Otto-von-Guericke University Magdeburg

Faculty of Economics and Management

Master Thesis

Electric Vehicle Purchasing Behaviour in Beijing,China

Author and matriculation number:

Akshatha Wuluvarana Ghanashyam Raj
226030

April 4, 2022

Advisors:

Univ.-Prof. Dr. rer. pol. habil. Sven Müller
Chair of Operations Management
Otto-von-Guericke University Magdeburg

Dr. Lorena Reyes-Rubiano
Chair of Operations Management
Otto-von-Guericke University Magdeburg

Wuluvarana Ghanashyam Raj
226030, Akshatha:
Electric Vehicle Purchasing Behaviour in Beijing,China
Master Thesis, Otto-von-Guericke University Magdeburg, 2022.

Abstract

The world is currently moving towards lessening the environmental footprint caused by the transportation sector and a major player for this are Electric Vehicles. China being one of the top countries who are tackling the issue of air pollution have been on a fast track to shift towards electric vehicles.

A survey was conducted among 504 Beijing citizens in 2017 to understand what factors influence the decision maker in choosing an electric vehicle as opposed to that of a conventional vehicle. The survey also focuses on a 2011 policy introduced in Beijing, which promotes the purchase of electric vehicles by stating that the buyer will not have to go through the license plate lottery that applies to everyone else when purchasing a conventional vehicle.

This thesis consists of a mixture of logit models with panel data which provides an insight on the influence of Socioeconomics and Demographics factors, Car specific attributes and Purchase decision behaviour of the decision maker. PythonBiogeme is used for the discrete choice modelling and the assessment is of the electric and hybrid vehicles rather than that of a conventional vehicle.

Acknowledgments

I would like to thank my supervisor, Dr.Sven Müller, who with his constructive feedback through each stage of this thesis provided me new perspectives and knowledge.

I like to express my deepest gratitude to my family for being my pillar of strength and constantly encouraging me despite the distance between us. My academic progress is only because of their unmovable support and faith in me.

Finally, I also thank my partner wholeheartedly who stood by me through the lows even with distance helping me keep afloat. I could never have reached this point without you.

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1. Introduction

With the current climate crisis going on, the world currently is trying to reverse the environmental damage caused by humans and move toward a healthy ecosystem. Switching to Electric Vehicles was one of the initiatives that was taken towards reversing the damage. Electric Vehicles help in reducing the greenhouse emissions significantly which in turn works towards restoring the quality of air.

Policy Makers and Vehicle Manufacturers have been taking aggressive actions to push electric vehicles into the market and reach the environmental goals that have been set. Effective policies for makers and customers, environmental awareness and improved charging infrastructure of the vehicles are the reason that Electric Vehicles are expanding and reigning the market.

China being one of the largest countries in the world and inhabiting the largest population currently leads the electric vehicle market globally, with capital Beijing ramping up the market expansion.

Researcher Chengxiang Zhuge of Tyndall Centre at the University of East Anglia Zhuge [2019] has projected the expansion of Beijing's electric vehicle market. As per Zhuge, China's vehicle exhaust emissions from automobiles in 2017 contributed between 13.5 to 52.1% of pollutants in cities like Beijing.

Beijing being the capital and a densely populated city, has pushed Electric Vehicles to be adopted using subsidies and incentives for the people as well as the manufacturers. In 2018, Beijing had 130,000 charging points, 93,000 of which is privately installed for home use while 20,000 is accessible to the public and 17,000 installed for the public transport system.

Multiple studies have been conducted to examine the role of social and psychological factors for adoption of electric cars using the theory of planned behaviour as a theoretical framework [Ajzen et al. [2011]]. The Theory of planned behaviour is developed from the theory of reasoned action, based on the theory of expectancy value, explaining individual decision-making process from the perspective of psychology [zhang2018modeling].

It helps in predicting and understanding human behaviour by weighing the potential determinants' behaviour through accumulation and reinforcement of thought tendency and motivation. The stronger the intention is, the more likely the action [Kraft et al. [2005],Yan et al. [2019a]]. The behaviour attitude, subjective norms, and perceived behaviour control jointly determine individual intention (Figure 1[Yan et al. [2019b]]).

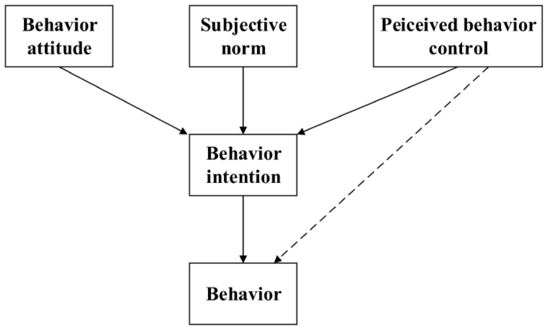

Figure 1.1: Planned behavior theory model [Ajzen [1991],Yan et al. [2019a]]

Behaviour attitudes represent potential consumers' assessment of the positive or negative impact of buying electric cars [Ajzen et al. [2011]]. If positive attitude can be generated for potential consumers towards electric cars by the government through supportive policies, subsidies for cost saving and also spread awareness of environment impact of electric vehicles then there can be an attitude shift in the behaviour as opposed to a negative attitude which might focus on the inconvenience that electric cars might cause in terms of charging and not meeting daily requirements.

Subjective norms represent the degree to which an individual perceives important people to expect an individual to perform a certain behavior [Wan et al. [2017]]. The dominance of the China government on it's citizens does influence the potential consumers for electric vehicles. Generally showing respect and obedience to behaviors advocated by the government is observed in the citizens of China.

Perceived behaviour control represents the individual's perception of the difficulty of performing a certain behaviour [Kraft et al. [2005]]. If potential consumers have sufficient resources economically and are supported by the government positively then a strong control over the perceived behaviour of buying electric cars is created.

Based on this, the Beijing Municipality introduced the License plates lottery system in 2011. The purpose was to lessen the traffic congestion and a remedy for the air pollution in Beijing while simultaneously increasing the purchase of electric vehicles. The distribution of new license plates was done through a bi-monthly public lottery which had more slots and shorter waiting times for electric vehicles compared to conventional vehicles. Also a major rule was that all conventional vehicles would remain idle for one day in a week and this was determined by the last digit of the license plate.

In a study by Li and Jones (2015)[Jones and Li [2015]], it was found that this policy could reduce CO2 emissions from 23.90 to 15.55 million tons in 2020 in Beijing, given that the current policy continued. In 2022, the Beijing Municipality will be raising the quota of new-energy vehicles(NEVs) in the new car license plate allocation from

60,000 to 70,000 and quota for conventional cars will be reduced from 40,000 to 30,000.

The goal of this thesis is to analyse the factors that influence positively towards purchasing of Electric Vehicles for the citizens of Beijing by using a Stated Preference(SP) survey conducted by Anna Theresa Bruckner. The attributes used for the analysis can be classified into three categories representing the Socioeconomic and Demographics, Car Ownership and Purchase Decision and Car specific attributes.

The analysis is as follows:

Chapter 2 discusses some of the theoretical framework on electric vehicle adoption and choice behaviour. Chapter 3 provides an overview of Discrete Choice Theory and the data-set used leading to Chapter 4 that discusses in detail the model used as well as the hypothesis formed to understand the influence of the attributes over purchase decision of electric vehicles.

Chapter 4 and 5 presents the results and an extension into understanding the survey respondent's choice through Elasticities. Chapter 6 gives an overview of the thesis as well as some insights into future work that can be done.

2. Theoretical Framework

Discrete choice models are used for analysing and predicting a decision maker's choice of one alternative from a finite set of mutually exclusive and collectively exhaustive alternatives[Koppelman and Bhat [2006]]. Since behavioural responses are either discrete or qualitative in nature, discrete choice models can have a wide range of applications. The main interest is in predicting decision-making behaviour of the decision maker and determining the influence of various attributes on the decision-making.

A proposed framework for the choice process is that an individual first determines the available alternatives then evaluates the attributes of each alternative relevant to the choice under consideration and finally, uses a decision rule to select an alternative from among the available alternatives(Ben-Akiva et al. [1985]).

The reasoning behind the decision maker's choice is to gain the maximum benefit or utility. The assumption is that utility of a choice is a function of the characteristics of the possible choices and the characteristics of the person making the choice.

Two types of choice data exist which can be used for analysis.Namely, Stated preference and revealed preference. Stated preference data is obtained from hypothetical scenarios or a set of choices presented by the investigator to the decision maker while revealed preference analyse the decision maker's recorded past choices.

2.1 Utility-Based Choice Theory

As stated by McFadden(1974)[McFadden [1984]], The utility maximization rule, states that the individual is certain to choose the highest ranked alternative i.e., highest utility under the observed choice conditions. Utility models that yield certain predictions of choice are called deterministic utility models.

The problem with deterministic utility models is in the complete understanding of the internal process of a decision maker when making a choice. There is no realistic possibility to obtain information on the decision maker's exact behaviour during choice making for analysis.

To help in bridging this gap in analysis, utility function can be represented by two components. The first component represents the portion of utility observed by the analyst and hence referred as the deterministic component. The second component is the unobservable portion, referred as the error term. Formally, this is represented as:

$$U_{it} = V_{it} + \epsilon_{it}$$

where,

U_{it} is the true utility of the alternative i to the decision maker t, (U_{it} is equivalent to $U(X_i\ , S_t\ )$ but provides a simpler notation),

V_{it} is the deterministic or observable portion of the utility estimated by the analyst,

ϵ_{it} is the error or the portion of the utility unknown to the analyst.

2.2 Logit models

Multinomial Logit is the most commonly used model for Discrete choice modelling. The basic Multinomial Logit model was first derived by McFadden in 1973 and also the first established Discrete choice model. But this model has three limitations, proportional substitution patterns i.e., IIA(independence-of-irrelevant-alternatives) assumption, no random taste variation due to common β coefficients across decision-makers, and no consideration of unobserved factors over time in repeated choice situations[Yan et al. [2019b]].

To deal with these limitations, a mixture of logit models can be used. This model is highly flexible that can approximate any random utility model (McFadden and Train [2000]).

2.3 Mixture of logit models and Panel data

Mixture of logit models is a highly flexible model that can approximate any random utility model (McFadden and Train [2000]). Even though they are computationally more complex than logit it overcomes the three limitations of standard logit by allowing for random taste variation, unrestricted substitution patterns, and correlation in unobserved factors over time.

When choice made in one period is dependent on choices made in the past or through experiences, the model can be classified as dynamic. For example, if the survey respondents have test driven an electric car and they find it better than the petrol car then there is a serial dependence on past realized state which has to be captured. This leads to dynamic Markov model with panel effect. [Bierlaire [2014]].

The relation between the dependent variable y_{it} and a single covariate x_{it} can be modeled by the following dynamic specification [Bun et al. [2015]]:

$$\mathrm{y}_{it} = \alpha y_{i,t-1} + \beta x_{it} + \eta_i + \varepsilon_{it}$$

where i = 1,...N , t= 1,...T

where η_{i} denotes unobserved time-invariant heterogeneity and it is the idiosyncratic error component. We assume that $y_{\mathrm{i}0}$ and $x_{\mathrm{i}0}$ are observed. The dynamic panel data model in the above equation allows the utility to permit the distinction between the long run, or equilibrium, relationship and the short-run dynamics.

3. Methodology

3.1 Data Collection

This thesis is based on a study by Anna Theresa Bruckner[Bruckner [2018]] from Karlsruhe University of applied sciences in 2017. A survey was created to understand the purchase behaviour of the respondents for electric, hybrid and conventional cars in Beijing,China.
The target audience are people living there for over two years and people who own a driving license. The survey had two filter questions to make sure this criterion is fulfilled. The survey is divided into three sections : Socioeconomics and Demographics, Car Ownership and Purchase Decision, and Choice Experiment.

Section I consists of 11 Questions covering the following aspects:

- Gender
- Age
- Education Level
- Marital Status
- Household Number
- Employment status
- Occupation
- Type of Housing
- Household Income
- Living District
- Working District

Section II consists of 5 Questions and are as follows:

- Number of Cars in Household

- Car Ownership
- Usage of car during Weekdays
- Usage of car during Weekends
- Car used on daily basis in terms of kilometres

Section III is the Choice experiment which consists of six blocks with different choices between electric, hybrid and conventional cars to choose from with the following aspects:

- Purchase Price
- Waiting time for Vehicle plate
- Recharge time
- Vehicle driving range
- Distance to nearest recharge centre

3.1.1 Variables and Descriptive Statistics

A total of 504 respondents answered the survey forming a dataset of 3024 observations. The variables of the dataset are described in Figure 3.1.

Attributes		Observations	Percentage (%)
Gender	Female	960	50.96
	Male	924	49.04
Age	19 or below	30	1.59
	20-34	660	35.03
	35-49	1020	54.14
	50-64	174	9.24
Education	Junior high	66	3.50
	High school	450	23.89
	Associate/polytechnic degree	504	26.75
	Bachelor	780	41.40
	Postgraduate or above	84	4.46
Marital Status	Single	348	18.47
	Married	1512	80.25
	Divorced/Separated/Widowed	24	1.27
Household Size	1	12	0.64
	2	252	13.38
	3	1260	66.88
	4	246	13.06
	5	102	5.41
	6	12	0.64
Employment Status	Student	72	3.82
	Part-time	60	3.18
	Unemployed	6	0.32
	Employed	1662	88.22
	Retired	84	4.46
Household Income (In Yuan)	4999 or less	6	0.32
	5000 – 9999	276	14.65
	10000-19999	1032	54.78
	20000 or above	570	30.25
Occupation	Entrepreneur	216	11.46
	State own enterprise employee	480	25.48
	Foreign Firm Employee	414	21.97
	Housewife/Retired/Unemployed	96	5.10
	Agriculture/Forestry/Fishery	96	5.10
	Clerk	156	8.28
	Civil Servant	144	7.64
	Self-employed/Freelance	126	6.69
	Student	72	3.82
	Others	84	4.46
House type	Own a commercial flat	1500	79.62
	Own a reform housing	30	1.59
	Own a self-constructed housing	96	5.10
	Renting	240	12.74
	Others	18	0.96
Cars owned	0	12	0.64
	1	1674	88.85
	2	180	9.55
	3 or more	18	0.96
Weekday Usage of car	0	66	3.50
	1	6	0.32
	2	186	9.87
	3	336	17.83
	4	1146	60.83
	5	144	7.64
Weekend Usage of car	0	198	10.51
	1	792	42.04
	2	894	47.45

Figure 3.1: Variables of the dataset

3.2 Software

The model implemented is a discrete mixture of logit models, also called latent class model and the data file is organized as panel data. To achieve this PythonBiogeme is utilized which is an open-source Python package designed for the maximum likelihood estimation of parametric models in general, with a special emphasis on discrete choice models. It relies on the package Python Data Analysis Library called Pandas. PythonBiogeme has been developed by Michel Bierlaire, Ecole Polytechnique Fédérale de Lausanne, Switzerland. The data is prepared in an excel sheet.

3.3 Hypotheses

Before the actual modelling of the model using PythonBiogeme, the hypotheses to understand the purchase behaviour of the electric vehicles are suggested. These hypotheses lay the foundation for defining the utility functions. The hypotheses can be categorised on attributes namely Socioeconomics and Demographics, Car Specific Attributes and Purchase Decision and Interaction Effects. Some of the hypotheses are adopted from Vitiello (2020) and Donner (2021).

3.3.1 Socioeconomics and Demographics Hypotheses

Hypothesis A.1: Men are more likely to buy an electric car:
The variable "gender" has two values: 1 for male and 2 for female. Research studies have shown that men are more likely to buy electric vehicles than women. Even though the gap between the genders is slowly closing, men are still the predominant gender when it comes to purchase of electric and hybrid vehicles.

Hypothesis A.2: People between the age of 20 to 64 are the most likely to buy electric cars:
The variable "age" has five categories ranging from under 19 years, 20 to 34 years, 35 to 49 years, 50 to 64 years, and above 65 years. Two assumptions are being considered. One that the younger age group has more environmental awareness and would prefer electric and hybrid cars to that of conventional cars. Next is the middle age group ranging from 35 to 64, where research shows that this group currently dominates the electric vehicle market in terms of ownership.

Hypothesis A.3: People that have a graduate academical degree or higher, are more likely to buy electric cars:
The variable "education" is a categorical variable ranging from primary school (or lower) to postgraduate (or higher). The idea here is that people who have a degree or higher have a better understanding of environmental crisis and also are employed at jobs with higher incomes and affordability is not an issue for purchasing of electric vehicles.

Hypothesis A.4: Currently Employed and Retired people are more likely to buy electric cars than unemployed people:
The variable "employstatus" is a categorical variable that reflects the employment status of the respondent. The options available are full-time employed, part-time employed, student, retired and unemployed. An assumption is made that people

who are employed would be favourable towards electric vehicles since there is no economic constraint and as per general research, retired people are a dominating category in purchase of electric vehicles.

Hypothesis A.5: People that own a house are more likely to buy electric cars:
The variable "housetype" describes the living situation of the respondent. The available options in the data are owning a commercial flat, owning a reform housing, owning a self-constructed housing, and renting. Usually, a house owner can afford a charging station for electric cars at their house. This factor influences the purchase decision of the individual.

Hypothesis A.6: Married people are more likely to buy an electric car:
The variable "maritalstatus" describes whether the respondent is single, married or divorced. Married people not only have the income source doubled but if they have kids or plan on starting a family, they tend to be more conscious of the environment around them influencing their purchase decision.

Hypothesis A.7: People that already own two or more cars are more likely to buy electric cars:
The variable "hhcarnum" gives the count of how many cars a household owns. Since the market is new to electric or hybrid car, it is safe to assume that a household that already owns a vehicle has a conventional car. This gives a flexibility in choosing an electric or hybrid car and also the household can distribute the vehicles based on functionality. For example, for long trips a conventional car can be used but for a trip within the city an electric car can be used.

Hypothesis A.8: The more a person uses a car during weekdays the more likely he is to buy an electric car:
The variable "CaruseWeekday" describes how many days of a working week (Monday to Friday) a car is used by the respondent as a numeric value ranging from 0 to 5. Weekday commutes are short trips for which an electric car suits the best. This can be an influencing factor on the purchase decision.

Hypothesis A.9: The more a person uses a car during weekends the less likely he is to buy an electric car:
The variable "CaruseWeekday" gives the number of days a car is used on weekends (Saturday and Sunday) as values of zero to two. Weekend commutes can be assumed to be long trips for which a conventional car might make sense more than an electric one which leads to this hypothesis.

3.3.2 Car Specific Attributes and Purchase Decision Hypotheses

Hypothesis B.1: People are more likely to buy an electric car when it is a SUV car instead of a Standard:
The variable "type" describes the type of car i.e., Standard and SUV. Electric cars and SUVs are two types of cars that are currently in huge demand, so electric SUVs are perhaps the most desirable models of all right now. SUVs have high range in terms of travel distance and also space which is a favourable factor in purchase decision.

Hypothesis B.2: The longer a person has to wait for a license plate the more likely he is to buy an electric car:

The variable “vehplate” describes the wait time to actually receive the license plate. The Beijing license plate lottery only applies for conventional and hybrid cars but in case of an electric vehicle no wait time is required. This incentive plays a major role in influencing the purchase decision.

Hypothesis B.3: The shorter the recharge time of the electric car is, the more likely a person is to buy such an electric car:
The variable “rechargetime” states the time period in hours for the full charge of the battery of an electric car. Having a short time, here less than 5 hours is more appealing for purchasing an electric vehicle and this factor forms this hypothesis.

Hypothesis B.4: The higher the driving range of the electric vehicle, the more like a person is to buy an electric car:
The variable “driving range” describes the range of distance in kilometres a car can be driven until its battery needs to be recharged. For long trips or multiple short trips, the battery plays a major role. So, if the car can travel for long distances, here more than 150 kilometers without stopping for recharge, it can influence to purchase an electric vehicle.

Hypothesis B.5: Having recharge stations at a closer distance, the more like a person is to buy an electric car:
The variable “distance2station” describes distance in kilometres to the nearest recharging station. For cases when an electric car owner does not have a recharge centre in their house like that of an apartment living, then having an external recharge station within 5 kilometers may influence the purchase decision.

3.3.3 Interaction Effects

Hypothesis C.1: Higher the household income, price of the electric vehicle is less important:
The variable “hhinc” describes the total household income and “price” indicates the range in which the cost of the car lies. This hypothesis is based on the idea that when a household is earning more then there is less resistance to purchase an electric vehicle which might cost more.

Hypothesis C.2: More the vehicle used on a daily basis, distance to the next charging station is more important:
The variable “VKTdaily” describes the total number of kilometres used on a daily basis and “distance2station” describes distance in kilometres to the nearest recharging station. If the respondent uses the car on a regular basis then the location of the charging station influences the purchase decision.

Hypothesis C.3: More the vehicle used on a daily basis, number of hours needed to recharge the electric vehicle is more important
The variable “VKTdaily” describes the total number of kilometres used on a daily basis and “rechargetime” states the time period in hours for the full charge of the battery of an electric car. The idea for this hypothesis is that if the respondent uses the car on a regular basis, then the recharge time plays a major role in the purchase decision. The faster the car can be recharged, the more convenient it is to use the car.

Hypothesis C.4: More the vehicle used on a daily basis, driving range of an electric vehicle is more important:
The variable “VKTdaily” describes the total number of kilometres used on a daily basis and “driving range” describes the range of distance in kilometres a car can be driven until its battery needs to be recharged. If the respondent drives on a regular basis then having a high driving range electric car attracts him to the possibility of purchasing the car. This hypothesis explores this idea.

Hypothesis C.5: More the vehicle used on a daily basis, more important is the driving range and the distance to the next charging station:
The variable “VKTdaily” describes the total number of kilometres used on a daily basis, “driving range” describes the range of distance in kilometres a car can be driven until its battery needs to be recharged and “distance2station” describes distance in kilometres to the nearest recharging station. This is a three-way interaction because the idea behind this hypothesis is that for a regularly used car both the driving range and distance to the next charging station together influence the purchase decision. Both these factors being positive for the respondent for an electric car, the decision to purchase an electric car is high.

4. Model Estimation

4.1 Dataset

The dataset is the survey results done by Anna Theresa Bruckner as already mentioned has 3024 observations . An “id” is given to each survey respondent and this makes it easier to access each survey result.

All variables are categorical in nature except that of “hhsize” which reflects the Household Size and “VKTdaily” which is the number of kilometres driven on daily basis. These four variables are numerical and entered in number format by the survey respondents.

“CaruseWeekday”, “CaruseWeekend” and “VKTdaily” have observations entered as “9999”. This represents missing values and a reason for this might be that the respondents have not answered these questions. A standard treatment for the missing data that can be applied is complete case (CC) analysis done by casewise deletion.

Hence, the observations with missing values for the three variables aforementioned are discarded and only complete observations are analysed. The main potential advantage of this approach is its simplicity, as standard complete data statistical analysis can be applied straightforwardly.

Due to this the total number of observations reduce to 1884. Some variables like “Resident City” are discarded since they are not relevant for the hypothesis.

4.2 Mixture of logit models, using Monte-Carlo integration with panel data

The model is a Mixture of logit models, using Monte-Carlo integration with panel data with 3 alternatives: Electric, Hybrid and Petrol. Since our focus is on understanding the purchasing behaviour for electric vehicles, we set the petrol car alternative as the reference alternative and keep it fixed. This is done so that we can compare the behaviour towards exclusively electric and hybrid vehicles.

The utility functions contains the Alternate Specific Constants, parameters to be estimated and the respective variables to prove the hypothesis are defined as:

```
V1 = ( ASC_Electric_RND + Beta_Purchase_Price_electric_2 * pp_e_2 + Beta_Purchase_Price_electric_3 * pp_e_3
+ Beta_Gender_Male_electric * gender_
+ Beta_Age_electric_2 * age_2 + Beta_Age_electric_3 * age_3 + Beta_Age_electric_4 * age_4
+ Beta_Education_electric_4 * edu_4 + Beta_Education_electric_5 * edu_5
+ Beta_Education_electric_6 * edu_6
+ Beta_Maritial_Status_electric_2 * ms_2
+ Beta_Household_Size_electric * hsize
+ Beta_Employment_Status_electric_1 * emp_1 + Beta_Employment_Status_electric_2 * emp_2
+ Beta_Employment_Status_electric_4 * emp_4
+ Beta_Housing_Type_electric_2 * htype_2 + Beta_Housing_Type_electric_3 * htype_3 + Beta_Housing_Type_electric_4 * htype_4
+ Beta_Income_electric_3 * inc_3 + Beta_Income_electric_4 * inc_4
+ Beta_Car_Number_electric_3 * carnum_3 + Beta_Car_Number_electric_4 * carnum_4
+ Beta_Weekday_Usage_electric * wduse
+ Beta_Weekend_Usage_electric * weuse
+ Beta_Kil_Usage_electric * kms
+ Beta_Type_electric * type_e_
+ Beta_Recharge_Time_electric_1 * rt_e_1 + Beta_Recharge_Time_electric_2 * rt_e_2
+ Beta_Driving_Range_electric_2 * dr_e_2 + Beta_Driving_Range_electric_3 * dr_e_3
+ Beta_Distance_RC_electric_1 * drc_e_1 + Beta_Distance_RC_electric_2 * drc_e_2
+ Beta_Pri_2_Int_3_electric * pp_e_2 * inc_3
+ Beta_Pri_2_Int_4_electric * pp_e_2 * inc_4
+ Beta_Pri_3_Int_3_electric * pp_e_3 * inc_3
+ Beta_Pri_3_Int_4_electric * pp_e_3 * inc_4
+ Beta_drc_1_kms_electric * drc_e_1 * kms
+ Beta_drc_2_kms_electric * drc_e_2 * kms
+ Beta_rt_1_kms_electric * rt_e_1 * kms
+ Beta_rt_2_kms_electric * rt_e_2 * kms
+ Beta_dr_2_kms_electric * dr_e_2 * kms
+ Beta_dr_3_kms_electric * dr_e_3 * kms
+ Beta_dr_2_drc_1_kms_electric * dr_e_2 * drc_e_1 * kms
+ Beta_dr_2_drc_2_kms_electric * dr_e_2 * drc_e_2 * kms
+ Beta_dr_3_drc_1_kms_electric * dr_e_3 * drc_e_1 * kms
+ Beta_dr_3_drc_2_kms_electric * dr_e_3 * drc_e_2 * kms )
V2 = ( ASC_Hybrid_RND + Beta_Purchase_Price_hybrid_2 * pp_h_2 + Beta_Purchase_Price_hybrid_3 * pp_h_3
+ Beta_Gender_Male_hybrid * gender_
+ Beta_Age_hybrid_2 * age_2 + Beta_Age_hybrid_3 * age_3 + Beta_Age_hybrid_4 * age_4
+ Beta_Education_hybrid_4 * edu_4 + Beta_Education_hybrid_5 * edu_5
+ Beta_Education_hybrid_6 * edu_6
+ Beta_Maritial_Status_hybrid_2 * ms_2
+ Beta_Household_Size_hybrid * hsize
+ Beta_Employment_Status_hybrid_1 * emp_1 + Beta_Employment_Status_hybrid_2 * emp_2
+ Beta_Employment_Status_hybrid_4 * emp_4
+ Beta_Housing_Type_hybrid_2 * htype_2 + Beta_Housing_Type_hybrid_3 * htype_3 + Beta_Housing_Type_hybrid_4 * htype_4
+ Beta_Income_hybrid_3 * inc_3 + Beta_Income_hybrid_4 * inc_4
+ Beta_Car_Number_hybrid_3 * carnum_3 + Beta_Car_Number_hybrid_4 * carnum_4
+ Beta_Household_Size_hybrid * hsize
+ Beta_Weekday_Usage_hybrid * wduse
+ Beta_Weekend_Usage_hybrid * weuse
+ Beta_Kil_Usage_hybrid * kms
+ Beta_Type_hybrid * type_h_
+ Beta_Vehicle_Plate_2 * vp_h_2 + Beta_Vehicle_Plate_3 * vp_h_3
+ Beta_Recharge_Time_hybrid_1 * rt_h_1 + Beta_Recharge_Time_hybrid_2 * rt_h_2
+ Beta_Pri_2_Int_3_hybrid * pp_h_2 * inc_3
+ Beta_Pri_2_Int_4_hybrid * pp_h_2 * inc_4
+ Beta_Pri_3_Int_3_hybrid * pp_h_3 * inc_3
+ Beta_Pri_3_Int_4_hybrid * pp_h_3 * inc_4
+ Beta_rt_1_kms_hybrid * rt_h_1 * kms
+ Beta_rt_2_kms_hybrid * rt_h_2 * kms )
```

Figure 4.1: Utility function for Electric(V1) and Hybrid(V2) Car

Based on Michel Bierlaire's Series on Biogeme, the availability of an alternative i is determined by the variable y_i, i=1, 2, 3, which is equal to 1 if the alternative is available, and 0 otherwise. The probability of choosing an available alternative i is given by the logit model:

$$P(i|1,2,3;x,\beta) = \frac{y_i e^{V_i x,\beta}}{y_1 e^{V_1 x,\beta} + y_2 e^{V_2 x,\beta} + y_3 e^{V_3 x,\beta}} \tag{4.1}$$

Given a data set of N observations, the log likelihood of the sample is

$$\mathcal{L} = \sum_n log P(i_n|1,2,3;x_n\beta) \tag{4.2}$$

where i_n is the alternative actually chosen by individual n, and x_n are the explanatory variables associated with individual n.

5. Estimation Results

PythonBiogeme generates a wealth of information in the estimation report. For understanding if the model is performing well, we can consider the following parameters:

- We can identify if singularity exists by checking if the eigenvalues are close to zero. Singularity is caused where there is a lack of variation in the data or an unidentified model. The final lines of the report have smallest eigenvalues, largest eigenvalues and condition number which is the ratio between smallest and largest eigenvalues.
  This model has the following values:
  - Smallest eigenvalue : 0.202219
  - Largest eigenvalue : 239233
  - Condition number : 1.18304e+06

  Since the smallest eigen value is 0.202219, the model does not have singularity present.
- The log-likelihood value of a regression model helps in measuring the goodness of fit for a model. The higher the value, the better a model fits a dataset.
  This model has the following values:
  - Initial log likelihood : -1932.969
  - Final log likelihood : -1616.224

  For comparison, Vitiello (2020) model is taken which has an Initial log likelihood of -3322.204 and a final log likelihood value of -2879.854 and Donner (2021) model has an Initial log likelihood of -2069.786 and a final log likelihood value of -1690.863.

  The current model is performing better than the previous models but the utility functions for all the models are different even though the dataset is the same. Hence, this cannot be taken as an absolute measure of performance but does give an insight that the model is performing fairly well.

5.1 Result Interpretation

5.1.1 p-Value Interpretation

To understand if the proposed hypotheses(Null hypotheses) are true, we depend on the p-Value. Calculated probability or p-Value is the probability of finding the observed results when the null hypothesis is true.

Conventionally the 5% (less than 1 in 20 chance of being wrong), 1% and 0.1% ($P < 0.05$, 0.01 and 0.001) levels have been used to accept the null hypothesis. Most commonly used are $p < 0.05$ as statistically significant. This is the significance level being chosen to accept the null hypothesis. A p-value greater than the significance level indicates that there is insufficient evidence and can be concluded that a non-zero correlation exists. A p-value close to 1 signifies no relevance to the alternatives.

5.1.2 Beta Coefficient Interpretations

The beta coefficients can be positive or negative and it represents the degree of change in the outcome variable for every 1 unit of change in the predictor variable.

Interpretation for beta coefficients is done by seeing first if they are positive or negative. If the beta coefficient is positive, then it means that for every 1 unit increase in the predictor variable, the outcome variable will increase by the beta coefficient value. If the beta coefficient is negative, then it means that for every 1 unit increase in the predictor variable, the outcome variable will decrease by the beta coefficient value.

5.2 Hypotheses

5.2.1 Socioeconomics and Demographics Hypotheses

Hypothesis A.1: Men are more likely to buy an electric car:

Result : This hypothesis is false for electric cars with a p-value of 0.805 but true for hybrid cars as it has a p-value for 0.000366. Men do prefer hybrid cars more than females but when it comes to electric cars both genders are to be considered.

Beta Coefficients : The coefficients are positive for both electric and hybrid cars i.e., 0.0627 and 0.66 respectively. This indicates a preference for electric and hybrid cars.

Hypothesis A.2: People between the age of 20 to 64 are the most likely to buy electric cars:

Result : The hypothesis is true for both electric and hybrid cars. The age group 20-34 has a higher chance of purchasing electric vehicles with a p-value of 0.265 for electric and 0.384 for hybrid over the other two groups then the group 35-49 with 0.153 for electric and 0.315 for hybrid and finally 50-64 with 0.0897 for electric and 0.216 for hybrid

Beta Coefficients : The coefficients are all negative for both electric and hybrid cars indicating that the preference is for conventional cars.

Hypothesis A.3: People that have a graduate academical degree or higher, are more likely to buy electric cars:

Result : The hypothesis is only true for respondents who hold a Bachelor degree for hybrid cars. Rest all categories it is false. The p-values for the all the categories are 0.724, 0.875, 0.519 for electric and 0.94 and 0.766 for hybrid cars.

Beta Coefficients : All the coefficients are positive for electric and hybrid cars with the exception of Associate degree/ polytechnic degree category of education level in electric cars. A degree holder who has a Bachelor degree or more has a for electric and hybrid cars.

Hypothesis A.4: Currently Employed and Retired people are more likely to buy electric cars than unemployed people:

Result : This hypothesis is true for employed people for electric cars with value of 0.376 and 0.395 while it is only true for retired people for hybrid cars with a value of 0.195. Retired category for electric cars is rejected and employed category for hybrid cars are rejected.

Beta Coefficients : The coefficients are positive for electric cars for all three categories. This indicates a preference for electric cars but for hybrid cars we have negative coefficients indicating a low preference for them.

Hypothesis A.5: People that own a house are more likely to buy electric cars:

Result : This hypothesis is true for people who own a house for electric cars with a p-value of 0.137 while people renting their house prefer hybrid vehicles with value of 0.205.

Beta Coefficients : There exists a contrast between electric and hybrid cars. Respondents who own a reform house have a negative influence for electric cars but positive influence for hybrid cars. Respondents who own a house and are renting have a positive influence towards electric cars but negative influence for hybrid cars.

Hypothesis A.6: Married people are more likely to buy an electric car:

Result : The hypothesis for this is true with values of 0.0143 and 0.0333 for electric and hybrid cars respectively.

Beta Coefficients : All the coefficients are positive for electric and hybrid cars. A preference to both electric and hybrid cars is observed with this variable.

Hypothesis A.7: People that already own two or more cars are more likely to buy electric cars:

Result : This hypothesis is true for people who own more than 3 cars tend to purchase electric cars (p-value 0.2) and people who own 2 or more cars tend to favour hybrid cars.

Beta Coefficients : All the coefficients are positive for electric and hybrid cars. A preference to both electric and hybrid cars is observed with this variable.

Hypothesis A.8: The more a person uses a car during weekdays the more likely he is to buy an electric car:

Result : This hypothesis is false for electric cars with a p-value of 0.801 but true that the respondents who use car on the weekday prefer hybrid car (p-value 0.0232)

Beta Coefficients : The coefficients are only positive for electric cars indicating a positive preference but negative for hybrid cars indicating that there is a low preference.

Hypothesis A.9: The more a person uses a car during weekends the less likely he is to buy an electric car:

Result : This hypothesis is true, the respondents who use car on the weekend more prefer both electric and hybrid cars (p-value 0.000206).

Beta Coefficients : The coefficients are all negative for both electric and hybrid cars indicating that the preference is for conventional cars.

5.2.2 Car Specific Attributes and Purchase Decision Hypotheses

Hypothesis B.1: People are more likely to buy an electric car when it is a SUV car instead of a Standard:

Result : This hypothesis is true for both electric and hybrid cars with p-values of 0.28 and 0.225 respectively.

Beta Coefficients : The coefficients are positive for electric cars indicating that the preference is high for electric cars but the coefficients are negative for hybrid cars indicating low preference for hybrid cars.

Hypothesis B.2: The longer a person has to wait for a license plate the more likely he is to buy an electric car:

Result : This hypothesis is calculated only for hybrid vehicles and the p-value is approaching zero indicating that this hypothesis is true.

Beta Coefficients : The coefficients are negative for hybrid cars indicating that the preference is for electric cars.

Hypothesis B.3: The shorter the recharge time of the electric car is, the more likely a person is to buy such an electric car:

Result : This hypothesis is true for both electric and hybrid cars with p-value of 0.00798 (recharge time less than an hour) and 0.354 (recharge time between an hour to five hours) and p-value of 0.0318 (recharge time less than an hour) and 0.28 (recharge time between an hour to five hours) for hybrid cars.

Beta Coefficients : All the coefficients are positive for electric and hybrid cars. A preference to both electric and hybrid cars is observed with this variable.

Hypothesis B.4: The higher the driving range of the electric vehicle, the more like a person is to buy an electric car:

Result : The hypothesis is true for both electric cars with p-values of 0.281 (driving range for 150km -250 km) and 0.024 (driving range more than 250 km).

Beta Coefficients : All the coefficients are positive for electric and hybrid cars. A preference to both electric and hybrid cars is observed with this variable.

Hypothesis B.5: Having recharge stations at a closer distance, the more like a person is to buy an electric car:

Result : The hypothesis is true for both electric cars with p-values of almost nearing zero (less than 1km) and 0.287 (between 1km - 5km).

Beta Coefficients : All the coefficients are positive for electric and hybrid cars. A preference to both electric and hybrid cars is observed with this variable.

5.2.3 Interaction Effects

Hypothesis C.1: Higher the household income, price of the electric vehicle is less important:

Result : The hypothesis is false for all categories except that of category of purchase price between 15000 yuan to 30000 yuan when household income is 20000 yuan or above of p-value 0.204 and category of purchase price greater than 30000 yuan when household income is between 10000 yuan to 19999 yuan or above of p-value 0.268 and category of purchase price greater than 30000 yuan when household income is 20000 yuan or above of p-value 0.0124.

Beta Coefficients : All the coefficients are positive for electric and hybrid cars. A preference to both electric and hybrid cars is observed with this variable.

Hypothesis C.2: More the vehicle used on a daily basis, distance to the next charging station is more important:

Result : This hypothesis is true that the distance to the next charging station is more important when vehicles used more on daily basis with p-values of 0.000456 and 0.156.

Beta Coefficients : The coefficients are all negative for both electric and hybrid cars indicating that the preference is low in this category.

Hypothesis C.3: More the vehicle used on a daily basis, number of hours needed to recharge the electric vehicle is more important

Result : This hypothesis is partially true. When recharge time is less than an hour, this hypothesis is true for both electric (p-value 0.255) and hybrid (p-value 0.09) cars but when the recharge time is greater than 5 hours then it is not true for electric (p-value 0.571) cars but true for hybrid cars (p-value 0.12).

Beta Coefficients : The coefficients are all negative for both electric and hybrid cars indicating that the preference is low in this category.

Hypothesis C.4: More the vehicle used on a daily basis, driving range of an electric vehicle is more important:

Result : This hypothesis is true that the driving range of an electric vehicle is more important when vehicles used more on daily basis with p-values of 0.449 and 0.321.

Beta Coefficients : The coefficients are all negative for both electric and hybrid cars indicating that the preference is low in this category.

Hypothesis C.5: More the vehicle used on a daily basis, more important is the driving range and the distance to the next charging station:

Result : This hypothesis is partially true. When driving range is between 150km -250km and distance to recharge station is less than an hour then it is true with p-value of 0.164 but with same driving range but distance to recharge station is between 1 to 5 hours, this hypothesis is false with p-value of 0.673 . This hypothesis is true for hybrid cars with p-values of 0.365 and 0.00412 for both categories.

Beta Coefficients : All the coefficients are positive for electric and hybrid cars. A preference to both electric and hybrid cars is observed with this variable.

6. Elasticities

According to Hensher, Rose and Greene (2015), Elasticity may be defined as a unitless measure that describes the relationship between the percentage change for some variable (i.e., an attribute of an alternative) and the percentage change in quantity demanded.

$$Elasticity = \frac{\text{Percentage Change in Probability}}{\text{Percentage Change in Attribute}}$$

Direct elasticities and Cross-elasticities are the two types of elasticities that have been defined by Economists. From Louviere et al.(2000), A direct elasticity measures the percentage change in the probability of choosing a particular alternative in the choice set with respect to a given percentage in an attribute of that same alternative and A cross-elasticity measures the percentage change in the probability of choosing a particular alternative in the choice set with respect to a given percentage in an attribute of a competing alternative.

There are two main methods for calculating elasticities namely Arc elasticity method and Point elasticity method. With the current dataset, measuring cross elasticity makes more sense since the goal is to understand the purchase behaviour towards electric cars against conventional cars.

6.1 Cross Elasticity

Cross elasticity is calculated by using Point elasticity method. The mathematical formulation [Axhausen et al. [2008]] for this is as follows: Consider now one of the variables involved in the model, for instance x_{ink}, the k_{th} variable associated by individual n with alternative i. The objective is to anticipate the impact of a change of the value of this variable on the choice of individual n, and subsequently on the market share of alternative i.

Based on Michel Bierlaire's Series on Biogeme, if the variable is continuous, we assume that the relative (infinitesimal) change of the variable is the same for every individual in the population, that is

$$\frac{\partial x_{ink}}{x_{ink}} = \frac{\partial x_{ipk}}{x_{ipk}} = \frac{\partial x_{ik}}{x_{ik}}, \tag{6.1}$$

$$x_{ik} = \frac{1}{\mathrm{N}_s} \sum_{n=1}^{\mathrm{N}_s} x_{ink} \tag{6.2}$$

The disaggregate cross point elasticity of the model with respect to the variable x_{ink} is defined as:

$$\mathrm{E}_{x_{ink}}^{P_n(i)} = \frac{\partial P_n(i|x_n, C_n)}{\partial x_{ink}} \frac{\partial x_{ink}}{P_n(i|x_n, C_n)} \tag{6.3}$$

It is called

- disaggregate, because it refers to the choice model related to a specific individual
- direct, because it measures the impact of a change of an attribute of alternative i on the choice probability of the same alternative
- point, because we consider an infinitesimal change of the variable

6.2 Model

The calculation of the disaggregate elasticities for each individual by PythonBiogeme are performed using the following statement:

```
cross_elas_elec_kms = Derive(prob_e, 'kms') * kms / prob_e
cross_elas_hyb_kms = Derive(prob_h, 'kms') * kms / prob_h
cross_elas_pet_kms = Derive(prob_p, 'kms') * kms / prob_p

cross_elas_elec_hsize = Derive(prob_e, 'hsize') * hsize / prob_e
cross_elas_hyb_hsize = Derive(prob_h, 'hsize') * hsize / prob_h
cross_elas_pet_hsize = Derive(prob_p, 'hsize') * hsize / prob_p
```

Figure 6.1: Calculation of Elasticity

The corresponding entry in the simulation dictionary is added as shown below:

```
simulate = {
    'weight': normalizedWeight,
    'prob_e': prob_e,
    'prob_h': prob_h,
    'prob_p': prob_p,
    'cross_elas_elec_kms'  : cross_elas_elec_kms,
    'cross_elas_hyb_kms'   : cross_elas_hyb_kms,
    'cross_elas_pet_kms'   : cross_elas_pet_kms,
    'cross_elas_elec_hsize': cross_elas_elec_hsize,
    'cross_elas_hyb_hsize' : cross_elas_hyb_hsize,
    'cross_elas_pet_hsize' : cross_elas_pet_hsize,
}
```

Figure 6.2: Simulation code

The calculation of the aggregate cross elasticity (6.3) is performed as follows:

```
cross_elas_term_e = (
    simulatedValues['Weighted prob elec']
    * simulatedValues['cross_elas_elec_kms']
    / denominator_e
).sum()
```

Figure 6.3: Calculation of the aggregate cross elasticity

6.3 Results

After computing the cross elasticities for Number of kilometres driven on a daily basis (VKTdaily) and Number of people in a household (hhinc) the following results were obtained.

- Aggregate cross elasticity of Electric Car with respect to VKTdaily: 0.358
- Aggregate cross elasticity of Hybrid Car with respect to VKTdaily: 0.389
- Aggregate cross elasticity of Petrol Car with respect to VKTdaily: -1.77
- Aggregate cross elasticity of Electric Car with respect to Household Size: 0.143
- Aggregate cross elasticity of Hybrid Car with respect to Household Size: 0.744
- Aggregate cross elasticity of Petrol Car with respect to Household Size: 1.73

The values are positive for electric and hybrid cars with respect to Number of kilometers driven on a daily basis indicating that if the usage frequency of the car increases then the market share increases when compared to conventional cars which are negative. It can be observed that the preference is more towards hybrid (0.389) than electric cars (0.358). A conclusion that can be drawn is that the respondents are more conscious of the environmental impact of using conventional cars on a daily basis and hence are willing to make the switch to electric and hybrid cars.

There is a positive influence on the market shares for all electric, hybrid and conventional cars when the household number is high. But the influence of conventional cars are higher with 1.73 then hybrid cars with 0.744 and the last preference lies with electric cars with 0.143. A reason might be that conventional cars have models with a larger seat capacity while hybrid and electric cars are lacking in that department. Another reasoning for this can also be that members with a high household number will have people using the cars at a higher frequency and charging the car might become a hassle.A positive note from this is that even though a small percentage, there is a positive influence towards electric cars and the government can build on this by offering some incentives to promote electric cars over hybrid and conventional cars.

6.4 Limitation

The assumption that independent variables for which the elasticities are being derived are continuous variables is taken into consideration when deriving the elasticity expressions. This causes an issue if there are categorical variables and unfortunately all other variables in this dataset are categorical. Hence only VKTdaily and hhinc can be computed.

Another drawback is that there is no there is no incremental change in the independent variables for which the elasticities are being derived when calculated and because of this it can be hard to know if the degree of elasticity measured in the past will be the same today or in the future. So it can be concluded that the elasticities calculated above can be used for only the particular population of the survey respondents and these values can fluctuate with time even with the same population.

7. Conclusion

This thesis was about understanding which attributes influence the citizens of Beijing positively towards electric cars. Since a variety of categories exist for each attribute and only a handful of them are used, we see a positive influence from each category in purchase behaviour. Some categories work in favour of electric while some for hybrid.

The difference between electric and hybrid cars exist due to the difference in the make of the cars. Hybrid cars can easily replace petrol cars in terms of driving range and capacity of people for example which electric cars lack. The upcoming innovation is better and since the survey is of 2011, a more current survey with the same attributes can be used to compare if changes exist in purchasing behaviour.

Since the survey used was mainly composed of categorical variables, it hinders the complete analysis of all the attributes. Also when the range is set for example for purchase price for electric, hybrid and petrol cars, different ranges are set which make it more difficult to use this attribute for analysis.

A bigger dataset which represents the true population can be more helpful since the current dataset lacks sample for certain attributes. If revealed preferences are also taken into consideration then a model can be prepared to understand these attributes better. But a survey which includes both stated and revealed preferences can be used to derive a much more concrete analysis on the purchasing behaviour.

7.1 Tools

- Microsoft Excel 2022
- Python version 3.9.7
- PythonBiogeme version 3.2.8

Appendix

A.1 Questionnaire

A.1.1 Filler Questions

Filter Questions:

S1. Have you lived in Beijing more than 2 years?
1. No [→ stop the survey]
2. Yes [→ continue the survey]

S2. Do you have a driver's license?
1. No, and no plan to get one in next two years [→ stop the survey]
2. No, but plan to get one in the next two years [→ continue the survey]
3. Yes [→ continue the survey]

A.1.2 Socioeconomics and Demographics

A1. Gender
1. Male
2. Female

A2. How old are you?
1. 19 or below
2. 20-34
3. 35-49
4. 50-64
5. 65 or above

A3. What is your educational level?
1. Primary school or lower
2. Junior high
3. High school
4. Associate degree/ polytechnic degree
5. Bachelor
6. Postgraduate or above

A4. What is your marital status?
1. Single (never married)
2. Married

3. Divorced/ Separated/ Widowed
4. No answer/ Refuse to answer

A5.How many people are there in your household? _____(number)

A6. What is your employment status?
1. Employed (full-time)
2. Employed (part-time)
3. Student
4. Retired
5. Unemployed
6. Other (Please specify)

A7. What is your occupation?
1. Entrepreneur
2. State own enterprise (SOE) employee
3. Foreign firm, employee
4. Housewife/ retried/ unemployed
5. Agriculture/ Forestry/ Fishery
6. Clerk
7. Civil servant
8. Self-employed/ freelance
9. Student
10. Other (please specify)

A8. What type of housing are you living in?
1. Owning a commercial flat
2. Owning a reform housing
3. Owning a self-constructed housing
4. Renting
5. Others (please specify)

A9. What is the monthly income of your household?
1. 4999 or less
2. 5000-9999
3. 10.000-19.999
4. 20.000 or above

A10.1 In which district do you live?
1. Dongcheng
2. Chongwen
3. Xicheng
4. Xuanwu
5. Chaoyang
6. Fengtai
7. Shijingshan
8. Haidaian
9. Mentougou
10. Fangshan
11. Tongzhou

12. Shunyi
13. Changping
14. Daxing
15. Huairou
16. Pinggu
17. Miyun
18. Yanqing

A10.2 In which district do you work?
1. Dongcheng
2. Chongwen
3. Xicheng
4. Xuanwu
5. Chaoyang
6. Fengtai
7. Shijingshan
8. Haidaian
9. Mentougou
10. Fangshan
11. Tongzhou
12. Shunyi
13. Changping
14. Daxing
15. Huairou
16. Pinggu
17. Miyun
18. Yanqing

A.1.3 Car Ownership and Purchase Decision

B1. How many cars in your household?
1. 0
2. 1
3. 2
4. 3 or more

B2. In terms of car ownership/ purchase decision, which type of the following category do you belong to?
1. I own a car
2. I bought a new car in the last three years
3. I have pre-ordered a car
4. I plan to buy a new car in the next three years
5. I have joined newsletter or online forums about cars
6. None of the above

B3: How many days during the weekdays do you use your car? _____(0-5 days)

B4: How many days during the weekends do you use your car? _____(0-2 days)

B5: How many kilometres do you drive on a daily basis? _____(0-9999 km)

A.1.4 Choice Experiment

Suppose these 3 vehicles below were the only vehicles for purchase, which would you choose?

	Conventional Car	Hybrid Car	Electric Car
Type	SUV	SUV	Standard
Purchase Price	<100k	150k-200k	50k-150k
Waiting Time for Vehicle Plate	"10-30"	<10	No
Recharge Time (in hours)	No	<1	"1-5"
Vehicle Driving Range			150-250km
Distance to nearest re-charging station (kms)			1-5

Note: The questionnaire includes a total of 6 choice experiments

A.2 PythonBiogeme Code

```
"""
Fpanel.py

Master Thesis       - Electric Vehicle Purchasing Behaviour in Beijing,China
Author              - Akshatha Wuluvarana Ghanashyam Raj
Matriculation Number - 226030

"""

import pandas as pd
import biogeme.database as db
import biogeme.biogeme as bio
from biogeme import models
import biogeme.messaging as msg
from biogeme.expressions import (
   Beta,
   DefineVariable,
   bioDraws,
   PanelLikelihoodTrajectory,
   MonteCarlo,
   log,
)
# Read the data
df_mxl = pd.read_excel('E:/A_Thesis/Data1.xlsx',sheet_name='Sheet1')
db_mxl = db.Database('df_mxl', df_mxl)

# They are organized as panel data. The variable ID identifies each individual.
db_mxl.panel("id")

# The following statement allows you to use the names of the variable
# as Python variable.
globals().update(db_mxl.variables)

#ASC
ASC_Electric = Beta('ASC_Electric', 0, None, None, 0)
ASC_Electric_S = Beta('ASC_Electric_S', 1, None, None, 0)
ASC_Electric_RND = ASC_Electric + ASC_Electric_S * bioDraws('ASC_Electric_RND', 'NORMAL_ANTI')

ASC_Hybrid = Beta('ASC_Hybrid', 0, None, None, 0)
ASC_Hybrid_S = Beta('ASC_Hybrid_S', 1, None, None, 0)
ASC_Hybrid_RND = ASC_Hybrid + ASC_Hybrid_S * bioDraws('ASC_Hybrid_RND', 'NORMAL_ANTI')

ASC_Petrol = Beta('ASC_Petrol', 0, None, None, 1)

#Gender
Beta_Gender_Male_electric = Beta('Beta_Gender_Male_electric', 0, None, None, 0)
Beta_Gender_Male_hybrid = Beta('Beta_Gender_Male_hybrid', 0, None, None, 0)
#Age
Beta_Age_electric_2 = Beta('Beta_Age_electric_2', 0, None, None, 0)
Beta_Age_electric_3 = Beta('Beta_Age_electric_3', 0, None, None, 0)
Beta_Age_electric_4 = Beta('Beta_Age_electric_4', 0, None, None, 0)
Beta_Age_hybrid_2 = Beta('Beta_Age_hybrid_2', 0, None, None, 0)
Beta_Age_hybrid_3 = Beta('Beta_Age_hybrid_3', 0, None, None, 0)
```

```
Beta_Age_hybrid_4 = Beta('Beta_Age_hybrid_4', 0, None, None, 0)
#Education
Beta_Education_electric_4 = Beta('Beta_Education_electric_4', 0, None, None, 0)
Beta_Education_electric_5 = Beta('Beta_Education_electric_5', 0, None, None, 0)
Beta_Education_electric_6 = Beta('Beta_Education_electric_6', 0, None, None, 0)
Beta_Education_hybrid_4 = Beta('Beta_Education_hybrid_4', 0, None, None, 0)
Beta_Education_hybrid_5 = Beta('Beta_Education_hybrid_5', 0, None, None, 0)
Beta_Education_hybrid_6 = Beta('Beta_Education_hybrid_6', 0, None, None, 0)
#Maritial Status
Beta_Maritial_Status_electric_2 = Beta('Beta_Maritial_Status_electric_2', 0, None, None, 0)
Beta_Maritial_Status_hybrid_2 = Beta('Beta_Maritial_Status_hybrid_2', 0, None, None, 0)
#Household Size
Beta_Household_Size_electric = Beta('Beta_Household_Size_electric', 0, None, None, 0)
Beta_Household_Size_hybrid = Beta('Beta_Household_Size_hybrid', 0, None, None, 0)
#Employment Status
Beta_Employment_Status_electric_1 = Beta('Beta_Employment_Status_electric_1', 0, None, None,
0)
Beta_Employment_Status_electric_2 = Beta('Beta_Employment_Status_electric_2', 0, None, None,
0)
Beta_Employment_Status_electric_4 = Beta('Beta_Employment_Status_electric_4', 0, None, None,
0)
Beta_Employment_Status_hybrid_1 = Beta('Beta_Employment_Status_hybrid_1', 0, None, None, 0)
Beta_Employment_Status_hybrid_2 = Beta('Beta_Employment_Status_hybrid_2', 0, None, None, 0)
Beta_Employment_Status_hybrid_4 = Beta('Beta_Employment_Status_hybrid_4', 0, None, None, 0)
#Housing Type
Beta_Housing_Type_electric_2 = Beta('Beta_Housing_Type_electric_2', 0, None, None, 0)
Beta_Housing_Type_electric_3 = Beta('Beta_Housing_Type_electric_3', 0, None, None, 0)
Beta_Housing_Type_electric_4 = Beta('Beta_Housing_Type_electric_4', 0, None, None, 0)
Beta_Housing_Type_hybrid_2 = Beta('Beta_Housing_Type_hybrid_2', 0, None, None, 0)
Beta_Housing_Type_hybrid_3 = Beta('Beta_Housing_Type_hybrid_3', 0, None, None, 0)
Beta_Housing_Type_hybrid_4 = Beta('Beta_Housing_Type_hybrid_4', 0, None, None, 0)
#Household Income
Beta_Income_electric_3 = Beta('Beta_Income_electric_3', 0, None, None, 0)
Beta_Income_electric_4 = Beta('Beta_Income_electric_4', 0, None, None, 0)
Beta_Income_hybrid_3 = Beta('Beta_Income_hybrid_3', 0, None, None, 0)
Beta_Income_hybrid_4 = Beta('Beta_Income_hybrid_4', 0, None, None, 0)
Beta_Income_petrol_3 = Beta('Beta_Income_petrol_3', 0, None, None, 0)
Beta_Income_petrol_4 = Beta('Beta_Income_petrol_4', 0, None, None, 0)
#Car Number
Beta_Car_Number_electric_3 = Beta('Beta_Car_Number_electric_3', 0, None, None, 0)
Beta_Car_Number_electric_4 = Beta('Beta_Car_Number_electric_4', 0, None, None, 0)
Beta_Car_Number_hybrid_3 = Beta('Beta_Car_Number_hybrid_3', 0, None, None, 0)
Beta_Car_Number_hybrid_4 = Beta('Beta_Car_Number_hybrid_4', 0, None, None, 0)
#Weekday Usage
Beta_Weekday_Usage_electric = Beta('Beta_Weekday_Usage_electric', 0, None, None, 0)
Beta_Weekday_Usage_hybrid = Beta('Beta_Weekday_Usage_hybrid', 0, None, None, 0)
#Weekend Usage
Beta_Weekend_Usage_electric = Beta('Beta_Weekend_Usage_electric', 0, None, None, 0)
Beta_Weekend_Usage_hybrid = Beta('Beta_Weekend_Usage_hybrid', 0, None, None, 0)
#Kilometers Usage
Beta_Kil_Usage_electric = Beta('Beta_Kil_Usage_electric', 0, None, None, 0)
```

```
Beta_Kil_Usage_hybrid = Beta('Beta_Kil_Usage_hybrid', 0, None, None, 0)
#Type of Vehicle
Beta_Type_electric = Beta('Beta_Type_electric', 0, None, None, 0)
Beta_Type_hybrid = Beta('Beta_Type_hybrid', 0, None, None, 0)
#Purchase Price
Beta_Purchase_Price_electric_2 = Beta('Beta_Purchase_Price_electric_2', 0, None, None, 0)
Beta_Purchase_Price_electric_3 = Beta('Beta_Purchase_Price_electric_3', 0, None, None, 0)
Beta_Purchase_Price_hybrid_2 = Beta('Beta_Purchase_Price_hybrid_2', 0, None, None, 0)
Beta_Purchase_Price_hybrid_3 = Beta('Beta_Purchase_Price_hybrid_3', 0, None, None, 0)
Beta_Purchase_Price_petrol_2 = Beta('Beta_Purchase_Price_petrol_2', 0, None, None, 0)
Beta_Purchase_Price_petrol_3 = Beta('Beta_Purchase_Price_petrol_3', 0, None, None, 0)
#Vehicle Plate
Beta_Vehicle_Plate_2 = Beta('Beta_Vehicle_Plate_2', 0, None, None, 0)
Beta_Vehicle_Plate_3 =  Beta('Beta_Vehicle_Plate_3', 0, None, None, 0)
#Recharge Time
Beta_Recharge_Time_electric_1 = Beta('Beta_Recharge_Time_electric_1', 0, None, None, 0)
Beta_Recharge_Time_electric_2 = Beta('Beta_Recharge_Time_electric_2', 0, None, None, 0)
Beta_Recharge_Time_hybrid_1 = Beta('Beta_Recharge_Time_hybrid_1', 0, None, None, 0)
Beta_Recharge_Time_hybrid_2 = Beta('Beta_Recharge_Time_hybrid_2', 0, None, None, 0)
#Driving Range
Beta_Driving_Range_electric_2 = Beta('Beta_Driving_Range_electric_2', 0, None, None, 0)
Beta_Driving_Range_electric_3 = Beta('Beta_Driving_Range_electric_3', 0, None, None, 0)
#Distance RC
Beta_Distance_RC_electric_1 = Beta('Beta_Distance_RC_electric_1', 0, None, None, 0)
Beta_Distance_RC_electric_2 = Beta('Beta_Distance_RC_electric_2', 0, None, None, 0)
#Interaction_purchaseprice_X_household income
Beta_Pri_2_Int_3_electric = Beta('Beta_Pri_2_Int_3_electric', 0, None, None, 0)
Beta_Pri_2_Int_4_electric = Beta('Beta_Pri_2_Int_4_electric', 0, None, None, 0)
Beta_Pri_3_Int_3_electric = Beta('Beta_Pri_3_Int_3_electric', 0, None, None, 0)
Beta_Pri_3_Int_4_electric = Beta('Beta_Pri_3_Int_4_electric', 0, None, None, 0)
Beta_Pri_2_Int_3_hybrid = Beta('Beta_Pri_2_Int_3_hybrid', 0, None, None, 0)
Beta_Pri_2_Int_4_hybrid = Beta('Beta_Pri_2_Int_4_hybrid', 0, None, None, 0)
Beta_Pri_3_Int_3_hybrid = Beta('Beta_Pri_3_Int_3_hybrid', 0, None, None, 0)
Beta_Pri_3_Int_4_hybrid = Beta('Beta_Pri_3_Int_4_hybrid', 0, None, None, 0)
#Interaction_distancetorc_X_kms
Beta_drc_1_kms_electric = Beta('Beta_drc_1_kms_electric', 0, None, None, 0)
Beta_drc_2_kms_electric = Beta('Beta_drc_2_kms_electric', 0, None, None, 0)
#Interaction_rechargetime_X_kms
Beta_rt_1_kms_electric = Beta('Beta_rt_1_kms_electric', 0, None, None, 0)
Beta_rt_2_kms_electric = Beta('Beta_rt_2_kms_electric', 0, None, None, 0)
Beta_rt_1_kms_hybrid = Beta('Beta_rt_1_kms_hybrid', 0, None, None, 0)
Beta_rt_2_kms_hybrid = Beta('Beta_rt_2_kms_hybrid', 0, None, None, 0)
#Interaction_drivingrange_X_kms
Beta_dr_2_kms_electric = Beta('Beta_dr_2_kms_electric', 0, None, None, 0)
Beta_dr_3_kms_electric = Beta('Beta_dr_3_kms_electric', 0, None, None, 0)
#Interaction_drivingrange_X_distancetorc_X_kms
Beta_dr_2_drc_1_kms_electric = Beta('Beta_dr_2_drc_1_kms_electric', 0, None, None, 0)
Beta_dr_2_drc_2_kms_electric = Beta('Beta_dr_2_drc_2_kms_electric', 0, None, None, 0)
Beta_dr_3_drc_1_kms_electric = Beta('Beta_dr_3_drc_1_kms_electric', 0, None, None, 0)
Beta_dr_3_drc_2_kms_electric = Beta('Beta_dr_3_drc_2_kms_electric', 0, None, None, 0)

hsize = DefineVariable('hsize', hhsize, db_mxl)
```

```
wduse = DefineVariable('wduse', CaruseWeekday, db_mxl)
weuse = DefineVariable('weuse', CaruseWeekend, db_mxl)
kms = DefineVariable('kms', VKTdaily, db_mxl)
gender_ = DefineVariable('gender_', gender == 1, db_mxl)
age_2 = DefineVariable('age_2',age == 2, db_mxl)
age_3 = DefineVariable('age_3', age == 3, db_mxl)
age_4 = DefineVariable('age_4', age == 4, db_mxl)
edu_4 = DefineVariable('edu_4', edu == 4, db_mxl)
edu_5 = DefineVariable('edu_5', edu == 5, db_mxl)
edu_6 = DefineVariable('edu_6', edu == 6, db_mxl)
ms_2 = DefineVariable('ms_2',marritalstatus == 2, db_mxl)
emp_1 = DefineVariable('emp_1', employstatus == 1, db_mxl)
emp_2 = DefineVariable('emp_2', employstatus == 2, db_mxl)
emp_4 = DefineVariable('emp_4', employstatus == 4, db_mxl)
htype_2 = DefineVariable('htype_2', housetype == 2, db_mxl)
htype_3 = DefineVariable('htype_3', housetype == 3, db_mxl)
htype_4 = DefineVariable('htype_4', housetype == 4, db_mxl)
inc_3 = DefineVariable('inc_3', hhinc == 3, db_mxl)
inc_4 = DefineVariable('inc_4', hhinc == 4, db_mxl)
carnum_3 = DefineVariable('carnum_3', hhcarnum == 3, db_mxl)
carnum_4 = DefineVariable('carnum_4', hhcarnum == 4, db_mxl)
type_e_ = DefineVariable('type_e_', type_e == 1, db_mxl)
type_h_ = DefineVariable('type_h_', type_h == 1, db_mxl)
pp_e_2 = DefineVariable('pp_e_2', price_e == 2, db_mxl)
pp_e_3 = DefineVariable('pp_e_3', price_e == 3, db_mxl)
pp_h_2 = DefineVariable('pp_h_2', price_h == 2, db_mxl)
pp_h_3 = DefineVariable('pp_h_3', price_h == 3, db_mxl)
pp_p_2 = DefineVariable('pp_p_2', price_p == 2, db_mxl)
pp_p_3 = DefineVariable('pp_p_3', price_p == 3, db_mxl)
vp_h_2 = DefineVariable('vp_h_2', vehplate_h == 2, db_mxl)
vp_h_3 = DefineVariable('vp_h_3', vehplate_h == 3, db_mxl)
rt_e_1 = DefineVariable('rt_e_1', rechargetime_e == 1, db_mxl)
rt_e_2 = DefineVariable('rt_e_2', rechargetime_e == 2, db_mxl)
rt_h_1 = DefineVariable('rt_h_1', rechargetime_h == 1, db_mxl)
rt_h_2 = DefineVariable('rt_h_2', rechargetime_h == 2, db_mxl)
dr_e_2 = DefineVariable('dr_e_2', drivingrange_e == 2, db_mxl)
dr_e_3 = DefineVariable('dr_e_3', drivingrange_e == 3, db_mxl)
drc_e_1 = DefineVariable('drc_e_1', distance2station_e == 1, db_mxl)
drc_e_2 = DefineVariable('drc_e_2', distance2station_e == 2, db_mxl)

V1 = ( ASC_Electric_RND + Beta_Purchase_Price_electric_2 * pp_e_2 +
Beta_Purchase_Price_electric_3 * pp_e_3
+ Beta_Gender_Male_electric * gender_
+ Beta_Age_electric_2 * age_2 + Beta_Age_electric_3 * age_3 + Beta_Age_electric_4 * age_4
+ Beta_Education_electric_4 * edu_4 + Beta_Education_electric_5 * edu_5
    + Beta_Education_electric_6 * edu_6
+ Beta_Maritial_Status_electric_2 * ms_2
+ Beta_Household_Size_electric * hsize
+ Beta_Employment_Status_electric_1 * emp_1 + Beta_Employment_Status_electric_2 * emp_2
    + Beta_Employment_Status_electric_4 * emp_4
```

+ Beta_Housing_Type_electric_2 * htype_2 + Beta_Housing_Type_electric_3 * htype_3 + Beta_Housing_Type_electric_4 * htype_4
+ Beta_Income_electric_3 * inc_3 + Beta_Income_electric_4 * inc_4
+ Beta_Car_Number_electric_3 * carnum_3 + Beta_Car_Number_electric_4 * carnum_4
+ Beta_Weekday_Usage_electric * wduse
+ Beta_Weekend_Usage_electric * weuse
+ Beta_Kil_Usage_electric * kms
+ Beta_Type_electric * type_e_
+ Beta_Recharge_Time_electric_1 * rt_e_1 + Beta_Recharge_Time_electric_2 * rt_e_2
+ Beta_Driving_Range_electric_2 * dr_e_2 + Beta_Driving_Range_electric_3 * dr_e_3
+ Beta_Distance_RC_electric_1 * drc_e_1 + Beta_Distance_RC_electric_2 * drc_e_2
+ Beta_Pri_2_Int_3_electric * pp_e_2 * inc_3
+ Beta_Pri_2_Int_4_electric * pp_e_2 * inc_4
+ Beta_Pri_3_Int_3_electric * pp_e_3 * inc_3
+ Beta_Pri_3_Int_4_electric * pp_e_3 * inc_4
+ Beta_drc_1_kms_electric * drc_e_1 * kms
+ Beta_drc_2_kms_electric * drc_e_2 * kms
+ Beta_rt_1_kms_electric * rt_e_1 * kms
+ Beta_rt_2_kms_electric * rt_e_2 * kms
+ Beta_dr_2_kms_electric * dr_e_2 * kms
+ Beta_dr_3_kms_electric * dr_e_3 * kms
+ Beta_dr_2_drc_1_kms_electric * dr_e_2 * drc_e_1 * kms
+ Beta_dr_2_drc_2_kms_electric * dr_e_2 * drc_e_2 * kms
+ Beta_dr_3_drc_1_kms_electric * dr_e_3 * drc_e_1 * kms
+ Beta_dr_3_drc_2_kms_electric * dr_e_3 * drc_e_2 * kms
)

V2 = (ASC_Hybrid_RND + Beta_Purchase_Price_hybrid_2 * pp_h_2 + Beta_Purchase_Price_hybrid_3 * pp_h_3
+ Beta_Gender_Male_hybrid * gender_
+ Beta_Age_hybrid_2 * age_2 + Beta_Age_hybrid_3 * age_3 + Beta_Age_hybrid_4 * age_4
+ Beta_Education_hybrid_4 * edu_4 + Beta_Education_hybrid_5 * edu_5
+ Beta_Education_hybrid_6 * edu_6
+ Beta_Maritial_Status_hybrid_2 * ms_2
+ Beta_Household_Size_hybrid * hsize
+ Beta_Employment_Status_hybrid_1 * emp_1 + Beta_Employment_Status_hybrid_2 * emp_2
+ Beta_Employment_Status_hybrid_4 * emp_4
+ Beta_Housing_Type_hybrid_2 * htype_2 + Beta_Housing_Type_hybrid_3 * htype_3 + Beta_Housing_Type_hybrid_4 * htype_4
+ Beta_Income_hybrid_3 * inc_3 + Beta_Income_hybrid_4 * inc_4
+ Beta_Car_Number_hybrid_3 * carnum_3 + Beta_Car_Number_hybrid_4 * carnum_4
+ Beta_Household_Size_hybrid * hsize
+ Beta_Weekday_Usage_hybrid * wduse
+ Beta_Weekend_Usage_hybrid * weuse
+ Beta_Kil_Usage_hybrid * kms
+ Beta_Type_hybrid * type_h_
+ Beta_Vehicle_Plate_2 * vp_h_2 + Beta_Vehicle_Plate_3 * vp_h_3
+ Beta_Recharge_Time_hybrid_1 * rt_h_1 + Beta_Recharge_Time_hybrid_2 * rt_h_2
+ Beta_Pri_2_Int_3_hybrid * pp_h_2 * inc_3
+ Beta_Pri_2_Int_4_hybrid * pp_h_2 * inc_4
+ Beta_Pri_3_Int_3_hybrid * pp_h_3 * inc_3
+ Beta_Pri_3_Int_4_hybrid * pp_h_3 * inc_4

```
+ Beta_rt_1_kms_hybrid * rt_h_1 * kms
+ Beta_rt_2_kms_hybrid * rt_h_2 * kms
        )
V3 = ASC_Petrol

# Associate utility functions with the numbering of alternatives
V = {1: V1, 2: V2, 3: V3}
# Associate the availability conditions with the alternatives
av = {1: 1, 2: 2, 3: 3}

# Conditional to the random parameters, the likelihood of one observation is
# given by the logit model (called the kernel)
obsprob = models.logit(V, av, chosen_veh)

# Conditional to the random parameters, the likelihood of all observations for
# one individual (the trajectory) is the product of the likelihood of
# each observation.
condprobIndiv = PanelLikelihoodTrajectory(obsprob)

# We integrate over the random parameters using Monte-Carlo
logprob = log(MonteCarlo(condprobIndiv))

# Define level of verbosity
logger = msg.bioMessage()
# logger.setSilent()
# logger.setWarning()
# logger.setGeneral()
logger.setDetailed()
# logger.setDebug()

# Create the Biogeme object
biogeme = bio.BIOGEME(db_mxl, logprob, numberOfDraws=1000)
biogeme.modelName = 'Fpanel'

# Estimate the parameters.
results = biogeme.estimate()

print(f'Output file: {results.data.htmlFileName}')
```

A.3 PythonBiogeme Elasticities Code

```
"""File Elas_tr.py
"""

import sys
import pandas as pd
import biogeme.database as db
import biogeme.biogeme as bio
from biogeme import models
import biogeme.results as res
from biogeme.expressions import Beta, Derive
from biogeme.expressions import Beta
import biogeme.messaging as msg
from biogeme.expressions import Beta, DefineVariable, bioDraws, log, MonteCarlo
# Read the data
df = pd.read_excel(r'E:/A_Thesis/Data1.xlsx',sheet_name='Sheet1')
db = db.Database('df', df)
globals().update(db.variables)

# Normalize the weights
sumWeight = db.data['Weight'].sum()
numberOfRows = db.data.shape[0]
normalizedWeight = Weight * numberOfRows / sumWeight

#ASC
ASC_Electric = Beta('ASC_Electric', 0, None, None, 0)
ASC_Electric_S = Beta('ASC_Electric_S', 1, None, None, 0)
ASC_Electric_RND = ASC_Electric + ASC_Electric_S * bioDraws('ASC_Electric_RND', 'NORMAL_ANTI')
ASC_Hybrid = Beta('ASC_Hybrid', 0, None, None, 0)
ASC_Hybrid_S = Beta('ASC_Hybrid_S', 1, None, None, 0)
ASC_Hybrid_RND = ASC_Hybrid + ASC_Hybrid_S * bioDraws('ASC_Hybrid_RND', 'NORMAL_ANTI')
ASC_Petrol = Beta('ASC_Petrol', 0, None, None, 0)
ASC_Petrol_S = Beta('ASC_Petrol_S', 1, None, None, 0)
ASC_Petrol_RND = ASC_Hybrid + ASC_Hybrid_S * bioDraws('ASC_Petrol_RND', 'NORMAL_ANTI')

#Gender

Beta_Gender_Male_electric = Beta('Beta_Gender_Male_electric', 0, None, None, 0)
Beta_Gender_Male_hybrid = Beta('Beta_Gender_Male_hybrid', 0, None, None, 0)
#Age
Beta_Age_electric_2 = Beta('Beta_Age_electric_2', 0, None, None, 0)
Beta_Age_electric_3 = Beta('Beta_Age_electric_3', 0, None, None, 0)
Beta_Age_electric_4 = Beta('Beta_Age_electric_4', 0, None, None, 0)
Beta_Age_hybrid_2 = Beta('Beta_Age_hybrid_2', 0, None, None, 0)
Beta_Age_hybrid_3 = Beta('Beta_Age_hybrid_3', 0, None, None, 0)
Beta_Age_hybrid_4 = Beta('Beta_Age_hybrid_4', 0, None, None, 0)
#Education
Beta_Education_electric_4 = Beta('Beta_Education_electric_4', 0, None, None, 0)
Beta_Education_electric_5 = Beta('Beta_Education_electric_5', 0, None, None, 0)
Beta_Education_electric_6 = Beta('Beta_Education_electric_6', 0, None, None, 0)
Beta_Education_hybrid_4 = Beta('Beta_Education_hybrid_4', 0, None, None, 0)
Beta_Education_hybrid_5 = Beta('Beta_Education_hybrid_5', 0, None, None, 0)
Beta_Education_hybrid_6 = Beta('Beta_Education_hybrid_6', 0, None, None, 0)
#Maritial Status
Beta_Maritial_Status_electric_2 = Beta('Beta_Maritial_Status_electric_2', 0, None, None, 0)
Beta_Maritial_Status_hybrid_2 = Beta('Beta_Maritial_Status_hybrid_2', 0, None, None, 0)
#Household Size
Beta_Household_Size_electric = Beta('Beta_Household_Size_electric', 0, None, None, 0)
Beta_Household_Size_hybrid = Beta('Beta_Household_Size_hybrid', 0, None, None, 0)
Beta_Household_Size_petrol = Beta('Beta_Household_Size_petrol', 0, None, None, 0)
```

```
#Employment Status
Beta_Employment_Status_electric_1 = Beta('Beta_Employment_Status_electric_1', 0, None, None, 0)
Beta_Employment_Status_electric_2 = Beta('Beta_Employment_Status_electric_2', 0, None, None, 0)
Beta_Employment_Status_electric_4 = Beta('Beta_Employment_Status_electric_4', 0, None, None, 0)
Beta_Employment_Status_hybrid_1 = Beta('Beta_Employment_Status_hybrid_1', 0, None, None, 0)
Beta_Employment_Status_hybrid_2 = Beta('Beta_Employment_Status_hybrid_2', 0, None, None, 0)
Beta_Employment_Status_hybrid_4 = Beta('Beta_Employment_Status_hybrid_4', 0, None, None, 0)
#Housing Type
Beta_Housing_Type_electric_2 = Beta('Beta_Housing_Type_electric_2', 0, None, None, 0)
Beta_Housing_Type_electric_3 = Beta('Beta_Housing_Type_electric_3', 0, None, None, 0)
Beta_Housing_Type_electric_4 = Beta('Beta_Housing_Type_electric_4', 0, None, None, 0)
Beta_Housing_Type_hybrid_2 = Beta('Beta_Housing_Type_hybrid_2', 0, None, None, 0)
Beta_Housing_Type_hybrid_3 = Beta('Beta_Housing_Type_hybrid_3', 0, None, None, 0)
Beta_Housing_Type_hybrid_4 = Beta('Beta_Housing_Type_hybrid_4', 0, None, None, 0)
#Household Income
Beta_Income_electric_3 = Beta('Beta_Income_electric_3', 0, None, None, 0)
Beta_Income_electric_4 = Beta('Beta_Income_electric_4', 0, None, None, 0)
Beta_Income_hybrid_3 = Beta('Beta_Income_hybrid_3', 0, None, None, 0)
Beta_Income_hybrid_4 = Beta('Beta_Income_hybrid_4', 0, None, None, 0)
Beta_Income_petrol_3 = Beta('Beta_Income_petrol_3', 0, None, None, 0)
Beta_Income_petrol_4 = Beta('Beta_Income_petrol_4', 0, None, None, 0)
#Car Number
Beta_Car_Number_electric_3 = Beta('Beta_Car_Number_electric_3', 0, None, None, 0)
Beta_Car_Number_electric_4 = Beta('Beta_Car_Number_electric_4', 0, None, None, 0)
Beta_Car_Number_hybrid_3 = Beta('Beta_Car_Number_hybrid_3', 0, None, None, 0)
Beta_Car_Number_hybrid_4 = Beta('Beta_Car_Number_hybrid_4', 0, None, None, 0)
#Weekday Usage
Beta_Weekday_Usage_electric = Beta('Beta_Weekday_Usage_electric', 0, None, None, 0)
Beta_Weekday_Usage_hybrid = Beta('Beta_Weekday_Usage_hybrid', 0, None, None, 0)
Beta_Weekday_Usage_petrol = Beta('Beta_Weekday_Usage_petrol', 0, None, None, 0)
#Weekend Usage
Beta_Weekend_Usage_electric = Beta('Beta_Weekend_Usage_electric', 0, None, None, 0)
Beta_Weekend_Usage_hybrid = Beta('Beta_Weekend_Usage_hybrid', 0, None, None, 0)
Beta_Weekend_Usage_petrol = Beta('Beta_Weekend_Usage_petrol', 0, None, None, 0)
#Kilometers Usage
Beta_Kil_Usage_electric = Beta('Beta_Kil_Usage_electric', 0, None, None, 0)
Beta_Kil_Usage_hybrid = Beta('Beta_Kil_Usage_hybrid', 0, None, None, 0)
Beta_Kil_Usage_petrol = Beta('Beta_Kil_Usage_petrol', 0, None, None, 0)
#Type of Vehicle
Beta_Type_electric = Beta('Beta_Type_electric', 0, None, None, 0)
Beta_Type_hybrid = Beta('Beta_Type_hybrid', 0, None, None, 0)

#Purchase Price
Beta_Purchase_Price_electric_2 = Beta('Beta_Purchase_Price_electric_2', 0, None, None, 0)
Beta_Purchase_Price_electric_3 = Beta('Beta_Purchase_Price_electric_3', 0, None, None, 0)
Beta_Purchase_Price_hybrid_2 = Beta('Beta_Purchase_Price_hybrid_2', 0, None, None, 0)
Beta_Purchase_Price_hybrid_3 = Beta('Beta_Purchase_Price_hybrid_3', 0, None, None, 0)
Beta_Purchase_Price_petrol_2 = Beta('Beta_Purchase_Price_petrol_2', 0, None, None, 0)
Beta_Purchase_Price_petrol_3 = Beta('Beta_Purchase_Price_petrol_3', 0, None, None, 0)
#Vehicle Plate
Beta_Vehicle_Plate_2 = Beta('Beta_Vehicle_Plate_2', 0, None, None, 0)
Beta_Vehicle_Plate_3 =  Beta('Beta_Vehicle_Plate_3', 0, None, None, 0)
#Recharge Time
Beta_Recharge_Time_electric_1 = Beta('Beta_Recharge_Time_electric_1', 0, None, None, 0)
Beta_Recharge_Time_electric_2 = Beta('Beta_Recharge_Time_electric_2', 0, None, None, 0)
Beta_Recharge_Time_hybrid_1 = Beta('Beta_Recharge_Time_hybrid_1', 0, None, None, 0)
Beta_Recharge_Time_hybrid_2 = Beta('Beta_Recharge_Time_hybrid_2', 0, None, None, 0)
```

```
#Driving Range
Beta_Driving_Range_electric_2 = Beta('Beta_Driving_Range_electric_2', 0, None, None, 0)
Beta_Driving_Range_electric_3 = Beta('Beta_Driving_Range_electric_3', 0, None, None, 0)
#Distance RC
Beta_Distance_RC_electric_1 = Beta('Beta_Distance_RC_electric_1', 0, None, None, 0)
Beta_Distance_RC_electric_2 = Beta('Beta_Distance_RC_electric_2', 0, None, None, 0)
#Interaction_purchaseprice_X_household income
Beta_Pri_2_Int_3_electric = Beta('Beta_Pri_2_Int_3_electric', 0, None, None, 0)
Beta_Pri_2_Int_4_electric = Beta('Beta_Pri_2_Int_4_electric', 0, None, None, 0)
Beta_Pri_3_Int_3_electric = Beta('Beta_Pri_3_Int_3_electric', 0, None, None, 0)
Beta_Pri_3_Int_4_electric = Beta('Beta_Pri_3_Int_4_electric', 0, None, None, 0)
Beta_Pri_2_Int_3_hybrid = Beta('Beta_Pri_2_Int_3_hybrid', 0, None, None, 0)
Beta_Pri_2_Int_4_hybrid = Beta('Beta_Pri_2_Int_4_hybrid', 0, None, None, 0)
Beta_Pri_3_Int_3_hybrid = Beta('Beta_Pri_3_Int_3_hybrid', 0, None, None, 0)
Beta_Pri_3_Int_4_hybrid = Beta('Beta_Pri_3_Int_4_hybrid', 0, None, None, 0)
#Interaction_distancetorc_X_kms
Beta_drc_1_kms_electric = Beta('Beta_drc_1_kms_electric', 0, None, None, 0)
Beta_drc_2_kms_electric = Beta('Beta_drc_2_kms_electric', 0, None, None, 0)
#Interaction_rechargetime_X_kms
Beta_rt_1_kms_electric = Beta('Beta_rt_1_kms_electric', 0, None, None, 0)
Beta_rt_2_kms_electric = Beta('Beta_rt_2_kms_electric', 0, None, None, 0)
Beta_rt_1_kms_hybrid = Beta('Beta_rt_1_kms_hybrid', 0, None, None, 0)
Beta_rt_2_kms_hybrid = Beta('Beta_rt_2_kms_hybrid', 0, None, None, 0)
#Interaction_drivingrange_X_kms
Beta_dr_2_kms_electric = Beta('Beta_dr_2_kms_electric', 0, None, None, 0)
Beta_dr_3_kms_electric = Beta('Beta_dr_3_kms_electric', 0, None, None, 0)
#Interaction_drivingrange_X_distancetorc_X_kms
Beta_dr_2_drc_1_kms_electric = Beta('Beta_dr_2_drc_1_kms_electric', 0, None, None, 0)
Beta_dr_2_drc_2_kms_electric = Beta('Beta_dr_2_drc_2_kms_electric', 0, None, None, 0)
Beta_dr_3_drc_1_kms_electric = Beta('Beta_dr_3_drc_1_kms_electric', 0, None, None, 0)
Beta_dr_3_drc_2_kms_electric = Beta('Beta_dr_3_drc_2_kms_electric', 0, None, None, 0)
hsize = DefineVariable('hsize', hhsize, db)
wduse = DefineVariable('wduse', CaruseWeekday, db)
weuse = DefineVariable('weuse', CaruseWeekend, db)
kms = DefineVariable('kms', VKTdaily, db)
gender_ = DefineVariable('gender_', gender == 1, db)
age_2 = DefineVariable('age_2',age == 2, db)
age_3 = DefineVariable('age_3', age == 3, db)
age_4 = DefineVariable('age_4', age == 4, db)
edu_4 = DefineVariable('edu_4', edu == 4, db)
edu_5 = DefineVariable('edu_5', edu == 5, db)
edu_6 = DefineVariable('edu_6', edu == 6, db)
ms_2 = DefineVariable('ms_2',marritalstatus == 2, db)
emp_1 = DefineVariable('emp_1', employstatus == 1, db)
emp_2 = DefineVariable('emp_2', employstatus == 2, db)
emp_4 = DefineVariable('emp_4', employstatus == 4, db)
htype_2 = DefineVariable('htype_2', housetype == 2, db)
htype_3 = DefineVariable('htype_3', housetype == 3, db)
htype_4 = DefineVariable('htype_4', housetype == 4, db)
inc_3 = DefineVariable('inc_3', hhinc == 3, db)
inc_4 = DefineVariable('inc_4', hhinc == 4, db)
carnum_3 = DefineVariable('carnum_3', hhcarnum == 3, db)
carnum_4 = DefineVariable('carnum_4', hhcarnum == 4, db)
type_e_ = DefineVariable('type_e_', type_e == 1, db)
type_h_ = DefineVariable('type_h_', type_h == 1, db)
pp_e_2 = DefineVariable('pp_e_2', price_e == 2, db)
```

```
pp_e_3 = DefineVariable('pp_e_3', price_e == 3, db)
pp_h_2 = DefineVariable('pp_h_2', price_h == 2, db)
pp_h_3 = DefineVariable('pp_h_3', price_h == 3, db)
pp_p_2 = DefineVariable('pp_p_2', price_p == 2, db)
pp_p_3 = DefineVariable('pp_p_3', price_p == 3, db)
vp_h_2 = DefineVariable('vp_h_2', vehplate_h == 2, db)
vp_h_3 = DefineVariable('vp_h_3', vehplate_h == 3, db)
rt_e_1 = DefineVariable('rt_e_1', rechargetime_e == 1, db)
rt_e_2 = DefineVariable('rt_e_2', rechargetime_e == 2, db)
rt_h_1 = DefineVariable('rt_h_1', rechargetime_h == 1, db)
rt_h_2 = DefineVariable('rt_h_2', rechargetime_h == 2, db)
dr_e_2 = DefineVariable('dr_e_2', drivingrange_e == 2, db)
dr_e_3 = DefineVariable('dr_e_3', drivingrange_e == 3, db)
drc_e_1 = DefineVariable('drc_e_1', distance2station_e == 1, db)
drc_e_2 = DefineVariable('drc_e_2', distance2station_e == 2, db)

V1 = ( ASC_Electric_RND + Beta_Purchase_Price_electric_2 * pp_e_2 + Beta_Purchase_Price_electric_3 * pp_e_3
+ Beta_Gender_Male_electric * gender_
+ Beta_Age_electric_2 * age_2 + Beta_Age_electric_3 * age_3 + Beta_Age_electric_4 * age_4
+ Beta_Education_electric_4 * edu_4 + Beta_Education_electric_5 * edu_5
    + Beta_Education_electric_6 * edu_6
+ Beta_Maritial_Status_electric_2 * ms_2
+ Beta_Household_Size_electric * hsize
+ Beta_Employment_Status_electric_1 * emp_1 + Beta_Employment_Status_electric_2 * emp_2
    + Beta_Employment_Status_electric_4 * emp_4
+ Beta_Housing_Type_electric_2 * htype_2 + Beta_Housing_Type_electric_3 * htype_3 + Beta_Housing_Type_electric_4 *
htype_4
+ Beta_Income_electric_3 * inc_3 + Beta_Income_electric_4 * inc_4
+ Beta_Car_Number_electric_3 * carnum_3 + Beta_Car_Number_electric_4 * carnum_4
+ Beta_Weekday_Usage_electric * wduse

+ Beta_Weekend_Usage_electric * weuse
+ Beta_Kil_Usage_electric * kms
+ Beta_Type_electric * type_e_
+ Beta_Recharge_Time_electric_1 * rt_e_1 + Beta_Recharge_Time_electric_2 * rt_e_2
+ Beta_Driving_Range_electric_2 * dr_e_2 + Beta_Driving_Range_electric_3 * dr_e_3
+ Beta_Distance_RC_electric_1 * drc_e_1 + Beta_Distance_RC_electric_2 * drc_e_2
+ Beta_Pri_2_Int_3_electric * pp_e_2 * inc_3
+ Beta_Pri_2_Int_4_electric * pp_e_2 * inc_4
+ Beta_Pri_3_Int_3_electric * pp_e_3 * inc_3
+ Beta_Pri_3_Int_4_electric * pp_e_3 * inc_4
+ Beta_drc_1_kms_electric * drc_e_1 * kms
+ Beta_drc_2_kms_electric * drc_e_2 * kms
+ Beta_rt_1_kms_electric * rt_e_1 * kms
+ Beta_rt_2_kms_electric * rt_e_2 * kms
+ Beta_dr_2_kms_electric * dr_e_2 * kms
+ Beta_dr_3_kms_electric * dr_e_3 * kms
+ Beta_dr_2_drc_1_kms_electric * dr_e_2 * drc_e_1 * kms
+ Beta_dr_2_drc_2_kms_electric * dr_e_2 * drc_e_2 * kms
+ Beta_dr_3_drc_1_kms_electric * dr_e_3 * drc_e_1 * kms
+ Beta_dr_3_drc_2_kms_electric * dr_e_3 * drc_e_2 * kms
   )
V2 = ( ASC_Hybrid_RND + Beta_Purchase_Price_hybrid_2 * pp_h_2 + Beta_Purchase_Price_hybrid_3 * pp_h_3
+ Beta_Gender_Male_hybrid * gender_
+ Beta_Age_hybrid_2 * age_2 + Beta_Age_hybrid_3 * age_3 + Beta_Age_hybrid_4 * age_4
+ Beta_Education_hybrid_4 * edu_4 + Beta_Education_hybrid_5 * edu_5
    + Beta_Education_hybrid_6 * edu_6
```

```
+ Beta_Maritial_Status_hybrid_2 * ms_2
+ Beta_Household_Size_hybrid * hsize
+ Beta_Employment_Status_hybrid_1 * emp_1 + Beta_Employment_Status_hybrid_2 * emp_2
    + Beta_Employment_Status_hybrid_4 * emp_4
+ Beta_Housing_Type_hybrid_2 * htype_2 + Beta_Housing_Type_hybrid_3 * htype_3 + Beta_Housing_Type_hybrid_4 *
htype_4
+ Beta_Income_hybrid_3 * inc_3 + Beta_Income_hybrid_4 * inc_4
+ Beta_Car_Number_hybrid_3 * carnum_3 + Beta_Car_Number_hybrid_4 * carnum_4
+ Beta_Household_Size_hybrid * hsize
+ Beta_Weekday_Usage_hybrid * wduse
+ Beta_Weekend_Usage_hybrid * weuse
+ Beta_Kil_Usage_hybrid * kms
+ Beta_Type_hybrid * type_h_
+ Beta_Vehicle_Plate_2 * vp_h_2 + Beta_Vehicle_Plate_3 * vp_h_3
+ Beta_Recharge_Time_hybrid_1 * rt_h_1 + Beta_Recharge_Time_hybrid_2 * rt_h_2
+ Beta_Pri_2_Int_3_hybrid * pp_h_2 * inc_3
+ Beta_Pri_2_Int_4_hybrid * pp_h_2 * inc_4
+ Beta_Pri_3_Int_3_hybrid * pp_h_3 * inc_3
+ Beta_Pri_3_Int_4_hybrid * pp_h_3 * inc_4
+ Beta_rt_1_kms_hybrid * rt_h_1 * kms
+ Beta_rt_2_kms_hybrid * rt_h_2 * kms
   )
V3 = ( ASC_Petrol_RND
+ Beta_Household_Size_petrol * hsize
+ Beta_Kil_Usage_petrol * kms
+ Beta_Weekday_Usage_petrol * wduse
+ Beta_Weekend_Usage_petrol * weuse
    )
# Associate utility functions with the numbering of alternatives
V = {1: V1, 2: V2, 3: V3}
prob_e = V1
prob_h = V2
prob_p = V3

# Calculation of the cross elasticities.
# We use the 'Derive' operator to calculate the derivatives.
cross_elas_elec_kms = Derive(prob_e, 'kms') * kms / prob_e
cross_elas_hyb_kms = Derive(prob_h, 'kms') * kms / prob_h
cross_elas_pet_kms = Derive(prob_p, 'kms') * kms / prob_p
cross_elas_elec_hsize = Derive(prob_e, 'hsize') * hsize / prob_e
cross_elas_hyb_hsize = Derive(prob_h, 'hsize') * hsize / prob_h
cross_elas_pet_hsize = Derive(prob_p, 'hsize') * hsize / prob_p

simulate = {
   'weight': normalizedWeight,
   'prob_e': prob_e,
   'prob_h': prob_h,
   'prob_p': prob_p,
   'cross_elas_elec_kms'  : cross_elas_elec_kms,
   'cross_elas_hyb_kms'   : cross_elas_hyb_kms,
   'cross_elas_pet_kms'   : cross_elas_pet_kms,
   'cross_elas_elec_hsize': cross_elas_elec_hsize,
   'cross_elas_hyb_hsize' : cross_elas_hyb_hsize,
   'cross_elas_pet_hsize' : cross_elas_pet_hsize,
}

biogeme = bio.BIOGEME(db, simulate)
biogeme.modelName = 'Elas_tr'
```

```
results = res.bioResults(pickleFile='Fpanel-Copy1.pickle')

# simulatedValues is a Panda dataframe with the same number of rows as
# the database, and as many columns as formulas to simulate.
simulatedValues = biogeme.simulate(results.getBetaValues())
# We calculate the elasticities
simulatedValues['Weighted prob elec'] = (
    simulatedValues['weight'] * simulatedValues['prob_e']
)
denominator_e = simulatedValues['Weighted prob elec'].sum()
cross_elas_term_e = (
    simulatedValues['Weighted prob elec']
    * simulatedValues['cross_elas_elec_kms']
    / denominator_e
).sum()
print(
    f'Aggregate cross elasticity of Electric Car wrt VKTdaily: '
    f'{cross_elas_term_e:.3g}'
)

# We calculate the elasticities
simulatedValues['Weighted prob hyb'] = (
    simulatedValues['weight'] * simulatedValues['prob_h']
)
denominator_h = simulatedValues['Weighted prob hyb'].sum()

cross_elas_term_h = (
    simulatedValues['Weighted prob hyb']
    * simulatedValues['cross_elas_hyb_kms']
    / denominator_h
).sum()
print(
    f'Aggregate cross elasticity of Hybrid Car wrt VKTdaily: '
    f'{cross_elas_term_h:.3g}'
)

# We calculate the elasticities
simulatedValues['Weighted prob pet'] = (
    simulatedValues['weight'] * simulatedValues['prob_p']
)
denominator_p = simulatedValues['Weighted prob pet'].sum()
cross_elas_term_p = (
    simulatedValues['Weighted prob pet']
    * simulatedValues['cross_elas_pet_kms']
    / denominator_p
).sum()
print(
    f'Aggregate cross elasticity of Petrol Car wrt VKTdaily: '
    f'{cross_elas_term_p:.3g}'
)

# We calculate the elasticities
simulatedValues['Weighted prob e'] = (
    simulatedValues['weight'] * simulatedValues['prob_e']
)
denominator_eh = simulatedValues['Weighted prob e'].sum()

cross_elas_term_eh = (
    simulatedValues['Weighted prob e']
```

```
    * simulatedValues['cross_elas_elec_hsize']
    / denominator_eh
).sum()
print(
    f'Aggregate cross elasticity of Electric Car wrt Household Size: '
    f'{cross_elas_term_eh:.3g}'
)
# We calculate the elasticities
simulatedValues['Weighted prob h'] = (
    simulatedValues['weight'] * simulatedValues['prob_h']
)
denominator_hh = simulatedValues['Weighted prob h'].sum()
cross_elas_term_hh = (
    simulatedValues['Weighted prob h']
    * simulatedValues['cross_elas_hyb_hsize']
    / denominator_hh
).sum()
print(
    f'Aggregate cross elasticity of Hybrid Car wrt Household Size: '
    f'{cross_elas_term_hh:.3g}'
)
# We calculate the elasticities
simulatedValues['Weighted prob p'] = (
    simulatedValues['weight'] * simulatedValues['prob_p']
)
denominator_ph = simulatedValues['Weighted prob p'].sum()
cross_elas_term_ph = (
    simulatedValues['Weighted prob p']
    * simulatedValues['cross_elas_pet_hsize']
    / denominator_ph
).sum()
print(
    f'Aggregate cross elasticity of Petrol Car wrt Household Size: '
    f'{cross_elas_term_ph:.3g}'
)
```

A.4 PythonBiogeme Code Results

Estimation report

Number of estimated parameters: 84
Sample size: 314
Observations: 1884
Excluded observations: 0
Init log likelihood: -1932.969
Final log likelihood: -1616.224
Likelihood ratio test for the init. model: 633.4908
Rho-square for the init. model: 0.164
Rho-square-bar for the init. model: 0.12
Akaike Information Criterion: 3400.447
Bayesian Information Criterion: 3715.396
Final gradient norm: 1.4597E-03
Number of draws: 1000
Draws generation time: 0:00:01.510491
Types of draws: ['ASC_Electric_RND: NORMAL_ANTI', 'ASC_Hybrid_RND: NORMAL_ANTI']
Nbr of threads: 8
Algorithm: Newton with trust region for simple bound constraints
Proportion analytical hessian: 100.0%
Relative projected gradient: 3.391762e-07
Relative change: 0.00155119341727378
Number of iterations: 7
Number of function evaluations: 22
Number of gradient evaluations: 8
Number of hessian evaluations: 8
Number of hessian evaluations: 8
Cause of termination: Relative gradient = 3.4e-07 <= 6.1e-06
Optimization time: 15:28:26.375791

Estimated parameters

Name	Value	Std err	t-test	p-value	Rob. Std err	Rob. t-test	Rob. p-value
ASC_Electric	-0.716	1.3	-0.551	0.581	1.26	-0.569	0.57
ASC_Electric_S	1.61	0.143	11.2	0	0.156	10.3	0
ASC_Hybrid	1.72	0.941	1.83	0.0674	0.83	2.07	0.0381
ASC_Hybrid_S	0.907	0.117	7.78	7.11e-15	0.123	7.37	1.76e-13
Beta_Age_electric_2	-1.23	1.1	-1.12	0.265	1.05	-1.18	0.24
Beta_Age_electric_3	-1.64	1.15	-1.43	0.153	1.09	-1.5	0.133
Beta_Age_electric_4	-2.1	1.24	-1.7	0.0897	1.17	-1.8	0.0714
Beta_Age_hybrid_2	-0.698	0.802	-0.87	0.384	0.78	-0.895	0.371
Beta_Age_hybrid_3	-0.841	0.838	-1	0.315	0.83	-1.01	0.311
Beta_Age_hybrid_4	-1.1	0.89	-1.24	0.216	0.861	-1.28	0.201
Beta_Car_Number_electric_3	0.275	0.437	0.628	0.53	0.446	0.615	0.538
Beta_Car_Number_electric_4	2.15	1.68	1.28	0.2	1.8	1.2	0.232
Beta_Car_Number_hybrid_3	0.782	0.306	2.56	0.0105	0.335	2.33	0.0196
Beta_Car_Number_hybrid_4	4.59	1.17	3.93	8.33e-05	0.649	7.06	1.66e-12
Beta_Distance_RC_electric_1	1.39	0.355	3.91	9.33e-05	0.4	3.47	0.000521
Beta_Distance_RC_electric_2	0.441	0.414	1.07	0.287	0.419	1.05	0.293
Beta_Driving_Range_electric_2	0.367	0.34	1.08	0.281	0.351	1.04	0.297
Beta_Driving_Range_electric_3	0.86	0.381	2.26	0.024	0.402	2.14	0.0323
Beta_Education_electric_4	-0.125	0.353	-0.353	0.724	0.384	-0.325	0.745
Beta_Education_electric_5	0.0542	0.344	0.157	0.875	0.378	0.143	0.886
Beta_Education_hybrid_6	0.142	0.476	0.298	0.766	0.517	0.274	0.784
Beta_Employment_Status_electric_1	0.686	0.775	0.885	0.376	0.782	0.877	0.38
Beta_Employment_Status_electric_2	0.87	1.02	0.85	0.395	1.06	0.818	0.413
Beta_Employment_Status_electric_4	0.541	1.09	0.498	0.618	1.1	0.492	0.623
Beta_Employment_Status_hybrid_1	-0.0355	0.555	-0.0639	0.949	0.565	-0.0627	0.95
Beta_Employment_Status_hybrid_2	-0.1	0.771	-0.13	0.896	0.701	-0.143	0.886
Beta_Employment_Status_hybrid_4	-1.06	0.821	-1.29	0.195	0.853	-1.25	0.212
Beta_Gender_Male_electric	0.0627	0.254	0.247	0.805	0.261	0.24	0.81
Beta_Gender_Male_hybrid	0.66	0.185	3.56	0.000366	0.18	3.66	0.00025
Beta_Household_Size_electric	-0.125	0.178	-0.701	0.483	0.225	-0.555	0.579
Beta_Household_Size_hybrid	-0.144	0.0667	-2.16	0.0307	0.065	-2.22	0.0265
Beta_Housing_Type_electric_2	-0.634	1.11	-0.571	0.568	1.05	-0.601	0.548
Beta_Housing_Type_electric_3	0.794	0.534	1.49	0.137	0.486	1.63	0.102
Beta_Housing_Type_electric_4	0.314	0.366	0.857	0.391	0.374	0.841	0.4
Beta_Housing_Type_hybrid_2	0.368	0.659	0.559	0.576	1.03	0.358	0.72
Beta_Housing_Type_hybrid_3	-0.263	0.427	-0.616	0.538	0.392	-0.67	0.503
Beta_Housing_Type_hybrid_4	-0.363	0.287	-1.27	0.205	0.27	-1.34	0.18
Beta_Income_electric_3	0.168	0.436	0.385	0.7	0.47	0.357	0.721
Beta_Income_electric_4	0.215	0.495	0.434	0.665	0.555	0.387	0.699
Beta_Income_hybrid_3	0.651	0.377	1.72	0.0846	0.342	1.91	0.0568
Beta_Income_hybrid_4	0.756	0.418	1.81	0.0704	0.395	1.92	0.0553
Beta_Kil_Usage_electric	0.014	0.013	1.08	0.281	0.0141	0.989	0.323
Beta_Kil_Usage_hybrid	-0.00275	0.00728	-0.378	0.706	0.00726	-0.379	0.705
Beta_Maritial_Status_electric_2	0.963	0.393	2.45	0.0143	0.391	2.46	0.0138
Beta_Maritial_Status_hybrid_2	0.598	0.281	2.13	0.0333	0.277	2.16	0.0311
Beta_Pri_2_Int_3_electric	0.201	0.453	0.444	0.657	0.46	0.437	0.662
Beta_Pri_2_Int_3_hybrid	0.142	0.491	0.289	0.773	0.442	0.321	0.748
Beta_Pri_2_Int_4_electric	0.628	0.494	1.27	0.204	0.498	1.26	0.207
Beta_Pri_2_Int_4_hybrid	0.353	0.524	0.674	0.501	0.476	0.742	0.458
Beta_Pri_3_Int_3_electric	0.618	0.558	1.11	0.268	0.6	1.03	0.303
Beta_Pri_3_Int_3_hybrid	0.123	0.529	0.232	0.817	0.647	0.189	0.85
Beta_Pri_3_Int_4_electric	1.48	0.593	2.5	0.0124	0.66	2.25	0.0247
Beta_Pri_3_Int_4_hybrid	0.918	0.554	1.66	0.0975	0.692	1.33	0.185
Beta_Purchase_Price_electric_2	-0.332	0.42	-0.792	0.428	0.446	-0.745	0.456
Beta_Purchase_Price_electric_3	-2.09	0.519	-4.03	5.55e-05	0.564	-3.71	0.000211
Beta_Purchase_Price_hybrid_2	-0.598	0.45	-1.33	0.183	0.408	-1.47	0.142
Beta_Purchase_Price_hybrid_3	-0.908	0.485	-1.87	0.0614	0.605	-1.5	0.134
Beta_Recharge_Time_electric_1	0.921	0.347	2.65	0.00798	0.374	2.46	0.0137
Beta_Recharge_Time_electric_2	0.32	0.345	0.926	0.354	0.352	0.908	0.364
Beta_Recharge_Time_hybrid_1	0.689	0.321	2.15	0.0318	0.325	2.12	0.0341
Beta_Recharge_Time_hybrid_2	0.355	0.328	1.08	0.28	0.331	1.07	0.283
Beta_Type_electric	0.229	0.186	1.23	0.218	0.199	1.15	0.249
Beta_Type_hybrid	-0.159	0.131	-1.21	0.225	0.151	-1.06	0.291
Beta_Vehicle_Plate_2	-0.614	0.151	-4.08	4.58e-05	0.152	-4.04	5.34e-05
Beta_Vehicle_Plate_3	-1.39	0.168	-8.24	2.22e-16	0.189	-7.34	2.09e-13
Beta_Weekday_Usage_electric	0.0341	0.135	0.252	0.801	0.14	0.244	0.807
Beta_Weekday_Usage_hybrid	-0.222	0.0979	-2.27	0.0232	0.0952	-2.33	0.0196
Beta_Weekend_Usage_electric	-0.714	0.192	-3.71	0.000206	0.195	-3.66	0.000253
Beta_Weekend_Usage_hybrid	-0.54	0.137	-3.94	8.07e-05	0.136	-3.98	6.78e-05
Beta_dr_2_drc_1_kms_electric	0.0196	0.0141	1.39	0.164	0.0153	1.28	0.2
Beta_dr_2_drc_2_kms_electric	0.00584	0.0138	0.423	0.673	0.0138	0.424	0.671
Beta_dr_2_kms_electric	-0.00916	0.0121	-0.757	0.449	0.0127	-0.719	0.472
Beta_dr_3_drc_1_kms_electric	0.0126	0.0139	0.906	0.365	0.0139	0.908	0.364
Beta_dr_3_drc_2_kms_electric	-0.0572	0.0199	-2.87	0.00412	0.0212	-2.7	0.0069
Beta_dr_3_kms_electric	-0.012	0.0121	-0.993	0.321	0.0119	-1.01	0.314
Beta_drc_1_kms_electric	-0.0466	0.0133	-3.51	0.000456	0.0143	-3.27	0.00108
Beta_drc_2_kms_electric	-0.0185	0.0131	-1.42	0.156	0.0135	-1.37	0.17
Beta_rt_1_kms_electric	-0.0116	0.0101	-1.14	0.255	0.00994	-1.16	0.245
Beta_rt_1_kms_hybrid	-0.0149	0.00882	-1.7	0.09	0.00853	-1.75	0.0796
Beta_rt_2_kms_electric	-0.00558	0.00984	-0.567	0.571	0.00986	-0.567	0.571
Beta_rt_2_kms_hybrid	-0.0141	0.0091	-1.55	0.12	0.00883	-1.6	0.109

Smallest eigenvalue: 0.202219

Largest eigenvalue: 239233

Condition number: 1.18304e+06

Figure A.1: Results

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I herewith assure that I wrote the present thesis independently, that the thesis has not been partially or fully submitted as graded academic work and that I have used no other means than the ones indicated. I have indicated all parts of the work in which sources are used according to their wording or to their meaning.

Magdeburg, 1st March 2022