are the age, household income, years of EV ownership, and the environmental value factor and risk-taking propensity factor obtained from section 7.3.

8.1.2.3 Model specifications

The utility functions of ICEVs and RENT are based on the costs, as shown by equation (108) and (109). The utility function of BEVs are based on the focus group discussion as described earlier in section 8.1.1. The reference level of the type of the destination chargers ($Des_{charger}$) is L1, which is assumed to be always available.

$$u_{icev_i} = \theta_1 * gas\ cost_{i,icev} + \varepsilon_{icev_i} \tag{108}$$

$$u_{rent_i} = \theta_2 * C_{rental_i} + \theta_3 * gas\ cost_{i,rent} + \varepsilon_{rent_i} \tag{109}$$

$$u_{bev_i} = \theta_4 * \frac{L}{r_{full}} + \theta_5 * \frac{\mathrm{Max}_{\mathrm{Spacing}}}{r_{full}} + \theta_6 * l_{restrooms} + \theta_7 * Restaurants + \theta_8 * Des_{charger_{(L2)}} + \theta_9 * Des_{charger_{(DCFC)}} + ASC\_BEV + \varepsilon_{rent_i} \tag{120}$$

8.1.3 Results

8.1.3.1 Overview of the results

I estimated a series of latent class models with different number of latent classes and chose the one with the best goodness of fit according to the BIC values. The final model, as shown in TABLE 13, identifies three latent classes. The Null deviance of the model is 1082 and residual deviance is 493. The pseudo R-squared of this model on vehicle choice is 0.54.

According to the membership probabilities, the overall share of class 1-3 are respectively 11%, 31% and 58%. The alternative specific constants for BEV (*ASC_BEV*) show with all the other variables being zero, the default modes of class 2 and class 3 are both BEVs and the default mode for class 1 is ICEV or RENT. The estimates of the class allocation model show that the years of ownership and environmental value factor are significant predictors of the class membership. Those with more experience of driving an EV (higher years of EV ownership) are more likely to fall into class 2 and class 3. They are more likely to choose BEVs for a long-distance trip with other variables being zero than more recently EV adopters. Those with high environmental values are more likely to fall into class 3 and more likely to use BEVs as the default choice for their long-distance trips.

TABLE 13 Model results of BEV owners' vehicle choice for long-distance trips

	Class 1		Class 2		Class 3	
Main model	Est.	P-value	Est.	P-value	Est.	P-value
ICEV: gas cost (\$)θ_1	-0.017	0.000	-0.017	0.000	-0.040	0.000
RENT: cost (\$)θ_2	-0.014	0.395	-0.015	0.179	0.059	0.010
RENT: gas cost (\$)θ_3	-0.020	0.012	-0.012	0.021	-0.075	0.000
BEV: relative distance ($\frac{L}{r_{full}}$) θ_4	-0.443	0.352	-0.585	0.019	-1.659	0.002
BEV: relative max spacing ($\frac{\text{Max}_{\text{Spacing}}}{r_{full}}$) θ_5	-2.142	0.037	-6.013	0.000	-9.342	0.000
BEV: furthest restroom break (miles) $l_{restrooms}$ θ_6	0.002	0.315	-0.001	0.197	0.002	0.271
BEV: *Restaurants* θ_7	0.163	0.801	-0.396	0.240	0.197	0.688
BEV: Des charger (Level 2) θ_8	0.946	0.071	1.015	0.000	-0.748	0.141
BEV: Des charger (DCFC) θ_9	0.358	0.546	1.068	0.001	1.428	0.039
BEV: *ASC_BEV*	-2.691	0.071	4.637	0.000	11.184	0.000
Membership probability	11%		31%		58%	
Class allocation model	Est.	P-value	Est.	P-value	Est.	P-value
Age	-	-	0.01	0.83	0.01	0.60
Household income level	-	-	-0.01	0.95	-0.01	0.86
Years of EV ownership	-	-	0.03	0.00	0.05	0.00
Environmental value factor	-	-	0.21	0.41	0.66	0.02
Risk taking propensity factor	-	-	-0.09	0.82	0.09	0.83

8.1.3.2 Effects of gasoline price

All the three classes show that both gasoline cost of ICEV and RENT are significant predictors of vehicle choice, which is quite different from the results of the models on home-based tour. This could be due to the fact that the gasoline cost for long-distance tours are significantly higher than home-based tours: gasoline price change from \$2.50 to \$4.00 might not lead to a big change in gasoline cost for a 30 miles trip, but rather large for an 800 miles trip for some BEV owners. The effect size of gasoline price on BEV owners' decision on the vehicle to use for a long-distance trip is heterogeneous among the three classes. When the maximum spacing of charging stations is 100 miles and the fuel economy of the ICEV is 20 miles per gallon, the impact of gasoline price on the probability of a BEV being chosen for an 800 miles road trip is displayed in Figure 32 for the three classes respectively. It shows that when the charging network is dense, the effect size of gasoline price on the probability of BEV being chosen is little for both class 2 and class 3. Increasing gasoline price can help encourage those in class 1 to use BEVs for long-distance trips.

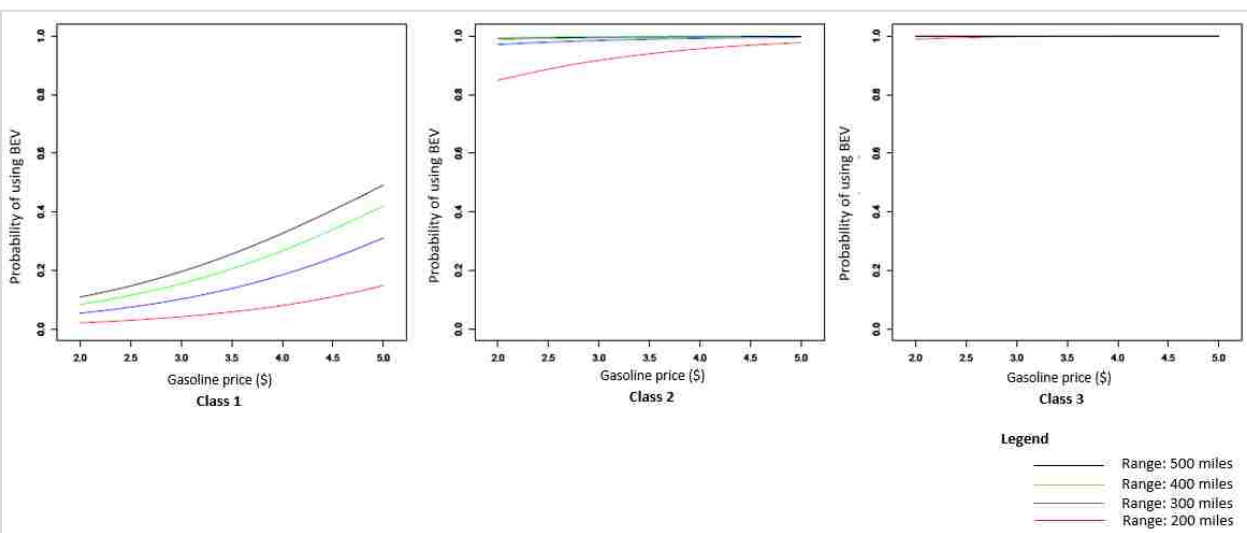


Figure 32 The influence of gasoline price on the probability of choosing BEV for long-distance trips

8.1.3.3 Effects of range and charging network

For all three classes, the relative distance and relative maximum spacing are significant predictors of the BEV owners' vehicle choice. Relative distance, as specified as the trip distance divided by the vehicle range, directly reflects the minimum number of charging events needed for this trip and indicates the importance of battery size, whereas relative max spacing, as specified as the maximum spacing between two consecutive stations, indicates the importance of the density of the charging network. Both increasing the battery size and increasing the number of charging stations can help enable BEV long-distance trips, as shown both by the model and by the focus group discussion, however, the relative significance of these two factors are different for the three classes. Comparing the relationship of the coefficients of the relative distance and relative maximum spacing, those in class 2 value the station density more heavily than those in the other two classes.

Based on the final model, for imaginary individuals that own an ICEV with the fuel economy of 20 miles per hour and a BEV, the impact of maximum charging station spacing and BEV range on the probability of using BEV for an 800 miles trip when the gasoline price is $3 per gallon can be found in Figure 33. For those in class 1, the probability of using BEV can only be increased to a little over 0.20 when the vehicle range is 500 miles and maximum spacing between charging stations is less than 100 miles. According to the class allocation model, these BEV owners are relatively newer adopters with lower environmental values. BEV owners in class 3 are relatively earlier adopters than class 1 and class 2 and who have the highest environmental values. The impact of the density of charging network on BEV owners in class 2 is highest among the three groups. For class 2, when the range of the BEV is 300 miles and the charging station spacings are smaller than 150 miles, the probability of the BEV being chosen for the trip is over 90%, same with when the BEV range is 500 miles and the charging station spacings are smaller than 350 miles.

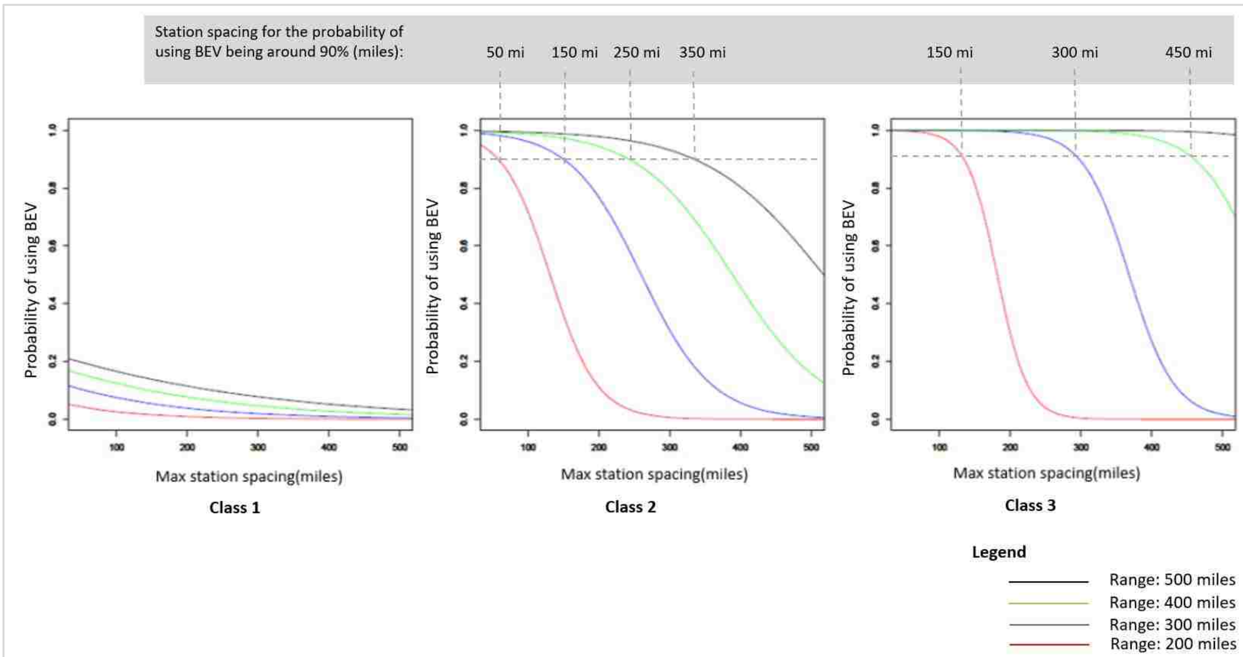


Figure 33 The influence of BEV range and maximum station spacing on the probability of choosing BEV for a long-distance trip

The EV market and infrastructure development need to consider the heterogeneity of the consumers. A vehicle with 500 miles of range might be particularly attractive to some potential EV adopters, like those in class 3, whereas other consumers might think it is necessary and enjoyable to take a break while charging after 300 miles (4 hours) of driving so having 500 miles in the pack might be a type waste, especially considering the high cost of EV batteries. Even if the battery technology develops rapidly in the future and the majority BEV models have 500 miles of range or more, it is important to know that the density of the public charging network can still play an important role in encouraging BEV use for long-distance trips.

8.1.3.4 Effects of amenities and destination chargers

All the three classes show that the variable furthest restroom break (the longest distance from one station with a restroom to the next on the trip route) and restaurants (whether there is a restaurant around at least one charging station) are not significant predictors of the vehicle choices for BEV owners' long-distance trips. Destination chargers are rather important for those in class 2 and class 3, which shows that in order to encourage the BEV use for long-distance trips, it is necessary to install Level 2 or Level 3 chargers at the popular destinations or long-distance trips, for example hotels. Having Level 2 chargers and DCFCs installed are also likely to help attract customs for the hotels or businesses.

8.1.4 Conclusions and discussions

This analysis identifies a latent class logistic regression model for understanding BEV owner's vehicle choice for long-distance trips. It shows that the gasoline cost of the ICEVs, the relative distance of the trip compared to the range, the relative maximum spacing compared to the vehicle range, and the destination chargers are all important enablers of long-distance BEV trips. Therefore, the possible measures to encourage BEV owners to choose their BEV for long-distance trips include the increase of gasoline price, bigger battery pack size, more public charging stations, and more coverage of Level 2 or DCFC charging stations at the hotels at the popular destination of long-distance trips. The model highlights the heterogeneity of the vehicle choice decision among BEV owners, which is important for both the EV market and the planners of charging infrastructure. Even if the battery technology develops rapidly in the future and the majority BEV models have 500 miles of range or more, it is important to know that the density of the public charging network can still play an important role of encourage vehicle use for long-distance trips. This model on the consumers' preference could be useful for the decision-makers in network design and planning of the charging facilities and investment of DCFC charging facilities.

8.2 Analysis 5: Charging choices for long-distance trips

Summary

Understanding BEV users' preferences and decision mechanisms of charging choices are not only important for the design and planning of DCFC network, but also for the decision-making in DCFC investment. The data for this analysis are from a stated choice experiment where the respondents were first presented with long-distance trip scenarios characterized by planned distances, gasoline price, number of charging stations, and the characteristics of each charging stations, and then asked to give advice on vehicle choices and if a BEV was chosen, whether to choose to charge at each station as the trip progressed. The charging choices are analyzed using both static discrete choice models and dynamic discrete choices models that account for the intertemporal payoff. The results show that battery state of charge (SOC) and whether the vehicle can reach the next station with the remaining range without deviating from the original plan (Deviation) are the primary factors contributing to the charging decisions. The characteristics of the charging stations, including charging cost, charging time, the time it takes to get to the station, and the amenities near the station are significant predictors, but contribute little to the model's predictive power. This is likely because when the charging network is not dense enough, BEV drivers tend to act in a 'survival mode' when they make charging decisions with the priority of making it to the destination and the considerations of the charging station characteristics only happen when the charging network is dense enough. The comparison of the SDCMs and DDCMs shows that SDCMs fit the model better than the more complicated DDCMs. This result might change when the density of charging network is higher, and the BEV users can not only make it to the destination reliably, but also can compare charging stations along the way based on the price, accessibility, etc (the "thrival mode"). By comparing the relative size of the coefficient estimates, I also showed the monetary value of Deviation, charging power, moving the charging stations closer to highway exits, and having amenities such as restrooms, restaurants, and WiFi near the charging stations. The negative cost of deviating from the original plan is $244 for long-distance trips, much higher than it for home-based trips ($24).

8.2.1 Overview

In the literature, relatively little charging behavior research has focused specifically on fast charging, although it is increasingly understood that fast charging represents a distinctive use case. One exception is work by Sun, Yamamoto, and Morikawa *(30, 42)*, who have approached the problem in two different ways. One of their approaches was to model the state of charge at the beginning of charging activities *(30)*. However, this suffers the same weakness as approaches based on hazard models *(46, 85)*, namely that modeling the start of charging in a continuous variable space (i.e. time or SOC) does not reflect the physical reality that drivers can only choose to charge at those distinct times when they encounter a charging station. Their second approach was using mixed logistic regression model to study drivers' choices from among sets of feasible fast-charging stations, given information on SOC, detour distance, and cost, among other factors *(86)*. By focusing on charging choices among discrete charging stations, this latter approach more accurately reflects the manner in which drivers encounter charging opportunities in the real world. However, this study is focused on one specific scenario where only one mid-trip charge is needed, which does not apply to long-distance trips where multiple chargers are needed.

As indicated by the choice experiment, I treat the charging choice at each charging station as a binary variable, but the choices between two stations could be dependent, as in the charging decision can also be influenced by the characteristics of the future charging choices. DDCM assumes that the decisions are made based on not only the current utility but also the expected utility at the future decision period. In this analysis, I estimate and compare a series of discrete choices model based on a series of decision heuristics, from simple to more complex. The following static discrete choice models (SDCM1) based on conditional logistic regression model framework are tested:

Heuristic 1 (SDCM1): the decision of charging only depends on the state of charge, as how much energy is left in the battery pack;

Heuristic 2 (SDCM2): the decision of charging depends on state of charge, and also whether the driver can get to the next station without deviating from the original route plan;

Heuristic 3 (SDCM3): the decision of charging depends on the state of charge, whether the driver can get to the next station without deviating from the original route plan and the time since the last stop, as in the time in car since the most recent stop;

Heuristic 4 (SDCM4): Besides the variables considered by SDCM3, BEV drivers also consider the characteristics of the charging stations, such as the charging cost, the charging time, the time it takes to access the station, and the amenities at the charging station.

These four SDCMs based on simple heuristics are compared with four DDCMs. DDCMs assume that the charging decision at one station does not only depend on the characteristics of this current station but also the characteristics of the following stations: as in the decision-makers are forward-looking. In this analysis, the first three of the four DDCMs assume that BEV drivers consider the characteristics of the next one station, next two stations, and next three stations respectively, and the fourth DDCM assumes that the characteristics of all and only the future stations in one plan unit are considered. The plan unit at station *t* refers to the collection of the stations that can be reached without charging based on the average energy consumption rate. For example, when the current remaining range of the vehicle is 100 miles, and there are four charging stations along the next 100 miles of the planned route, then the plan unit at the station *t* includes all these four stations and the driver is assumed to consider the characteristics of these four and only these four future stations when deciding whether to charge at the current station.

The comparison of the SDCMs and the DDCMs show whether the BEV drivers are forward-looking when making decisions on charging, and the comparisons among the four DDCMs show how forward-looking they are: how many future stations they are likely to consider. The results of this analysis can inform the decision-making and support the analyses on planning of intercity charging infrastructure network.

8.2.2 Specifications of the models

The model frameworks and estimation processes of the SDCMs and DDCMs are described in detail in section 4.3.2 and section 4.3.3. The following two sub-sections are on the variables and the model specifications.

8.2.2.1 Variables and specification of the static discrete choice models (SDCMs)

(1) State of Charge (SOC_t)

SOC_t indicates the state of charge at station *t*, which equals to the remaining range divided by the full range of the BEV. It does not only influence the amount of energy the vehicle can gain at a charging station but also the charging speed, as shown in Figure 34. After reaching

80%, the charging speed decreases significantly: the time for charging from SOC of 20% to SOC of 80% is about the same from 80% to a full charge. The distribution of SOC at the beginning of the charging events from our experiment also shows that that most drivers choose to charge at a relatively lower SOC level (Figure 35).

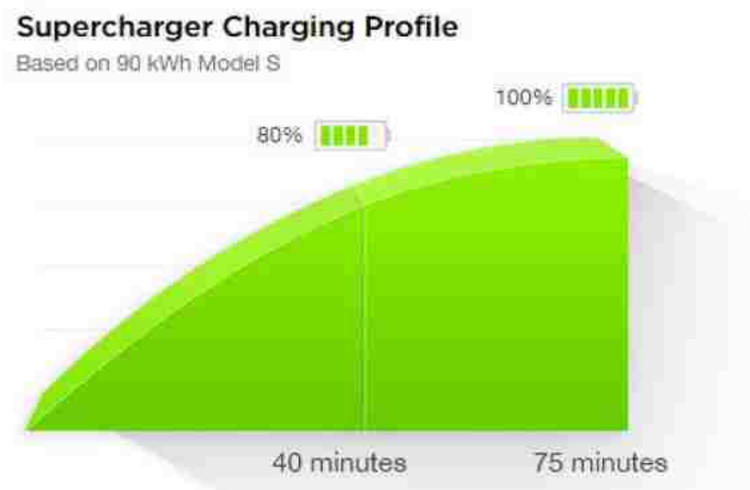


Figure 34: charging curve for Tesla Model S *(87)*

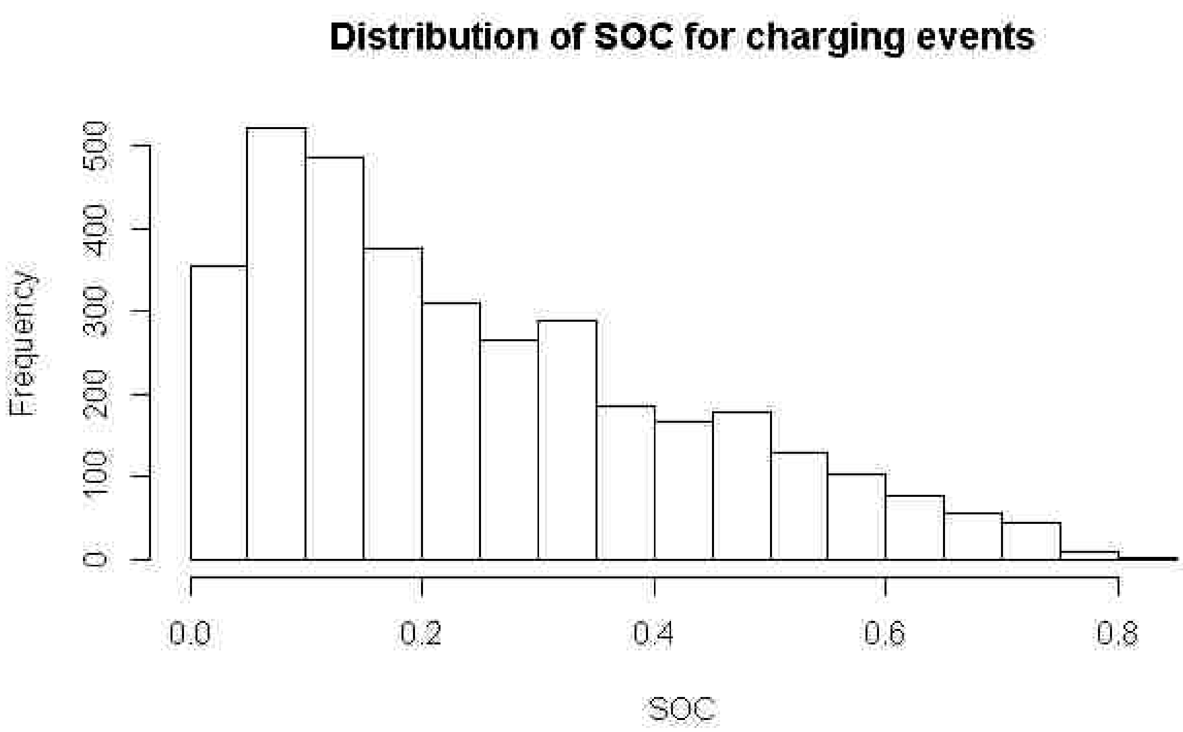


Figure 35: The percentage of charging with the change of the remaining range

(2) Time since last charge ($Hours_t$)

Time since last charge shows the time since the last stop for charging. It could be a significant predictor of charging choices since it reflects whether the driver has the need to stop for a break while charging at the same time. During the focus group discussion, a few respondents also mentioned that sometimes the primary goal of stopping at a charging station is to rest, and they choose to add some range to their cars at the same time if possible.

(4) Deviation (DEV_t)

Deviation shows whether BEV drivers need to deviate from the original plan if they choose not to charge. It is calculated according to relationship between the remaining range of the vehicle upon arriving at one station and the distance to the next charging opportunity. When the remaining range is larger than the distance to the next charging station, DEV equals to one, otherwise it is 0.

In real life, Deviation from the original plan on a long-distance trip does not necessarily mean that BEV drivers are stranded in the middle of trip. Instead, it could mean that the BEV driver needs to change his/her driving behavior to reduce energy consumption in order to reach the next charging opportunity or having to find a charger off the original trip route. In the survey tool, when the remaining range of the vehicle is not enough to reach the next charging station, we indicated that this experiment is over by showing the respondents “There isn’t enough electric range to get to the next charging station! Please continue with the next scenario!”. Different respondents with different EV experience level are likely to have different interpretations of Deviation. Instead of specifying the meaning of it, we leave it to the respondents' understanding and imagination and try to capture the average effect of all of these different possibilities in the modeling process.

(5) Charging cost (${C_{charging}}_t$)

${C_{charging}}_t$ is calculated as the charging cost to reach to a full range, which is decided by the remaining range upon arriving at station *t* (rr_t), the full range of the vehicle (r_{full}), the energy consumption rate (*ECR*) of the BEVs, and the charging price specified in the choice experiment scenario (${p_{charging}}_t$), as shown by equation 121.

$$ {C_{charging}}_t = (r_{full} - rr_t) \times ECR \times {p_{charging}}_t \tag{121} $$

(ECR: Average electricity consumption rate in kWh / mile)

(6) Charging time (${T_{charging}}_t$)

$T_{charging}$ is calculated as the charging time to reach to a full range at a station. It is calculated based on the full range, the remaining range, the energy consumption rate, and the charging power at station *t* ($Power_t$).

$$ T_{charging} = (r_{full} - rr_t) \times \frac{ECR}{Power_t} \tag{122} $$

(ECR: Average electricity consumption rate in kWh / mile)

Besides these six variables, the following variables specified in the scenarios are also included in the models: the time to access the charging stations (*Access time*) and the amenities at the stations – whether there is a restroom, restaurant, and WiFi. The utility of charging at station *t* is then the linear combination of these variables, and the system component of the utility of not to charge at station *t* only includes deviation (DEV_{it}).

$$u_{charging_{it}} = \theta_0 + \theta_1 * SOC_{it} + \theta_3 * Hours + \theta_4 * C_{charging_{it}} +$$

$$\theta_5 * T_{charging_{it}} + \theta_6 * T_{access_{it}} + \theta_7 * Amenity_{restroom_{it}} + \theta_8 * Amenity_{more_{it}} + \varepsilon_{charging_{it}} \quad (123)$$

$$u_{not\ charging_{it}} = \theta_2 * DEV_{it} + \varepsilon_{not\ charging_{it}} \quad (124)$$

8.2.2.2 Variables and specification of the DDCMs

The derived variables in section 8.2.2.1 are also included in the DDCMs. The essential difference between the DDCMs and the SDCMs for the charging choices is that on top of the current utility specified according these variables, the decision is also based on the utilities of the future stations. Since the energy consumption, as in the values of the remaining range are not certain in the future stations, the future utilities, which are based on the remaining range at the future stations, cannot be known for sure, but the expected future utilities can be calculated based on an assumption about the distribution of energy consumption.

The remaining range upon arriving at stop *t+1* ($rr_{i,t+1}$) equals the remaining range upon arriving at stop *t* (rr_{it}) plus the range obtained at the stop *t* ($r_{obtained_{it}}$), minus the range consumed on the way from stop *t* to stop *t+1* ($r_{consumed_{it}}$), as expressed in the following equation. For this analysis, $rr_{it} + r_{obtained_{it}}$ is assumed to be equal to the full range, as in the whenever the drivers stop for charging, the vehicles are charged to a full range.

$$rr_{i,t+1} = rr_{it} + r_{obtained_{it}} - r_{consumed_{it}} \quad (125)$$

The range consumed ($r_{consumed_{i,t}}$) for a certain distance is uncertain due to factors such as road and traffic conditions, which create variation in actual per-mile energy consumption. Variability in range consumed leads to uncertainty of the remaining range upon arriving at subsequent charging stations. The distribution $g(r_{consumed_{i,t}} | l_{it})$ models the BEV users' belief about the range consumed for driving the distance from station t to station t+1: l_{it} and it is assumed to dependent on the BEV's uncertain factor of energy consumption (ρ_i) as described in section 7.2.2.2. When the maximum range and minimum range reported by the respondent differ greatly, then the uncertain factor ρ_i is bigger. When the maximum range and minimum range reported by the respondents are equal to each other, then it is assumed that the range consumption for a certain distance is rather consistent for this vehicle, as in ρ_i equals 0. In this case, the energy consumption for the given distance l_{it} is equal to l_{it}.

As explained in 8.2.1, the expected future utility of station *t* is calculated according to different number of future stations for the four DDCMs: DDCM1 only considers the next station, DDCM2 considers the following two stations, DDCM3 considers the future three stations, whereas DDCM4 considers all the stations that the vehicle is likely to be able to reach without charging, as in the plan unit of the current station.

8.2.3 Results

8.2.3.1 General overview of the estimates

The results of the four models based on static conditional logistic regression model (SDCM 1-4) and four dynamic discrete choice models (DDCM 1-4) are shown in Table 14. These models consistently show that the following variables are significant predictors of charging choices of BEV drivers on a long-distance trip and the directions of the effect is consistent with intuition: (1) when the state of charge of the battery (SOC) is lower, the driver is more likely to choose to charge; (2) whether the driver can get to the next station without deviating from the originally planned (Deviation) is negatively associated with the probability of charging; (3) charging cost at a the station is negatively correlated with the probability of charging; (4) charging time at the station is negatively correlated with charging; (5) Access time, as in the time it takes to get to a station, is negatively correlated with charging; (6) the amenities at the station, specifically restrooms, dining facilities, and also WiFi can increase the probability of charging . The reference level of the variable Amenity is no amenity at all. Having a restroom alone does not significantly influence the charging choices of the BEV drivers. Time since the last charge, as in how long the driver has been driving since the last charging activity, is not significantly associated with the charging decisions.

TABLE 14 Results of the models on charging choices

Variables	NULL	SDCM1	SDCM2	SDCM3	SDCM4	DDCM1	DDCM2	DDCM3	DDCM4
(Intercept) θ_0	2.983***	3.126***	0.318**	0.879***	2.034***	1.588***	1.307***	1.640***	1.032***
SOC (%) θ_1		-7.560***	-3.043***	-3.561***	-4.584***	-3.039***	-3.021***	-3.246***	-3.122***
Deviation (DEV) θ_2			−2.466***	−2.474***	−2.440***	−1.676***	−1.622***	−1.424***	−1.628***
Time since last charge (h) θ_3 $(Hours)$				-0.143	-0.069	-0.050	-0.062	-0.061	-0.051
Charging cost ($) θ_4 $(C_{charging})$					-0.010***	-0.010***	-0.011***	-0.012***	-0.010***
Charging time (h) θ_5 $(T_{charging})$					-0.242**	-0.229**	-0.218***	-0.267***	-0.232***
Access time (min) θ_6 (T_{access})					-0.025***	-0.023***	-0.022***	-0.024***	-0.028***
Amenity: restroom only θ_7 $(Amenity_{restroom})$					0.049	0.046	0.045	0.043	0.047
Amenity: restroom, dining & WIFI θ_8 $(Amenity_{more})$					0.213**	0.214***	0.223***	0.275***	0.209***
Log-likelihood	-4518	-3079	-2739	-2636	-2557.5	-2690	-2712	-2669	-2602
Pseudo R-squared	_	0.319	0.394	0.417	0.434	0.405	0.400	0.409	0.424
N	6355	6355	6355	6355	6355	6355	6355	6355	6355
AIC	9036	6160	5482	5278	5133	5398	5442	5356	5222
BIC	9036	6162	5486	5283	5149	5414	5458	5372	5238

** p-value<0.05; *** p-value<0.01

8.2.3.2 The effect size – contribution to prediction power

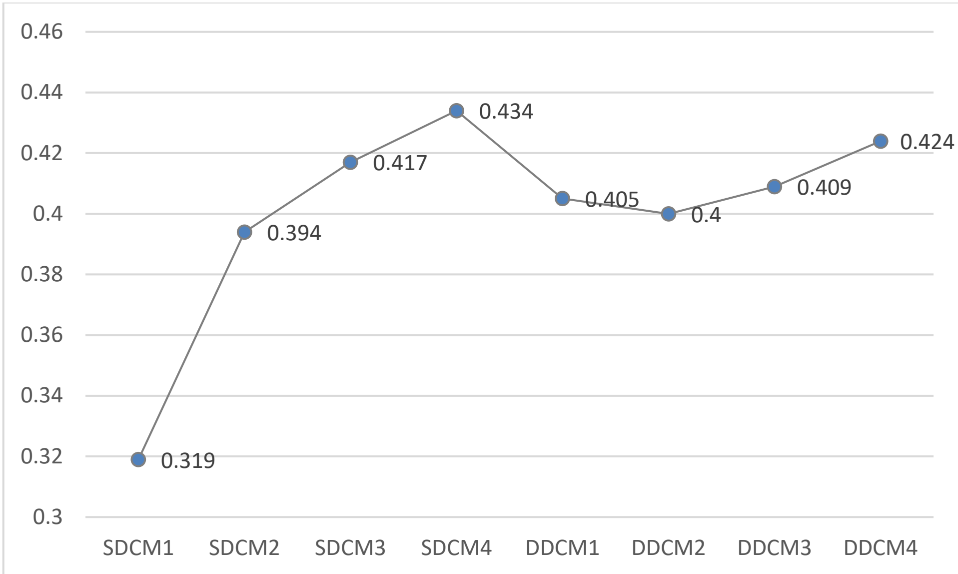


Figure 36: The Pseudo R-squared of the SDCMs and DDCMs on charging choices

The improvement of the goodness of fit of the static models (from SDCM 1-4) indicates the relative effect size of these predictors. The Pseudo R-squared of the model with only SOC as the predictor (SDCM1) is 0.319. Adding the other variables increases the likelihood, AIC, BIC, and pseudo R-squared, but not by a lot, see Figure 36. The inclusion of DEV in the model shows that greatest improvement of goodness of fit compared with the inclusion of any other variables, whereas adding the characteristics of the charging stations (charging cost, charging time, access time, and amenity) only results in the increase of Pseudo R-squared by 0.017 even though they are all significant predictors of the charging choices. This shows that for this sample, charging decisions largely depend on the trip characteristics: how much range left in the vehicle and whether the vehicle can reach the next station without deviating from the original route plan. The focus group discussion also shows that these two factors are the primary variables that influence the charging choices. The characteristics of the charging stations are important, but not critical. When the charging network is rather sparse, the primary consideration of BEV drivers' charging choices is likely to remain as the SOC and DEV: whether the car needs to charge badly, and whether the car can get to the next station. I call this the "survival mode" of charging decision. Only when the charging network is dense enough, as in when there are a lot of stations with similar SOC and DEV values, will the characteristics of the charging choices have larger effect size. I call this the "thrival mode" of the charging decisions on a long-distance trip, where there are redundant DCFCs and the BEV users do not need to prioritize only the SOC and whether the car can reach the next station, but also compare the charging cost, the charging time, the access time, and the amenities at the stations. I like this analogy to help understand this phenomenon: I am on a desert and have to choose one between two different paths, one of which has significantly better view than the other at the destination. The view is not likely to influence my choice when I know I only have enough water to travel for 2 miles whereas the destination with the better view is 5 miles away. It is only when I have enough water to reach either of the two destinations, will I include the view in my decision process.

8.2.3.3 Comparing the SDCMs and DDCMs

Adding another layer of complexity by assuming that the charging decision is made based on not only the current but also the future charging stations, the DDCMs (DDCM 1-4) bring down the goodness of fit, as shown in Table 13. This is not surprising. DDCMs assume that the individuals make tradeoffs between the current utility and the future expected utility, for example, someone may consider not to charge at the current station but to charge at the next station when he/she observes that the next station is closer to the freeway, or has a charger with higher charging power, or cheaper, or has a restaurant nearby. When the characteristics of the charging stations do not contribute a lot to the prediction power of the model, as in when the individuals prioritize the state of charge and remaining range over the characteristics of the charging stations, it makes sense that the model based on the intertemporal payoff does not fit the data as well. However, this is likely to be different for a denser charging network. When there are sufficient and even redundant charging stations in the network and BEV users do not worry about getting stranded, they are more likely to compare the cost, charging time, access time and amenities among all the viable stations and it is possible that DDCM performs better than SDCM in this case. The comparisons among the four DDCMs also show that DDCM4 based on the concept of the plan unit (the collection of future stations that can be reached without charging) offers the best model fit, though this needs to be further studied when the charging stations are more ubiquitous.

8.2.3.4 The monetary value of deviation

Deviation from the original plan does not necessarily mean that the driver will get stranded. It could mean that he/she needs to adjust the driving behavior and be careful with energy consumption or has to find a charger off the route. Comparing the relationship of the coefficient estimates of DEV and charging cost of SDCM 4, it is shown that the on a long-distance BEV trips, the drivers are willing to pay \$244 to avoid having to deviate from the originally planned route. This is a lot higher than the cost of deviation detected for home-based trips, which is \$24. My speculation is that for home-based tools, the respondents are confident about finding public chargers outside of the destinations and the cost of having to make a mid-trip stop to charge is not very high. Whereas on a long-distance trip, it might be rather difficult or costly to find a charger off the route. It is also likely that BEV owners tend to be more cautious and conservative when they are on long-distance trips.

8.2.3.5 The monetary value of charging time, access time and amenities

According to the relationship between the coefficient estimates of charging cost and charging time, \$12 of charging cost decrease has the same effect on the utility with the charging time being reduced by half an hour, which is equivalent to increasing the charging power by 28 kW. When increasing charging power from 50kW to 150kW, BEV owners are willing to pay \$22.4 more to gain 200 miles of range (assuming the energy consumption rate of the BEV is 0.35 kWh/miles). Similarly, according to the relationship between the coefficient estimates of charging cost and access time, \$25 of charging cost increase has the same effect on the utility function of charging with moving the charging station 10 minutes further off the highway. BEV users are also willing to pay around \$20 more to stop at a charging station with amenities such as restroom, dining facilities and WiFi instead of charging station without any amenities. These could potentially be informative for charging infrastructure planners and DCFC investors.

TABLE 15 The willingness to pay of relevant variables according to the SDCM4

Variables	Willingness-to-pay
charging time(h)	\$24
Deviating from the original plan	\$244
Access time(h)	\$150
Charging stations with restrooms	\$5
Charging stations with restrooms, dining options and WiFi	\$21

8.2.3.6 Heterogeneity

I estimated multiple latent class models with different number of classes and same model specification with SDCM 4 to capture the heterogeneity of the charging decision patterns and then decided on four classes. which has the best goodness of fit. The results are shown in TABLE 16. This model fits the data a lot better than SDCM 4.

TABLE 16 Latent class model of BEV charging choices on a long-distance trip

Variables	**Class 1**		**Class 2**		**Class 3**		**Class 4**	
Main model	**Est.**	**P-value**	**Est.**	**P-value**	**Est.**	**P-value**	**Est.**	**P-value**
(Intercept) θ_0	9.506	0.000	1.622	0.083	1.634	0.025	-1.693	0.183
SOC (%) θ_1	-13.042	0.000	-8.878	0.000	-4.271	0.000	4.179	0.010
Deviation θ_2 *(DEV)*	-1.641	0.000	0.077	0.720	0.727	0.000	0.069	0.815
Time since last charge (h) θ_3 $(Hours)$	0.142	0.744	3.455	0.000	3.921	0.000	0.326	0.561
Charging cost ($) θ_4 $(C_{charging})$	-0.002	0.637	-0.013	0.001	-0.017	0.000	-0.0003	0.955
Charging time (h) θ_5 $(T_{charging})$	-0.638	0.073	0.668	0.059	-1.090	0.000	-0.124	0.769
Access time (min) θ_6 $(T_{charging})$	-0.023	0.314	0.005	0.825	-0.043	0.003	-0.070	0.008
Amenity: restroom only θ_7 $(Amenity_{restroom})$	-0.643	0.071	-0.370	0.276	0.142	0.514	0.313	0.426
Amenity: restroom, dining & WIFI θ_8 $(Amenity_{more})$	0.120	0.726	-0.652	0.062	0.694	0.001	-0.147	0.725
Membership probability	19%		29%		37%		15%	
Class allocation model	Est.	P-value	Est.	P-value	Est.	P-value	Est.	P-value
(Intercept)	-	-	2.81	0.18	1.14	0.58	-0.26	0.91
Age	-	-	-0.06	0.84	0.00	0.94	0.01	0.86
Household income	-	-	0.24	0.62	0.12	0.30	0.09	0.49
Years of EV ownership	-	-	-0.12	0.38	-0.13	0.19	-0.13	0.28
Environmental value factor	-	-	0.16	0.79	-0.22	0.67	-0.04	0.95
Risk-taking propensity factor	-	-	-0.42	0.43	-0.58	0.24	-0.15	0.80

The four classes identify rather different decision mechanisms and the class allocation model does not show significant predictors that can help identify the characteristics of the group. Class 1 indicates that charging decisions solely depend on the battery state of charge (SOC) and whether the car can reach the next station without having to deviate from the original route plan. On top of these two variables, class 3 identifies a group of BEV users that also consider the characteristics of the charging stations, which is the highest share of the sample and probably what contributes the most to the estimates of SDCM 4. Class 2 identifies a group of BEV users who mostly only consider SOC, the time since last charging stop (as in the time in car), and the charging cost. Class 4 indicates some BEV users make their charging decisions based on only the SOC and the access time of the charging stations.

8.2.4 Conclusions & discussions

In this Chapter, I modeled the charging behavior of BEV drivers on a long-distance trip using both static and dynamic discrete choice models with different model specifications. The models consistently show that the following factors are significant predicter of the charging choices: (1) battery state of charge SOC, (2) whether the vehicle can reach the next station with the remaining range without deviation from the original plan, e.g, being stranded, having to find chargers off the route, or having to slow down to reduce energy consumption, etc), denoted as DEV; (3) charging cost and charging time at the station; (4) the access time of the station; (5) the amenities at the station. The latent class model also highlighted the heterogeneity of the decision-making patterns of BEV drivers' charging choices on a long-distance trip and shows that the driving time since last charging stop is also a significant factor for a subset of the BEV drivers.

SOC and DEV are shown to contribute to the majority of the predictive power of the model, whereas the characteristics of the charging stations, though are significant predictors, offer only a little improvement of the goodness of fit of the model. This is likely because when the charging network is not dense enough, BEV drivers are likely to act in a 'survival mode' when they make charging decisions: try to get to the destination. Considerations of the characteristics of the charging stations will only happen when there are enough or redundant charging stations. The comparison of the SDCMs and DDCMs shows that SDCMs fit the model better than the more complicated DDCMs. This result might change when the density of charging network is higher, and the BEV users can not only make it to the destination reliably, but also can compare charging stations along way based on the price, accessibility, etc (the "thrival mode").

By comparing the relative size of the coefficient estimates, I also showed the monetary value of the cost of DEV, the monetary value of charging power increase, the monetary value of moving the charging station closer to the exist of the highway, and the monetary value of having amenities such as restrooms, restaurants, and WiFi. These can potentially inform the decision-making of planners or investors of the DCFC network.

9 Conclusions

In this dissertation, I have strived to (1) use statistical modeling to gain understandings of how PEV users make decisions on which vehicle to use and where to charge for home-based trip tours and long-distance trips, (2) develop interactive survey tools to elicit choice processes involving complex, interconnected decisions, and (3) develop and evaluate the dynamic discrete modeling framework with the consideration of heterogeneity and compare the model performance with static models based on simpler heuristics. The studies of the decisions on home-based tours and long-distance trips were carried out relatively independently considering that the charging activities of home-based trip tours usually happen at the natural trip destination, whereas for long-distance trips, PEV drivers usually stop specifically for charging.

My results show that for home-based tours, the primary predictors of vehicle choices and charging decisions of BEV owners include charging cost and deviation (whether one needs to deviate from a planned tour with the remaining range, e.g., to make a mid-trip stop specially for refueling). I identified two decision patterns of BEV owners on the vehicle choice and charging decisions using DDCMs: BEV owners in class 1 are willing to pay $10 in charging costs to avoid having to deviate from a planned tour, whereas those in class 2 are willing to pay $24. This shows that Level 1 or Level 2 chargers at frequent destinations (workplaces, shopping centers, etc.) can help encourage BEV use, but using fast chargers off the route for a mid-trip charge is also a practical option for some BEV users on home-based trip tours. When it is too costly to build charging facilities at some popular trip destinations, having fast chargers along the route can also encourage BEV owners to use their BEVs for home-based trips. These results also show "Range anxiety" is not a huge issue for current BEV owners on home-based tours. Using charging infrastructure development to encourage BEV adoption might be more beneficial than reducing “range anxiety” among the current users, which could entail building charging stations at locations that attract the attention of potential adopters, such as public parking garages in a city center.

Interestingly, when BEVs are on long-distance trips, the cost of deviation is significantly higher: $244, which indicates that BEV owners are likely to be more cautious and view finding a charger off the route much more costly when they are on long-distance trips. Comparing the cost of deviation for home-based tours and long-distance trips, my analyses suggest that to support the existing users, the most cost-effective places to invest in charging infrastructure are inter-city corridors instead of in-city locations. My results also show that the following measures can help attract BEV owners to charge their vehicles at a certain station: (1) move charging station closer to highway exit. BEV owners are willing to pay $25 more to charge at a station 10 minutes closer to the highway exit; (2) provide amenities at the charging station. BEV users are also willing to pay around $20 more to stop at a charging station with amenities such as restroom, dining facilities and Wi-Fi instead of charging station without any amenities; (3) increase charging power. When increasing charging power from 50kW to 150kW, BEV owners are willing to pay $22.4 more to gain 200 miles of range. These values can enter the equation of the cost-benefit analysis for investing in charging facilities. Sometimes tradeoffs might need to be made, for example, moving the charging station closer to high way exit might mean less amenities at the station because the station might need to be further away from a commercial area. Even though charging cost, amenities, etc. have significant influence on the charging decisions, deviation and SOC contribute to the most prediction power for the current BEV users. When the charging network is still sparse, whether the BEV has enough range to get to the next station is still the primary focus of the decision-making. However, this could change in the future when the charging network is denser and multiple charging stations have similar DEV and SOC levels.

For long-distance trips, the primary predictors of whether a BEV is chosen include the gasoline cost, the trip distance relative to the vehicle range, station spacings relative to vehicle range. Both increasing battery pack size and reducing station spacing can encourage current BEV owners to use their BEVs for long-distance trips, and one of the two does not substitute the other due to the heterogeneity of the user preferences. Even if a lot of the BEV models offered by the market have 500 miles of range, the density of the public charging network can still play an important role in enabling BEVs for long-distance trips, especially when the battery remains expensive. Offering charging opportunity at the destinations (e.g., hotels) can also encourage BEV use for long-distance trips.

For both the vehicle choice and charging decisions of PEVs on home-based trip tours, I compared the DDCMs with a series of SDCMs based on simpler decision heuristics and found that though DDCMs offer slightly better prediction rate, this improved predictive power comes at a significant cost when it comes to computation time and complexity of model development. For the purpose of demand forecasting of a charging network or site selection for the charging facilities, the SDCMs based on simpler heuristics are recommended. For the charging decisions of BEV drivers on long-distance trips, my comparison between the SDCMs and DDCMs shows that the SDCMs outperform the DDCMs for the current sample. However, this could change in the future when the charging network is dense.

For both home-based tours and long-distance trips, respondents with longer history of using electric vehicles tend to behave more optimistically: BEV owners who are relatively earlier adopters value deviating from the original route much less heavily than more recent adopters, and earlier PHEV adopters are willing to pay more to avoid using gasoline. This discrepancy could have two possible explanations: either earlier adopters have innate qualities that make them different from more recent adopters (e.g., more enthusiastic about new technology, or higher environmental values), or their preferences changed over time as they became more familiar with the charging network or the vehicle performance with the increase of experience of using an EV. Which of these two is true is important for learning the future evolvement of the PEV owners' preferences since if their preferences change with the accumulation of PEV using experience, the current new adopters will become more optimistic in the future. Unfortunately, there is no way to test this based on the data I have.

For both the home-based tours and long-distance trips, and for both vehicle choices and charging decisions, the decision patterns are likely to be heterogeneous among PEV users. The efforts related to the prediction of the future EV charging demand, the policy-making on battery and charging infrastructure development, and the planning/design of the charging network all need to consider these different preferences of the consumers.

10 Limitations and Future Research

SP data used in this research work allowed me to test the effects of various factors, such as gasoline price, charging price, in a way that is hard to achieve using RP data as in reality these variables do not usually have great variations in a short period of time. It is a suitable approach also because it allows me to collect information on PEV users' choices for scenarios that do not exist in real life but are likely to be true in the future: for example, when the charging power is as high as 200 kWh, or when the charging network is relatively dense. However, it also shows one great limitation of this work: the hypothetical bias. One future research direction is to study these PEV use decisions using RP data when the market penetration of PEVs are higher and the charging network is more mature. The modeling frameworks used here can be adapted directly for RP studies with some changes of the model specifications. However, the greatest challenge with a study on RP data might be the data source since both the trip information and the charging activities are necessary for the analysis.

Another limitation of this work is that the two samples are likely to be self-selected PEV enthusiasts, who may differ from those of other PEV owners today. However, given the early stage of the PEV market, even the best sample of PEV owners today would likely be unrepresentative of future mainstream owners. A study based on a more representative sample in the future could be of merit. A cross-sectional study or a study based on panel data can also help understand why earlier adopters behave differently than more recent adopters. A focus group discussion with a group of experienced PEV users and newer PEV adopters can also help understand to what extent driving experience can help alleviate "range anxiety".

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