Parking choice and the role of Social Influence

Master's thesis

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Summary
Objectives and methodology
The implementation of parking policies has provided limited success in terms of meeting the goals set out by municipalities such as reducing congestion and pollution (Shoup, 2006). Models trying to predict the behaviour of car drivers often only include attributes of the parking facility as predictors. One of the factors that may play a role in the decision making process is the influence of an individual's social circle which has not yet been commonly discussed topic in the field of parking research (Sunitiyoso, Avineri, & Chatterjee, 2011). This research aims to contribute to the possibility that social influence may be a factor in the decision for an individual to choose for a certain parking facility.

Data from an earlier study by (Iqbal, 2018) was gathered with the use of a web-based questionnaire which featured four attributes relating to the characteristics of the parking facility itself being: parking tariff, walking distance to the final destination, type of parking space and type of security. Also included were the advice of four groups that may exist in one's social network being: family, friends, colleagues and experts. Respondents were asked to choose between five ranking option that indicated the likelihood of choosing to park at the presented parking facility.

Data of 377 respondents that completed the survey have been included in the estimation of three different logit models: multinomial logit (MNL), latent class (LC), and mixed logit (ML). The differences in these models allow for more insight in the preferences of respondents regarding the attributes that have been used in the survey. MNL models are restricted in the sense that the interpretation of the results can only be ascribed to the average opinion of the sample of respondents. LC models allow for a distinction of respondents in latent classes with response patterns determining the differences between the classes. The likelihood of a respondent belonging to a certain class can then be derived by matching the estimated parameters of one class with the parameters from a single respondent. ML models are used to identify whether heterogeneity is present for certain attributes which in turn can be further investigated by using, for example, socio-demographic characteristics to see whether these can be defined as the source of the heterogeneity being present.

Results and conclusions
The MNL model showed that the most influential attribute regarding the choice to park at a given location is the parking tariff. The second most influential attribute was found to be the security measures being present with a large preference for security staff over security cameras.

Latent classes were not able to be estimated with the inclusion of all attributes. This indicates that respondents were either too homogenous in their responses or that no regularity could be based on response patterns. Estimating latent classes when only including alternative-specific constants (ASC's) showed that there is a group of respondents that rarely stated they were unlikely to park at the described parking facility given in the survey. Because no more information could be derived with the use of the LC model further analysis has been done with the use of the MNL model with data being separated based on socio-demographic characteristics of the respondents which were: age, gender, educational level, nationality and family situation (whether respondents had children or not). Of these five characteristics, two were further investigated as they were estimated to show differences when separated into two groups. Four MNL models were estimated, two based on gender and two based on nationality of the respondents.

The MNL model that included only male respondents showed more significant parameter estimates for different attributes indicating that they were either more homogenous in their taste preferences or considered more attributes to be of importance. Differences showed that male respondents were more likely to prefer a short walking distance to their final destination compared to women and that they disliked on-street-parking more than women as the latter attribute was not found to be significant

for the model with only female respondents. Social influence was found to be significant for the positive ranking options. The male only model showed three significant parameter estimates concerning advice from family, friends and experts for the “very likely” ranking option with the latter two stating the parking facility was the cheapest and advice of family being that the parking facility was the safest. The female only model only showed one significant parameter estimate concerning social influence which was an expert stating that the parking facility was the safest for the “very likely” ranking option.

Comparing the models whereby the response sample was based on region of origin (one model for EU citizens and one model for non-EU citizens) showed that parking tariff was less likely to be of importance for non-EU citizens compared to EU-citizens. If the described parking facility was on-street the probability that a positive ranking option was chosen decreased according to the model with only non-EU respondents whereas the same attribute was not estimated to be significant for the model with only EU-citizens. Similarly to the models comparing gender, social influence seemed to play a role for the positive scoring options whereby the model with only EU-citizens estimated advice from all four included groups to be significant. Non-EU citizens were most likely concerned with the advice of their family. Both models also show that whenever the advice is concerned, the likelihood of a positive ranking option being chosen increased whenever their family stated the parking facility was the safest.

The mixed logit model confirmed that heterogeneity was present for all ranking options as was also found in the MNL and LC models. Estimated standard deviations were found to be significant for the ASC’s for all ranking options indicating that not only the model did not capture all attributes that would explain the reason why a certain ranking option was chosen but also that respondents have different reasons for choosing said option. Other attributes with a significant standard deviation estimated were the parking tariff, walking distance, parking type and security level. Further analysis whereby socio-demographic characteristics of respondents were taken into account confirmed the findings as done with the MNL model that heterogeneity was present for regional differences concerning the importance of parking tariffs and walking distance.

With regards to the significance of the models each addition proved to be significant in terms of model fit according to the four goodness-of-fit methods used in this study. The MNL model although limited in its use did prove to be of worth, especially when manually separating respondents into groups based on socio-demographic characteristics and comparing the models. Comparing the MNL and ML model it is clear that the interpretation of the MNL model is easier but it also lacks the depth of taking heterogeneity into account which was found to be present in the dataset. The ML model performed better but also required much more parameters complicating the interpretation of results and also making the model less parsimonious, i.e. less likely to be practical for other datasets. Future research should take into consideration if individual tastes are needed to be investigated or whether taste preferences based on groups are good enough for the model.

Samenvatting

Doel en gebruikte methodieken

De implementatie van instrumenten om het parkeergedrag aan te passen heeft beperkte successen opgeleverd voor gemeentes met het oog op het verminderen van verkeersdrukte en luchtvervuiling (Shoup, 2006). Modellen die het gedrag van automobilisten proberen te voorspellen voor hun parkeerkeuze maken vaak gebruik van factoren die beperkt zijn tot de kenmerken van de parkeerplaats zelf. Een van de factoren die wel eens een rol zouden kunnen spelen in het besluitvormingsproces van automobilisten is de invloed van iemand’s sociale netwerk. De relatie tussen deze twee is tot nog toe weinig onderzocht (Sunitiyoso, Avineri, & Chatterjee, 2011). Dit onderzoek hoopt bij te dragen aan de mogelijkheid dat sociale invloed een rol speelt bij het besluit van een automobilist om voor een bepaalde parkeerplek te kiezen.

Data van een eerdere studie (Iqbal, 2018) is gebruikt om deze mogelijkheid te onderzoeken. Een enquête op het internet is gebruikt waarbij vier kenmerken gerelateerd aan de parkeerplaats, te weten, parkeertarief, loopafstand tot bestemming, het type parkeergelegenheid en veiligheidsmaatregelen, zijn meegenomen en advies van vier soorten groepen die zouden kunnen voorkomen in iemand’s sociale netwerk. Deze waren, familie, vrienden, collega’s en experts. Respondenten werden gevraagd om aan te geven hoe groot zij de kans achtten dat zij voor de gepresenteerde parkeerplaats zouden kiezen. De antwoordmogelijkheden bestonden uit vijf opties op basis van een Likert schaal van zeer onwaarschijnlijk tot zeer waarschijnlijk.

Gegevens van 377 repsondenten welke de enquête hebben volbracht zijn meegenomen tijdens het modelleren met drie verschillende modellen: multinomiaal logit (MNL), latente klasses (LC), en mixed logit (ML). De verschillen van de geschatte parameters bij deze modellen geven inzicht in de voorkeuren van de respondenten waaruit afgeleid kan worden welke factoren zij het meest belangrijk vinden wlke meegenomen zijn in de enquête. De interpretatie van het MNL model is gelimiteerd doordat er alleen wordt gekeken naar een gemiddelde van alle respondenten. LC modellen kunnen op basis van de antwoorden van respondenten een patroon ontdekken waarbij er klasses kunnen worden gedifinieerd. Respondenten kunnen vervolgens ingedeeld worden met behulp van een kansberekening om bij een bepaalde klasse te horen op basis van de antwoorden die zij gegeven hebben. ML modellen worden gebruikt om heterogeniteit vast te stellen in de voorkeuren van respondenten. Als de aanwezigheid hier van is vastgesteld kan verder worden onderzocht wat de bron hiervan is. Daarbij kan men bijvoorbeeld denken aan socio-demografische kenmerken.

Resultaten en conclusies

Het MNL model liet zien dat het parkeertarief het belangrijkste kenmerk was voor een automobilist om voor een bepaalde parkeergelegenheid te kiezen. Veiligheid bleek ook een grote rol te spelen. Respondenten gaven aan dat de aanwezigheid van beveiligingspersoneel van grote invloed was terwijl de aanwezigheid van beveiligingscamera’s niet hetzelfde effect liet zien.

LC modellen konden niet geschat worden indien alle kenmerken uit de enquête werden meegenomen. Het is mogelijk dat respondenten in zoverre te homogeen waren in hun voorkeuren dat er geen onderscheid gemaakt kon worden op basis van hun antwoorden. Wanneer alleen alternatief-specifieke constantes werden meegenomen in het model konden er twee verschillende klasses worden onderscheiden. Het verschil tussen deze twee klasses uitte zich in de voorkeuren voor de positieve beoordelingen voor de beschreven parkeerplaats. Hieruit kan worden afgeleid dat er een groep respondenten is welke nauwelijks een negatieve beoordeling hebben gegeven. Omdat er verder geen informatie te verkrijgen was met een LC model is ervoor gekozen om op basis van socio-demografische kenmerken van de respondenten MNL modellen te schatten en hierbij de verschillen te bestuderen. De volgende socio-demografisch kenmerken zijn bestudeerd: leeftijd, gender, onderwijsniveau, nationaliteit, en familiesituatie (of respondent kinderen hadden of niet). Van deze

vijf kenmerken zijn er twee verder onderzocht, te weten, gender en nationaliteit omdat deze de grootste verschillen vertoonden. Vier MNL modellen zijn dus geschat, twee op basis van gender en twee op basis van nationaliteit.

Het MNL model waarbij alleen de antwoorden van mannelijke respondenten werd meegenomen liet veel meer significante parameters zien. Dit kan betekenen dat zij vaker gelijksoortig antwoorden gaven of dat er simpelweg meer kenmerken belangrijk zijn voor hen. Andere verschillen tussen de twee modellen op basis van gender lieten zien dat mannelijke responden een korte loopafstand preferen en het parkeren op straat tot een grotere kans leidt dat zij ervoor kiezen om er niet te parkeren. De rol van het sociale netwerk werd voor zowel mannelijke als vrouwelijke respondenten significant bevonden. Drie parameters voor advies van familie, vrienden en experts werden significant bevonden voor de positieve beoordelingen van een parkeerplaats. Van vrienden en experts betrof het advies dat de parkeerplaats het goedkoopst was terwijl het bij het advies van familie ging om de veiligheid van de parkeerplaats. Het model met alleen antwoorden van vrouwelijke respondenten betrof het advies van experts welke meldde dat de parkeerplaats het veiligst was ten opzichte van de alternatieven.

Bij de vergelijking van modellen op basis van afkomst is ervoor gekozen om respondenten in te delen in inwoners van Europe en respondenten die buiten Europa wonen. De verschillen lieten zien dat Europese respondenten veel sterker geneigd zijn om te kijken naar het parkeertarief terwijl dit kenmerk voor niet-Europese respondenten van minder groot belang was. De kans dat een parkeerplek positief beoordeeld werd als deze zich aan de straat bevond was minder groot volgens het model model met alleen maar niet-Europese respondenten. Ook bij deze twee modellen was er een verschil te zien als het om de invloed van het sociale netwerk gaat. Bij het model met alleen Europese respondenten werd een advies van elk van de vier meegenomen groepen significant gevonden voor de meeste positieve beoordeling van een parkeerplaats terwijl dit voor niet-Europese respondenten alleen voor het advies van familie gold. Beide modellen lieten echter zien dat advies van familie vooral van belang is als het om de veiligheid van een parkeergelegenheid gaat.

Het ML model bevestigde dat heterogeniteit aanwezig was in elk van de beoordelingsopties. Dit bevestigde de bevindingen welke eerder zijn gedaan met het MNL en LC model. De geschatte standaarddeviatie werden voor elke alternatieve-specifieke constantes significant bevonden. Hieruit kan afgeleid worden dat de kenmerken welke zijn meegenomen in de enquête niet het volledige besluitvormingsproces van de respondenten kan beschrijven. Tevens bevestigd het dat er verschillende onderliggende redenen zijn voor respondenten waardoor zij deze keuze maakte. Kenmerken waarbij een significante standaarddeviatie werd bevonden waren: parkeertarief, loopafstand, het type parkeergelegenheid en veiligheid. Verdere analyse waarbij de eerder genoemde socio-demografisch kenmerken zijn onderzocht als bron van deze heterogeniteit bevestigde dat afkomst inderdaad als bron kan worden aangeduid als het om de voorkeur van parkeertarief en loopafstand gaat.

Op basis van vier ‘goodness of fit’ indicatoren kon worden vastgesteld dat de bevindingen van elk model siginifcant waren. Het MNL model heeft het nadeel dat er slechts gekeken kan worden naar een gemiddelde van voorkeuren van respondenten. Echter, Het onderscheiden van respondenten op basis van socio-demografische kenmerken leverde nieuwe inzichten op welke niet uit het volledige model gehaald konden worden. Een vergelijking tussen het MNL en ML model liet zien dat afgaande op de vier ‘goodness-of-fit’ indicatoren het ML model beter presteert. Hiervoor waren echter wel meer geschatte parameters nodig wat de interpretatie bemoeilijkt. Voor het gebruik van deze modellen is het van belang om te bedenken of heterogeniteit een rol speelt en of deze meegenomen dient te worden in de interpretatie van resultaten.

Table of content

1 Introduction

Problem analysis

Current research regarding parking is often focused on the attributes of the parking facility as it is assumed that those are the factors that stimulate a car driver to choose for a certain parking facility (Sunitiyoso, Avineri, & Chatterjee, 2011). However, a decision made by an individual may seem to be done independently but often it involves the influence of family, friends or peers (Simon, 1956). The resulting question is then whether social influence may play part in the decision making process of the car driver. Although plenty of research has been done on the effects of social influence on individuals in the field of social psychology the combination with parking is limited. Most of the research which include patterns of social interaction are studied with the use of multi-agent models (Arentze & Timmermans, 2008). The role of social influence regarding parking preferences is unknown as not many studies have been done on this subject.

Research questions

The assumption is that social influence may play role in the decision making process of car drivers when choosing for a certain parking facility. To investigate this the following research questions will be answered:

"What is the role of social influence with regards to decision making?"

"What does the current literature state about parking preferences and how has this been researched?"

These two questions will be answered based on a literature study.

"What are the underlying processes of the multinomial logit-, latent class-, and mixed logit models?"

"How do the models perform with regards to model fit and what information can be derived from it?"

These two questions will show the models compare to each other and whether the differences between the models allow for better understanding of the data gathered with the survey

"What model gives the best fit to estimate and explain the parking preferences of the respondents?"

The answer to this research question will explain what model is deemed to fit the data the best but also considering the application of the model in a broader sense.

Research goal

This study aims to investigate what attributes are significant in the decision making process of an individual deciding where to park his car and to determine what models shows the best fit to analyse the given data. The goals can be summarised as follows:

- Identify the attributes that play a role in the decision making process of a car driver to choose for a certain parking facility constrained by the information given in the dataset
- Compare three different model approaches (MNL, LC, ML) based on their effectiveness on determining what attributes are most important for the respondents and what information can be derived with the use of these models

Research design

In order to provide answers to the research questions a literature study will be conducted to investigate how social influence affects individuals in their decision making process. First the effects of social influence on individuals will be researched to gain insight in the processes that take place when making a decision in the context of social influence. Then, the current state of research regarding parking is done to find what attributes are most often included in the research and which ones are deemed to influence the decision of a car driver the most. Next, three models (MNL, LC, and ML) will be investigated in their applicability for this study. The dataset that has been used will be investigated with regards to how the information was gathered and what needs to be done to be of use with respect to the aforementioned objectives of this research. The data will then be used in the estimation of the three models and the results of those models will be discussed. Finally a comparison of the models will be made and results will show if social influence plays a role and what model is best used to predict how this affects the decision of the car driver. An overview of the research design is given in Figure 1.

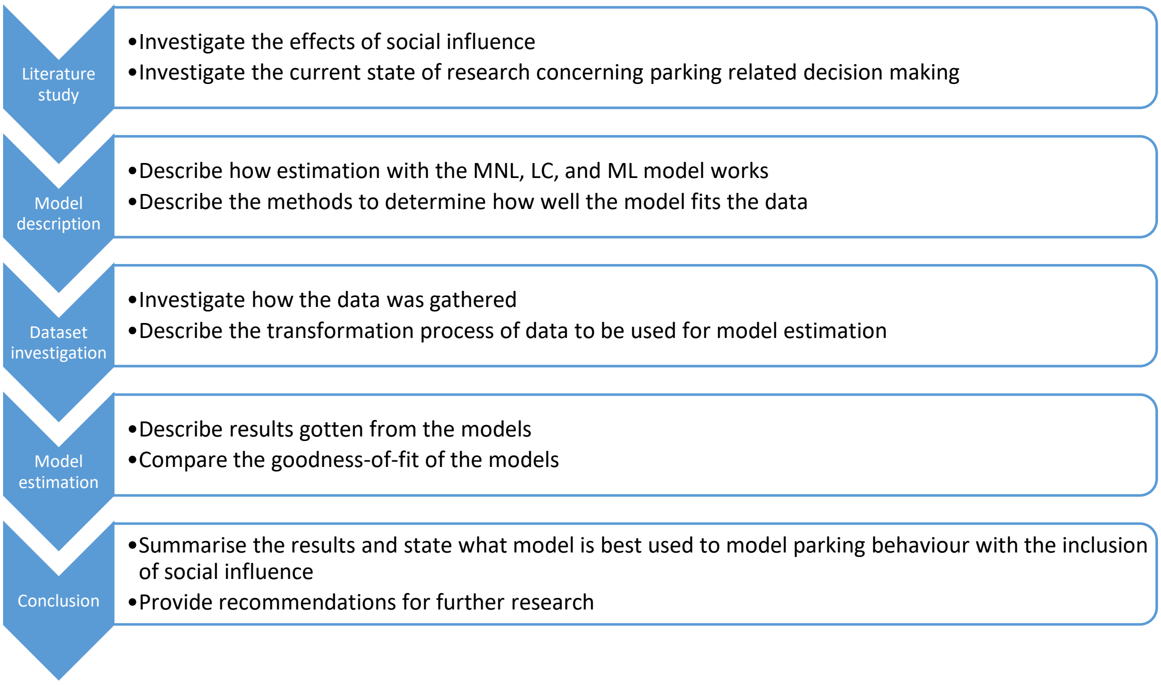


Figure 1: Research design

Reading guide

The research questions formulated in the introduction will be answered with the information gathered during this study which are presented in the following chapters:

Chapter two concerns the literature study in which the effects of social influence are discussed. Furthermore, an overview of the current research regarding parking attributes is given.

Chapter three introduces the three models that are used in this research to estimate the parameters which give information regarding the preferences of the respondents regarding parking. Each model is discussed and explained what information can be derived with it and how it will be used in this study.

Chapter four introduces the dataset that has been used in this study. Firstly the setup of the questionnaire is introduced featuring a description of the attributes and their levels that have been used. Secondly, a description is given on how the data was transformed and an example is given on what the transformed dataset looks like. Lastly, the results of the survey are given.

Chapter five presents the results of the model estimation process. The results of the MNL model are introduced and the interpretation of those results are discussed after which a second MNL model is discussed whereby only the parameters that were found to be significant in the first model are used. A comparison is then made between the two models and the model fit is discussed. Then, the results of the LC model are discussed. Because very little information could be derived with the use of the LC model it has been chosen to continue with the MNL model but this time using a portion of the full dataset based on gender and nationality of the respondents. Thereafter, the results of the ML model are discussed and model fit is discussed and compared with the previous estimated models.

Chapter six summarises the results gotten from the literature study and model estimation. The models are compared to each other and the applicability of the models regarding the modelling of parking behaviour is discussed. Lastly, remarks about possible further research is given.

2 Literature study

Decision making is a complex process which is still subject to intensive research. A simplified abstraction of decision making is that a person determines what factors are relevant when making this decision and what the consequences are. Certain courses of action are then weighted and in addition the most preferable option is chosen. Different people may make different choices despite being constrained to the same choice set. Researchers are trying to find answer as to why that may be. The decision making process reflects a meeting of individual, developmental and contextual factors (Harren, 1979).

There are several known abstractions of the decision making process. One of these abstractions is the GOFER model developed by (Mann, Harmoni, & Power, 1991):

1. Goals clarification: survey values and objectives;
2. Options generation: consider a wide range of alternative actions;
3. Facts-finding: search for information;
4. Effects consideration: weigh the positive and negative consequences of the options;
5. Review and implementation: plan how to review the options and implement them.

For each decision an individual makes he is (sub)consciously expected to follow these steps. Despite the fact that some decision are made within a split second the process remains the same albeit constrained by time and thus lacking in thorough investigation of alternatives and information.

With this in mind, the literature study is set up as follows:
Firstly, the role of social influence is researched in the literature in relation with decision making processes for an individual. Secondly, a brief overview is given on the attributes that are deemed important when choosing for a certain parking facility are researched within the current literature. Research on the combination of the two is very limited. Finally a conclusion is presented with the findings of this literature study.

2.1 Social influence

Social influence is a major topic within the field of social psychology. It studies how the behaviour or thoughts of an individual change when subjected to influence from social groups. Examples of influential factors are imitation, roles, reference groups and culture.

2.1.1 Conformity

Conformity is a phenomenon that is well known to be existent in almost all social creatures. A change in behaviour or belief is often by the influence of another person or group. Conformity can be divided into three different types (Kelman, 1958):

1. Compliance
2. Identification
3. Internalisation

These three types of conformity are believed to describe most of the ways in which we conform to society constrained with personal preferences.

1. Compliance

Compliance is the act of responding to a particular request in a positive manner. The request can be explicit such as door-to-door collection for a certain charity or implicit such as advertisement of a political party stating the qualities of its leader without directly asking for a vote (Cialdini & Goldstein, 2004). People accept the influence of others because they expect to gain approval or avoid disapproval by conforming. The adopted behaviour does not necessarily have to comply with the beliefs of that person.

2. Identification

Identification is when a person accepts social influence because he believes it is important to maintain or establish a self-defining relationship to another person or group. A person is likely to behave in a certain manner if it is expected of him, reinforcing the identification aspect. For example, when a student is expected to get a good grade for an exam he is more likely to achieve it despite, perhaps, not caring about the result at all. Instead, satisfaction for that student is then derived from meeting the expectation of others.

3. Internalisation

Internalisation occurs when an individual changes his behaviour or beliefs based on influence from his social network with the constraint that the individual accepts these changes as his own. The difference with compliance is thus based on the adoption of this behaviour or beliefs because it is congruent with one's own value system. An example would be the adoption of a religion.

2.1.2 Factors influencing the probability of accepting advice

Locus of control

A concept developed by (Rotter, 1966) who stated that the behaviour of individuals can be predicted by how much they perceive their own actions to be of influence on the situation. The result of a situation is determined by the actions of oneself or the actions of others. The belief that an event has occurred outside of the control of the individual is known as external control and the belief that a certain event has occurred due to one's own actions is known as internal control. For example, a student may perceive the grading from a test as being the result of his time spent studying the subject (internal control) or he may ascribe it to the difficulty of the test (external control). People with a high amount of perceived internal control are more likely to deviate from social norms as they possess a stronger belief in their own capabilities. As a result, they are less likely to take advice from someone if it does not match their own beliefs. The opposite is then true for people with a perceived high external control where they are more likely to follow up on advice from others as they have less faith in their own influence on a situation.

Appeal to authority

Obedience is often also related to the perceived authority of others. When an individual recognises the authority of another person as legitimate they are much more likely to comply with a request from that person. This type of obedience is taught from a very early age. For example, a student may respond positively on a request made by his teacher whereas the same request done by a fellow student may result in a different response. Because the student recognises the authority of his teacher he is more likely to comply with the request. A famous study conducted by (Milgram, 1963) showed that people were willing to go quite far to comply with requests from an authority figure even if it conflicted with personal conscience. It is thus possible that someone would follow up the advice of a person they deem to have authority over them even if they do not believe it is the right choice.

Informational influence

When a person is aware that he lacks the knowledge on how to handle a certain situation he often looks at others to see what they would do in the same situation. This is a form of internalisation where the belief is that other people may have more knowledge on the subject. Studies conducted by (Jenness, 1932) and (Asch, 1951) showed that when uncertainty is a factor people are more likely to conform to the group mean. Jenness (1932) researched the estimates for the amount of beans in a jar by people separately and later in a group. The results showed that the individual estimates differed from the estimates when individuals consulted with a group showing that the uncertainty in people's first estimate led to being influenced by the estimate of others. Asch (1952) studied the effect of conformity within a group by means of a simple exercise. An individual was supposed to match a line from one picture with the same line from another picture. The correct answer was a clear cut but when an individual was in the presence of others who stated the wrong answer, the individual starts to doubt their own judgement and in one third of the cases conforms to the group answer. Further studies on this subject showed that when the complexity of the task increased (and thus the uncertainty) the conformity increased as well.

An experiment conducted by (Camilleri & Berger, 1967) showed that people are willing to change their preliminary decision based on information gathered from others if it is assumed that the other person knows more about the situation then the decision maker himself. In this study, students were coupled in groups of two and where asked to make a decision between two alternatives individually. Without knowing what option the other person chose, they were then told how often they and the person they were coupled with chose the right answer. In truth, there was no right or wrong answer. Students were then asked to give a final answer, still independent of the student they were coupled with. Results showed that students were more likely to change their answer if they were told that the other student chose the correct option more often and showed an opposite reaction if they were told they chose the correct option more often than the other student. The study showed that people are more likely to change their preliminary decision if they perceive that another person has made a different decision while being given the same choice set and it is assumed that they possess more knowledge regarding the subject.

2.1.3 Importance of message structure

For a verbal argument message to have any impact on an individual it must meet certain demands. A model proposed by (Areni, 2002) decomposes verbal arguments into three categories which combined, affect the probability of message acceptance:

- Product claims;
- Data supporting the claims;
- Conditional rules specifying the relationship between the data and the claims.

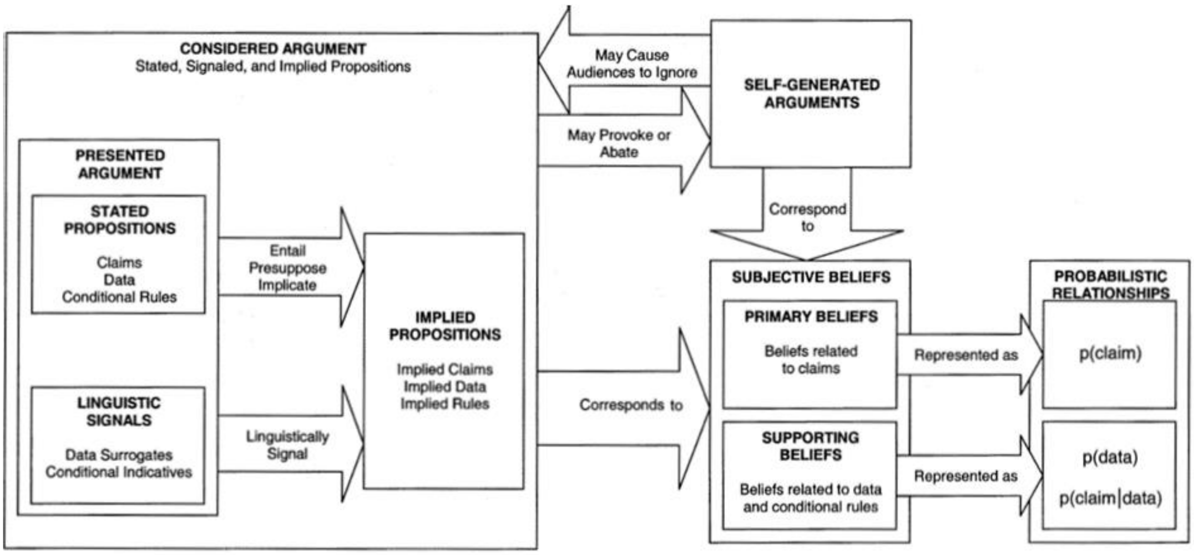


Figure 2: Proposition probability model (Areni, 2002)

Figure 2 shows the proposition probability model (PPM). The considered argument relates to the initial claim or statement that an individual will consider. A message recipient will form or modify his beliefs based on the propositions that make up the argument. In descriptive terms, a claim is more likely to be considered “likely true”, “possible”, or “hard to believe” instead of outright accepting or rejecting it, i.e. a probability of truth is assigned to the claim by the message recipient. Furthermore, the probability of acceptance is influenced by self-generated arguments which are considered to be endogenous. These can be linked to the knowledge of the recipient related to the presented claim be it through research or experience. The impact of these self-generated arguments can lead to recipients ignoring the initial claim made and instead generate their own reasons for accepting or rejecting the proposition. If the self-generated arguments deem the claim plausible then the recipient sees no need to validate the truthfulness of the initial claim (Evans, 1989).

In the field of advertising the presentation of the argument and supporting data is a major factor to influence people to accept the claim. The most basic argument structures are enthymemes and syllogisms.

Enthymeme

And enthymeme is the simplest form of an argument where a claim is supported by a single data statement (Corbett & Connors, 1998). This is a common argument structure used in advertising where the data statement is supporting the claim by means of implication rather than an outright statement. That means the message recipient is supposed to infer the relation between the claim and the supporting data statement which is known as the conditional rule. The probability of the claim being accepted can be formulated as:

$$p(x) = p(x|y) \times p(y) + p(x|z) \times p(z); p(y) + p(z) = 1 \qquad (2\text{-}1)$$

x = claim
y = data supporting the claim
z = not data

The z-term can be considered a random error term as it presents any reason as to why the claim may not be accepted.

As an example of an enthymeme, consider a farmer stating that his potatoes are among the best due to the unique properties of the soil in the Netherlands. The claim (x) here is that his potatoes are among the best which is supported by the unique properties of the soil in the Netherlands (y). The link between the unique properties of the soil and the quality of the potatoes is the conditional rule which is implied and not directly stated. For the claim to make sense the message recipient must infer the rule that the properties of the soil affect the quality of the potatoes.

Syllogism

A syllogism differs from an enthymeme in the sense that the conditional rule is directly stated instead of implied. A claim is implicated on the basis of a rule and the presented data confirms or denies the consequent of that rule. The presented argument is often structured with a minor premise that presents the data, a major premise that corresponds to the conditional rule and the conclusion that represents the claim.

Other examples of argument structures such as multiple base arguments, hierarchical arguments or jurisprudence models are essentially modifications of the two argument structures as presented above.[1]

There are two bases on which claims can be rejected by a message recipient. The first one is based on the relation between the supporting data and the any conditional rules. If the message recipient does not see how the claim follows from the supporting data than the argument can be judged to be invalid. In order to convince someone to accept a message it is therefore important that they believe the supporting data to be true and related to the claim itself which is the second basis on which an argument can be rejected.

[1] A thorough explanation of these terms and their implications can be found in (Areni, 2002)

Another consideration that needs to be taken into account when determining the probability of message acceptance is the importance ascribed to the claim by the message recipient. Claims regarding a topic that are considered to be very important to the message recipient require a higher probability of supporting data to be true if it is to be accepted. This also relates to supporting data becoming more important if the message recipient is unsure about its stance regarding the initial claim (Eagly & Chaiken, 1993). This can also lead to the acceptance of a claim despite it being false. When doubt exists regarding the truthfulness of the claim but the supporting data is believed the claim can still be accepted as true due to the inferred relation between the claim and the data, i.e. if the message recipient believes the supporting data is true then he is more likely to believe the claim is true as well (Revlin & Von Leirer, 1978).

2.2 Parking attributes

Most research focused on parking are based on the characteristics of a parking facility that influence the decision of a car driver on where to park (Sunitiyoso, Avineri, & Chatterjee, 2011). One of the most obvious influential attributes of a parking facility would be the parking tariff which is often considered to play a key role in determining drivers' parking behaviour (Griffioen-Young, Janssen, van Amelsfoort, & Langefeld, 2004) (Frank, Greenwald, Kavage, & Devil, 2011).

(Vickrey, 1954) suggested that in order to regulate the congestion of public parking spaces in municipalities a variable parking tariff should be implemented. When less than 85% of parking spaces are occupied parking the parking tariff should be zero as the occupancy of this public good is of marginal cost to others. When demand increases however, the likelihood of drivers cruising for a parking spot also increases leading to more congestion and pollution. This also increases the marginal cost of other users using the same space. These other users do not have to be car drivers but can also be pedestrians or inhabitants near the roads or parking spaces a car driver is looking to use. As there is a fixed supply of parking facilities, in order to keep space available the price must then be increased. Because public parking space is considered to be a public good or service the price is not based on the free market, rather, it is intended to serve the goals of the public.

Where a municipality may have the goal to regulate congestion and general efficient use of space a parking company may focus on parking tariff to maximise his own profit. Unlike a municipality a parking company is often limited in its locations where it can provide parking space assuming that people make use of the parking space to do something in the vicinity of the parking facility itself.

Related to this, it is still possible that people choose to drive around in search for a free parking spot or one that is close to their final destination rather than paying or walking a bit further. This has been researched by (Shoup, 2006). In his study, he found that it is hard to quantify what percentage of congestion is based on drivers cruising for a parking spot and those that need to pass through although (Polak & Axhausen, 1990) found that the search time can constitute up to 25% of the total travel time. The thought is that planners have not taken into account that cruising for a parking spot was a source of congestion in the city. Research concerning cruising for parking itself, according to (Shoup, 2006), is limited because it has been researched in places where researchers expect to find people cruising for parking and thus potentially ignoring significant data. A model including seven variables, as given below, was used to give an example of modelling parking behaviour:

- p Price of curb parking (€/h);
- m Price of alternative (e.g. off-street parking) (€/h)
- t Parking duration (h);
- c Time spent searching for parking at the curb (h);
- f Fuel cost of cruising (€/h);
- n Number of people in the car;
- v Value of time spent cruising (€/h/person).

Several relations between these variables can be inferred when expressed in monetary value. For example, the cut-off point for the time spent cruising for a parking spot before an individual would have been better off immediately choosing for the (more expensive) parking alternative can be derived with the following formula:

$$c' = \frac{t(m-p)}{f+nv} \quad (2\text{-}2)$$

With this, it can be derived that a driver is more likely to continue cruising if curb parking is cheap, the alternative is expensive, fuel is cheap and an individual places a low value on saving time. Although mathematically sound, it is difficult to predict parking behaviour based on these seven variables alone as it does not fully capture the factors that may influence the decision to choose for a certain parking spot. Shoup (2006) himself gives six complications which render the model incomplete. The first one is that heterogeneity is most likely to exist for the value of time spent cruising but also that a single individual may change his value depending on time of day, mood or any other reason. The second complication is that it is hard to predict how long it will take before a driver finds a parking space on forehand. This is because an individual will most likely not have the information on hand regarding the occupancy of available parking space, similarly, because not all information is available to the driver on forehand, it is possible that a driver chooses to park at a relatively expensive parking space because he does not know that there is an alternative available that is cheaper or closer to his final destination. Another consideration is that people may prepare for their trip differently. Where one individual will try to find as much information as he can regarding his route and preferred parking spot, another individual may choose to drive to his destination and try to find a parking place once he arrives at his destination. Lastly, it is known that this model does not include all variables taken into account when choosing for a certain parking facility. Walking distance, for example, is assumed to play a significant role but was not included in the example model. The paper then describes that something as mundane as parking is very difficult to model given the huge amount of variables and heterogeneity that play a role in the decision to choose for a certain parking facility.

Real-time information

(Teng, Qi, & Martinelli, 2006) found that the information regarding parking car drivers have before they departed influenced the time spent searching for a parking spot and in turn, influenced the perceived difficulty of drivers had with parking. The study gives an overview of the literature regarding parking guiding systems which are aimed at reducing the time spent looking for a parking spot and state that before such measurements are implemented there is a necessity to investigate to what extent car drivers feel parking difficulty and what technology is preferred to mitigate this difficulty and what the cost of the implementation of such a system would be. A distinction was made between pre-trip planning and en-route information which require different technologies to provide information. A binary and multinomial probit model were used to identify the preferences of parker's regarding information technologies. Their conclusion was that the websites and in-vehicle devices were the preferred technologies regarding pre-trip information. Making the decision on where to park en-route, roadside displays were preferred to in-vehicle devices due to the information being up to date. This suggests that despite new technologies being available and increasingly offering more and more information the roadside displays are still preferred as a source of information on available parking spaces and municipalities would be wise to take this into consideration when determining their policy on parking measurements.

Parking guidance systems are measures implemented by municipalities to mitigate the congestion within the city and reduce air pollution by car drivers cruising for parking places. Plenty of studies are available on proposed models for parking guiding systems which can include various attributes that are taken into account with the design of such systems. An example is given below (Giuffrè, Siniscalchi, & Tesoriere, 2012):

- Difficulty in reaching a parking lot;
- Level of use of a particular parking lot (occupancy rate);
- Impact of changes in demand for parking (number of arrivals and duration);
- Changes in the provision of parking areas (locations and number).

Smart parking technologies may increase the satisfaction level of a parking facility due to convenience for the car driver while also reducing operation, maintenance and enforcement costs for parking facility operators (Shaheen, Rodier, & Eaken, 2005). The convenience for the car driver is derived from the ease with which users are able to inquire information, reserve and pay for parking all without ever leaving their car. These time saving technologies may then make the difference for a car driver to choose to park and ride transit or using their car to drive to their final destination. Regular commuters were found to be more likely to use transit-based parking information than parking guidance information systems as they are more concerned with catching (or missing) a train during peak hours. The study concluded that pre-trip information and security on the availability of parking space were determinant factors for a car driver to use park their car and use public transport to reach their final destination.

The demand for real-time information was also studied by (Crowder & Walton, 2003) investigating the use of intelligent transportation systems to direct car drivers to an empty parking spot. The best option to reduce congestion and reallocate parking supply should provide real-time parking information and make use of wireless technology coupled with wireless applications for transportation. Digital information dissemination should be considered with regard to the transportation information gaps. Focus groups of participants were used to identify issues concerning parking at the campus of the University of Texas. Supply, permit costs, car storage and safety were considered to be the most important. In terms of guidance systems a distinction was found between regulars (e.g. students and professors) and visitors. Variable message signs were thought to be the best option to direct visitors to the best parking spot whereas the regulars, who are familiar with the layout of the campus, were more likely to drive to their destination ignoring these messages. The focus groups did indicate that internet and cellular applications would most likely become the best alternative if the university was willing to restructure their current supply allocation and permit structures.

Different forms of parking information could potentially contribute to a better utilisation of existing supply of parking space and reduce congestion in cities by providing car drivers with information aiding them in their decision making process at different stages of their journey (Axhausen, Polak, & Boltze, 1993). The impact of the implementation of parking guidance systems were described in this paper with the use of two case studies. In Nottingham, England, a broadcast system provided listeners of the radio station with up-to-date information regarding available parking space and queuing times in the centre of Nottingham three times an hour during the day. Car drivers were made aware that this information was available on the radio by road side advertisements or on the radio itself. Most of the users that were aware of the service decided to make use of the service when in the car, a small proportion decided to gather the information before making the trip the centre of Nottingham and were found to be more likely to use the park and ride facilities. Half of the people that did not use the broadcasted information to their advantage felt that they did not need assistance in finding a parking facility and were unwilling to switch radio stations. Further results showed that car drivers that listened to the service before taking their trip were more likely to spend less time searching for a parking space by an average of 2.5 minutes. The study of the parking guidance system in Frankfurt which implemented a visual messaging system with road signage showed that a vast majority of respondents was aware that the system existed but only half of them decided to make use of it. Incidental visitors were more likely to make use of the system than regular visitors and inhabitants of the city. Nevertheless, the system was found to be easy to understand. Despite increasing demand for parking space the average search time for a parking space has decreased for users of off-street parking facilities but the data also suggested that users of the parking guidance system had a longer parking search time than the non-users. In their literature review (Abidi, Krichen, Alba, & Molina, 2015) came to the same conclusion. A possible reason for this may be that the guiding systems are mostly used by incidental visitors who are unfamiliar with the parking situation in the area and thus take longer to find an appropriate parking space despite the additional information provided by the parking guiding system.

The parking guidance systems in the studies described above are deemed useful but their usefulness is not fully utilised. According to (Geng & Cassandras, 2012) a possible downside of these systems is that drivers may not find vacant parking spots by following the directions on the signs given by the parking guidance systems and instead of searching for parking spaces, car drivers now compete for the same parking spot as they are being directed to the same parking facility. Despite attempts to model the behaviour of car drivers in search for parking spaces it is often found that the models are lacking in correctly predicting the behaviour of these car drivers. Most models assume that all information is available to the car driver, and is aware of the alternatives that are available. Furthermore, most models do not include the learning experience of drivers which can lead to a change in their behaviour (Thompson & Richardson, 1998). An overview of commonly mentioned attributes that are taken into account to model parking behaviour are given in Table 2-1.

Table 2-1: Commonly mentioned attributes in studies regarding parking preferences

Mentioned attributes	**Reference**
Walking distance from parking to final destination	(Ji, Wang, & Deng, 2008), (Geng & Cassandras, 2012), (Giuffrè, Siniscalchi, & Tesoriere, 2012), (Thompson & Richardson, 1998)
Type of parking facility	(Axhausen, Beyerle, & Schumacher, Choosing the type of parking: a stated preference approach, 1988) (Ji, Wang, & Deng, 2008), (van der Goot, 1982), (Habib, Morency, & Trépanier, 2012)
Parking fee	(Ji, Wang, & Deng, 2008), (Mei, Xiang, Chen, & Wang, 2010), (Geng & Cassandras, 2012)
Available parking spaces	(Ji, Wang, & Deng, 2008), (Shaheen, Rodier, & Eaken, 2005), (Crowder & Walton, 2003), (Giuffrè, Siniscalchi, & Tesoriere, 2012), (Thompson & Richardson, 1998)
Driving time to parking facility	(Ji, Wang, & Deng, 2008), (Mei, Xiang, Chen, & Wang, 2010), (Giuffrè, Siniscalchi, & Tesoriere, 2012)
Parking route	(Kaplan & Bekhor, 2011), (Axhausen K. W., Polak, Boltze, & Puzicha, 1994), (Crowder & Walton, 2003), (Abidi, Krichen, Alba, & Molina, 2015)
Parking-search duration	(Axhausen K. W., Polak, Boltze, & Puzicha, 1994) (Mei, Xiang, Chen, & Wang, 2010), (Falcocchio, Teng, Ulerio, Afshar, & Huang, 2000)
Travel demand	(Habib, Morency, & Trépanier, 2012)
Parking time restriction	(van der Goot, 1982), (Mei, Xiang, Chen, & Wang, 2010)
Manoeuvring room	(Griffioen-Young, Janssen, van Amelsfoort, & Langefeld, 2004)
Availability of information	(Teng, Qi, & Martinelli, 2006), (Shaheen, Rodier, & Eaken, 2005), (Axhausen K. W., Polak, Boltze, & Puzicha, 1994)
Convenience of payment methods	(Shaheen, Rodier, & Eaken, 2005)

2.3 Conclusion

Social Influence

Social influence can play a big role in the decision making process of individuals. Conforming to social norms is something that (almost) all humans do. A change in behaviour or thought pattern may also be unnoticeable to an individual himself hence why most studies concerning the role of social influence are done with experiments to test certain hypotheses. In the literature, three types of conformity were discerned. Complying with a request is done with the belief that the individual is to gain approval or avoid disapproval due to conforming. The change in behaviour may not stroke with the beliefs of that individual but is done because the expected result of complying outweighs the option of not complying. It is also possible that an individual changes his behaviour because he believes others expect him to. No specific request is made for a change in behaviour but the individual feels that the adoption of this behaviour is needed to maintain or establish a relationship with another person or group. A third reason as to why an individual may change his beliefs or behaviour is due to the adoption of the ideas or behaviour of others without a specific need to do so. There is no external pressure felt from the individual to change his behaviour or beliefs but as it is congruent with his own value system he self-generates the argument as to why these beliefs or behaviour should be adopted.

Individuals are more likely to accept the influence of others if they believe they have very little control over the situation. The belief in one's own ability to influence the outcome of the situation is a determining factor in the acceptance of social influence. Those with a low perceived internal control are more likely to change their behaviour even if it does not match their own beliefs. Perceived hierarchy also plays an important role in the acceptance of social influence. A person who is perceived to have authority over an individual is more likely to be able to influence that individual as the consequences of ignoring the request are deemed to be of a greater risk than from those that are not perceived to be an authority figure. Complying with a perceived authority figure does not have to have a negative connotation, it can also be that the authority figure is believed to have greater information regarding a subject and therefore is believed to able to make a better judgement than the individual himself. Information plays a key role in the decision making process of an individual. The process of accepting information from others is influenced by the knowledge of an individual regarding the subject and the perceived believability of the information. When self-generated arguments do not conflict with the given information or any supporting data an individual is highly likely to accept the information as truth.

Parking attributes

There is a vast amount of different characteristics taken into account in different studies trying to model parking behaviour and preferences of a car driver. Common attributes that are often included in parking or models are include parking tariff, availability of space and parking search duration.

Parking guidance systems aim to limit the parking search duration of a car driver to mitigate congestion in cities. Although users found the signage to be an improvement over a normal situation with no en-route information given at all the parking search duration did not decrease in all cases which is most often the reason to implement such a measure in the first place. Real-time information is becoming increasingly more important for car drivers. Pre-trip information was found to significantly decrease the parking search duration time for those that decided to make use of it. Parking guidance systems were deemed to be of limited use because most models assume that car drivers act rationally whereas practice seems to indicate that this is far from the truth. Therefore, researchers suggest that real-time information is vital for car drivers to as it can help them make a more informed decision.

3 Methodology

This chapter describes the models that will be used to estimate the part-worth utilities of the attributes.

3.1 Utility

The basic theory behind the models is based on an important assumption regarding decision making. For each decision maker it is assumed that he acts rationally which means that he is assumed to choose the option that maximises his utility subject to the constraints of the situation in which the choice is made. When two or more alternatives are presented to a decision maker a trade-off between the attributes of the alternatives and its levels will be made and the alternative with the highest utility function for the decision maker is the one that will be chosen. The utility function can be described as (Hensher, Rose, & Greene, 2005):

$$U_{ni} = V_{ni} + \varepsilon_{ni} = \sum_{k=1}^{K} \beta_k X_{nik} + \varepsilon_{ni} \tag{3-1}$$

U_{ni} = overall utility of alternative i for individual n
V_{ni} = observed component of utility of alternative i for individual n
ε_{ni} = unobserved component of utility of alternative i for individual n
β_k = utility weight for attribute level k
X_{nik} = attribute X of alternative i for individual n with level k

In words, the observed part of the utility (V_{ni}) is equal to the sum of the utility weights (β_k) multiplied by its attribute variables (X_{nik}). A distinction is made between the observed and unobserved components of utility. Within a certain choice set an individual will consider the attributes that are associated with alternatives presented. A researcher may not be able to define all the attributes that an individual considers when making a choice which leads to the presence of unobserved sources of utility.

With the assumption that a decision maker will maximise its utility within a set of J alternatives the probability that alternative i will be chosen over other alternatives j can be written as (Train, 2009):

$$P_{ni} = prob(U_{ni} > U_{nj}\ ;\ \forall j \neq i) \tag{3-2}$$

P_{ni} = probability of individual n choosing alternative i out of a set of j alternatives

3.2 Multinomial logit

The multinomial logit (MNL) model is widely used to analyse choice data. It calculates the choice probability of an individual n choosing alternative i over alternative j within a choice set of J alternatives. To do so the exponential of the utility of alternative i is divided by the sum of the exponential of the utility of all the alternatives within the choice set (V_{ni}) including the utility component of alternative i. This can be written as a formula in the form of (Hensher, Rose, & Greene, 2005):

$$P_{ni} = \frac{e^{V_{ni}}}{\sum_{j=1}^{J} e^{V_{nj}}}\ ; j = 1, \dots, i, \dots, J\ i \neq j \tag{3-3}$$

P_{ni} = the probability that individual n chooses alternative i over alternative j
$e^{V_{ni}}$ = exponential of the observed utility of alternative i for individual n
$\sum_{j=1}^{J} e^{V_{nj}}$ = sum of exponentials of the observed utility indices for all J alternatives

There are four assumptions which may limit the interpretation of the results (Bhat, 2002):

Independent and identically distributed random utility components

The assumption of the IID-condition can be divided into two parts. The assumption of independence means that it is assumed that there are no common unobserved factors that influence the utilities of the different alternatives. The identical distribution refers to the variance in the unobserved factors which is assumed to be equal across the alternatives. Note that with this assumption the unobserved component of utility (ε_{ni}) becomes ε as this term is assumed to be equal among all respondents and alternatives.

Response homogeneity

The MNL model does not take personal preferences into account which means that the assumption is that the utility for a certain alternative is the same for each decision maker. In other words, it is assumed each decision maker places the same importance on the attributes given in his choice set.

Error variance-covariance homogeneity

It is assumed that the error variance-covariance structure of the alternatives is identical across all decision makers. It implies the same competitive structure among alternatives for all individuals.

Independence of irrelevant alternative

The independence of irrelevant alternatives (IIA) means that, all else being equal, a decision maker's choice between two alternative outcomes is unaffected by what other choices are available. In other words, the ratio of probabilities of choosing between alternatives from a certain choice set is independent of the attributes or other alternatives. The downside of this property is that this condition does not take into account any perceived similarity of alternatives. For example, if an individual has the choice to go by a red bus or car a simple MNL model would assume the probability of choosing either alternative to be 0.5. If one were to add a third option of going by a blue bus, the probability ratio between the alternatives must stay the same to meet the IIA condition thus the probability of each alternative becomes 0.33. However, an individual might find the distinction between going by red or blue bus to be so similar he does not differentiate between those two alternatives and thus effectively returning to the first situation of only two alternatives (bus or car). The MNL model thus has a tendency to over-estimate the choice probabilities for alternatives that are perceived to be similar.

Similarity of alternatives is unlikely to be a factor within the given dataset as respondents were asked to give a particular score to a parking facility given its attributes. One could argue that the IIA condition does not hold for this particular dataset because eliminating one of the alternatives would lead to an uneven distribution over the other answers However, because respondents are asked to give a ranking for a given choice set rather than choosing between alternatives the IIA condition is not relevant for this study.

3.3 Latent class

Latent class (LC) models are a derivative of the MNL model which take heterogeneity into account by assigning respondents to a certain group known as latent classes. Rather than assuming homogeneity in taste preferences for the whole sample of respondents the LC model assumes homogeneity of taste preference for each defined class. Because the estimated utility of an alternative for a respondent may not be equal to the estimated utility for that of a latent class the probability of belonging to a certain class can be written as:

$$P_{nq} = \frac{e^{z_n \theta_q}}{\sum_{q=1}^{Q} e^{z_n \theta_q}}, q = 1, \dots, Q, \theta_Q = 0 \qquad (3\text{-}4)$$

P_{nq} = probability of individual n belonging to class q

Z_n = set of observable, situation invariant, characteristics which enter the model for class membership
Θ_q = vector of the utility weights belonging to characteristics of z specified for class q

As stated, the utility weights (θq) for the Qth class are fixed to zero. This way, the utility weights for the Q-1 classes can be contrasted with the Qth class to show the differences between the classes. Introducing an attribute in the model can show if it explains the difference in taste preferences. Because homogenous taste preferences are estimated, it makes sense to introduce characteristics by which a subset of the respondent sample can be identified.

The probability of a certain alternative being chosen over other alternatives is the same as in the MNL model with the included restriction of belonging to a certain class. This can be formulated as (Greene & Hensher, 2003):

$$P_{ni|q} = \frac{e^{x_{ni}\beta_q}}{\sum_{q=1}^{Q} e^{x_{ni}\beta_Q}} \tag{3-5}$$

$P_{ni/q}$ = probability of individual n choosing alternative i within class q
X_{ni} = attribute x of alternative i for respondent n
β_q = estimated parameter(s) for class q
β_Q = estimated parameter(s) for all Q classes

The probability of alternative i being chosen by respondent n is thus equal to the sum of the probability that respondent n belongs to class q times the probability that respondent n chooses alternative i given that he belongs to class q:

$$\sum_{q=1}^{Q} P_{nq} P_{ni|q} \tag{3-6}$$

3.4 Mixed logit

The mixed logit (ML) model can account for taste heterogeneity by estimating the range of each utility weight among the respondents. Consider the utility function as given in formula (3-1) where it is assumed that the parameter β varies among respondents instead of being fixed as is assumed in the standard MNL model. This gives the following equation:

$$U_{ni} = V_{ni} + \varepsilon_{ni} = \beta_n x_{ni} + \varepsilon_{ni} = (\alpha_n + \vartheta_n) x_{ni} + \varepsilon_{ni} \tag{3-7}$$

α_n = mean of parameter β_n
ϑ_n = a random term that captures the non-observable individual effects (often representing the standard deviation of the tastes among the population)

With the assumption that ε_{ni} is IID extreme value type 1, the logit probability for respondent n choosing alternative i out of J alternatives becomes (Train, 2009):

$$L_{ni} = \frac{e^{\beta_n x_{ni}}}{\sum_{j=1}^{J} e^{\beta_n x_{nj}}} \tag{3-8}$$

Because the respondents' individual taste differences are unknown the coefficients vary in the population with a density denoted by $f(\beta_n \mid \alpha, \vartheta)$. The taste of the respondents is thus not observed so to solve for the probability the integral of L_{ni} is calculated over all possible values of β, giving:

$$P_{ni} = \int L_{ni} f(\beta|\vartheta) d(\beta) \tag{3-9}$$

Due to its open-form, the ML approximation of the probabilities is calculated by performing random draws from the density function $f(\beta/\vartheta)$

$$\dot{P}_{ni} = \frac{1}{R} \sum_{r=1}^{R} L_{ni}\,(\beta^r) \tag{3-10}$$

$\dot{P}_{ni}$ = simulated probability of respondent n choosing alternative i
R = number of draws
β^r = value of β drawn from the density function $f(\beta/\vartheta)$

Because the simulated probability needs to be calculated for each draw separately the estimation of the ML model is a time intensive task. It is for this reasons that Halton sequences are often preferred over random draws as it has been shown that a similar accuracy can be gotten while using only a tenth of the amount of draws. There is no real consensus on the minimum amount of draws needed to estimate a ML model with a good fit. (Borgers, Kemperman, Toll, & Timmermans, 2010) suggest that 500 draws would yield a fairly good estimation.

3.5 Goodness of fit

Several measures have been constructed to measure the estimation power of a model. These so-called goodness-of-fit methods can indicate whether the model is any good at predicting the observed values within the dataset.

3.5.1 Log-likelihood

For all the models the maximum likelihood estimation (MLE) is used to find parameter values that maximise the likelihood function. The probability that respondent n chooses the alternative that he was observed to choose can be written as:

$$\prod_{i} (P_{ni})^{y_{ni}} \tag{3-11}$$

P_{ni} = probability of respondent n choosing alternative i
y_{ni} = 1 if alternative i was chosen, otherwise 0

With the assumption that the respondent's choice was made independent of that of other respondents, the probability that all respondents chose the alternative they were observed to choose would then be the same only multiplied by the sample size N. The log-likelihood is the natural logarithm of the likelihood as a function of the vector β which contains the parameter estimates for the model. The log-likelihood function can then be written as:

$$LL(\beta) = \sum_{n=1}^{N} \sum_{i} y_{ni} \ln P_{ni} \tag{3-12}$$

$LL(\beta)$ = log-likelihood function at the estimated parameters
N = sample size

A model is considered optimal when the estimates for the parameter β are equal to zero. This can be found by taking the derivative with respect to the parameters.

3.5.2 Likelihood ratio statistic

In order to determine whether the model is statistically significant the log-likelihood function of the estimated model can be compared to that of the base model. If the former is statistically closer to zero it can stated that the estimated model is an improvement over the base model. The formula for the likelihood ratio statistic is:

$$LRS = -2[LL(0) - LL(\beta)] \tag{3-13}$$

$LL(0)$ = log-likelihood at zero parameters (known as the null-model)
$LL(\beta)$ = log-likelihood at the estimated parameters β

Because the log-likelihood is always negative, the LRS is simply two times the magnitude of the difference between the constrained and unconstrained maximums of the log-likelihood function (Train, 2009). The resulting value is then compared to a chi-square statistic (χ^2) with the degrees of freedom (r) being equal to the difference in the number of parameters estimated for the two models. If the value exceeds the critical value of χ^2 at the chosen significance level (*p*-value, often set at 0.05) the model is deemed to be an improvement

Because the value for the log-likelihood is somewhere between $-\infty$ and 0 the value for the log-likelihood including the parameters ($LL(\beta)$), when closer to zero than that of the null-model ($LL(0)$), indicates an improvement of the model-fit.

3.5.3 Likelihood ratio index (rho square / ρ^2)

For discrete choice models the likelihood ratio index also known as McFadden's Rho-Square is often used to measure how well the models fit the data. It compares the model with the estimated parameters against the model in which all parameters are equal to zero. The formula is given by (Train, 2009):

$$\rho^2 = 1 - \frac{LL(\beta)}{LL(0)} \tag{3-14}$$

The result is a value for ρ^2 between 0 and 1, with 1 indicating that the model is perfect at predicting the observed values and 0 for a model which performs no better than the null model. To interpret this value note that because the relationship of the variables is not necessarily linear the likelihood ratio is the percentage increase in the log-likelihood function above the value taken at zero parameters (Train, 2009).

This statistic is slightly skewed as a model with more parameters will always have a higher log-likelihood thus indicating that it is a better fit. To compensate for this the amount of parameters can be included to essentially penalise the model for including too many variables that do not affect the dependent variable. When comparing two models from the same dataset the one giving a higher value is deemed to be a better model fit. The formula is given by:

$$\rho^2_{adjusted} = 1 - \frac{LL(\beta) - K}{LL(0)} \tag{3-15}$$

K = number of estimated parameters

The ρ^2*-statistic* is only relevant for the MNL model and cannot be used to compare the LC and ML models as it is only useful for nested logit models. This is the case for the MNL model because it is assumed that the ratio of probabilities of the attributes is independent of attributes or existence of the other alternatives.

3.5.4 Information criteria: AIC and BIC

Solely comparing the log-likelihood function between different models will always favour the model with more parameters as the log-likelihood function can only increase when more parameters are added. As such two common methods to evaluate whether the difference in the log-likelihood between two models is significant enough to warrant the inclusion of the extra parameters (Kingdom & Prins, 2016). A large amount of parameters is more likely to fit the data better but in turn becomes less parsimonious, that is, the model is then less likely to be adequate for a similar set of data with different values. It is therefore that a balance is sought between estimating enough parameters to estimate the model but not to the point whether the model is only applicable to one particular set of data. Aikake's Information Criterion (AIC) is a relative goodness-of-fit which allows for comparison between models which make use of the same set of observations, where a lower AIC value is to be preferred. It can be formulated as (Akaike, 1973):

$$AIC = \frac{-2 \times LL(\beta) - K}{N} \tag{3-16}$$

The Bayesian Information Criterion (BIC) is another measure of model fit which indicates what model gives the highest likelihood of observing the data as put into the model. Like the AIC its value is only useful for comparison with another model using the same set of observations. It can be calculated as follows (Schwarz, 1978):

$$BIC = \frac{-2 \times LL(\beta) + K \times LN(N)}{N} \tag{3-17}$$

As can be seen, both criterions penalise the addition of more parameters as parsimony would be lost but reward the model for a higher log-likelihood. The penalisation of the BIC is greater compared to the AIC. The difference between the two criterions is that AIC considers a true model as unknown and tries to approximate it with a simpler model. The BIC on the other hand, tries to identify the model the highest probability as being the true model. Using both criteria together reassures on the robustness of the model despite having different theoretical target quantities (Kuha, 2004).

4 Dataset

This chapter describes the dataset that was used as well as the transformation of the variables.

4.1 Survey questions

The data used for this research is the result of a previous research done on the role of social influence in car drivers' parking choice decision making (Iqbal, 2018). To gather the information needed, a questionnaire was constructed which was divided into three sections:

- Personal parking experiences and experiences with social influence;
- Role of social influence when choosing a parking facility;
- Socio-demographic characteristics (age, nationality, education, etc.).

The first section questioned respondents about their usage of three predefined parking type facilities (on-street parking, parking garage, and parking lot) and their trip frequency, which was divided into five levels ranging from never to often, of using for three possible trip purposes of making use of a parking facility:

- For work or study;
- For shopping;
- For leisure activities.

Following up on the parking experiences, the respondents were asked how likely they were to follow up on the advice, within the context of travel mode, travel route, or choice of parking facility, of four different groups that may be part of their social circle:

- Family members;
- Friends;
- Colleagues;
- Experts (persons with detailed knowledge of the situation).

The third section of the survey asked respondents personal information regarding the following topics:

- Gender;
- Age;
- Education;
- Nationality;
- Offspring (whether the respondents had children or not).

4.2 Survey design

The questionnaire was set up in such a way that respondents were asked to evaluate the attributes for a specific hypothetical parking facility that they were presented with in combination with advice from one's social circle and state how likely they were to choose this parking facility ranging from very unlikely to very likely over 5 steps. The survey makes use of a Likert scale design whereby a symmetry is present in the possible answers to be given with the neutral option being the middle two increasingly positive answers were possible (likely and very likely) and two increasingly negative answers were possible (unlikely and very unlikely). The given answers known as the choice outcome present an ordinal ranking. The survey thus made use of stated preference (SP) strategy which presents the respondents with a hypothetical situation which they are asked to evaluate. A positive feature of a stated preference survey is that the variables and their levels are defined by the researcher allowing for estimation of their relative importance. A downside of the stated preference method as opposed to the revealed preference (RP) method is that it may not confound with actual real data. Due to the difficulty of collecting RP data however, SP is a commonly used method for surveys (Hensher, Rose, & Greene, 2005).

4.2.1 Attributes and levels

Attributes were defined which were expected to influence the decision of the respondent regarding their likelihood of parking at the presented parking facility. A total of eight attributes were included with four of them relating to the characteristics of the parking facility and the other four relating to the influence of one's social surroundings. Each of the four characteristics of the parking facility was given three attribute levels as can be seen in Table 4-1.

Table 4-1: Characteristics and their defined levels of the parking facility

	Level 1	Level 2	Level 3
Parking tariff	€1	€2	€3
Walking distance	100m	300m	500m
Parking type	On-street	Parking lot	Parking garage
Level of security	No security	Security staff	Security cameras

All attributes are ranked ordinally although it could be argued that this is not certain for the parking type or level of security.

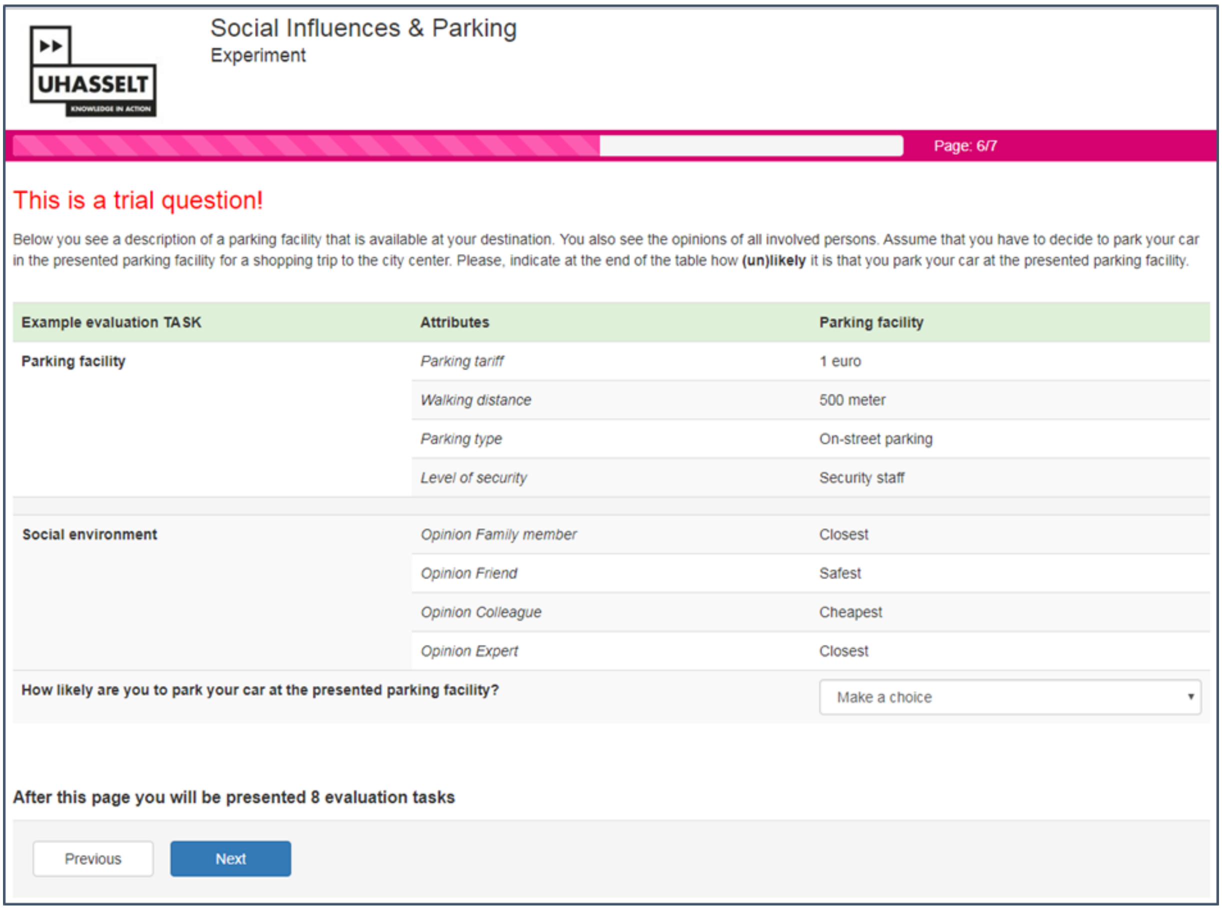
The other four attributes are related to the influence of the four groups as mentioned earlier. They would give one type of advice for the parking facility, these are:

- The parking is the closest one to your final destination;
- The parking is the cheapest one compared to other parking facilities;
- The parking is the safest one compared to other parking facilities;
- The person provides no opinion.

The attributes thus are the opinions of the groups that could provide social influence and the levels of those attributes are the types of advice given as above. The advice is related to the characteristics of the parking facility which means that it could be a factor in the interpretation of the results.

4.2.2 Experiment design

With these eight attributes and their corresponding levels a total of 20,736 ($3^4 \times 4^4$) combinations of choice sets are possible. Because it would be unfeasible to ask respondents to fill in 20.736 questions, the full factorial design has been scaled down to a fractional factorial design leading to a total of 32 choice sets. Because of the inequality of the amount of levels between the attributes some levels of the attributes do not appear the same number of times nor do the combination pairs of attribute levels. The result is that the first attribute levels for the attributes describing the characteristics of the parking facility appear twice as often as the other levels of that attribute. With the 32 choice sets being used, only the main effects can be estimated. For the estimation of interaction effects between attributes a larger design would have been necessary. An example of choice task a respondent could have been presented with is shown in Figure 3.



Social Influences & Parking
Experiment

UHASSELT

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This is a trial question!

Below you see a description of a parking facility that is available at your destination. You also see the opinions of all involved persons. Assume that you have to decide to park your car in the presented parking facility for a shopping trip to the city center. Please, indicate at the end of the table how **(un)likely** it is that you park your car at the presented parking facility.

Example evaluation TASK	**Attributes**	**Parking facility**
Parking facility	*Parking tariff*	1 euro
	Walking distance	500 meter
	Parking type	On-street parking
	Level of security	Security staff
Social environment	*Opinion Family member*	Closest
	Opinion Friend	Safest
	Opinion Colleague	Cheapest
	Opinion Expert	Closest
How likely are you to park your car at the presented parking facility?		Make a choice

After this page you will be presented 8 evaluation tasks

Previous Next

Figure 3: Example of a choice task within the survey

4.2.3 Coding of attributes

For model estimation, the data often needs to be transformed to calculate the utility of an alternative or attribute level. This is the case for this particular dataset where the attribute and its level could be identified by its nominal or ordinal measurement level. To do this an attribute with its levels is coded in such a way that it becomes binary. The presence of an attribute level is represented by a 1 if it is present and a 0 if it is not. This way, non-linear effects of the attributes can be tested. Two popular coding structures are dummy- and effects coding (Hensher, Rose, & Greene, 2005). The difference between the two is the way the base level is represented. An example of an effects coding structure of a three-level attribute is given in Table 4-2.

Table 4-2: Example of an effects-coding structure with a three-level attribute (Daly, Dekker, & Hess, 2016)

	Recoded variables			Utility contribution
Level of x	E1	E2	*E3*	
1	1	0	*0*	β_1
2	0	1	*0*	β_2
3	-1	-1	*1*	$-\beta_1 - \beta_2$
Associated parameter	β_1	β_2	$\beta_3 = 0$	

As can be seen, an attribute with three levels is recoded into three new variables with each their own associated parameter (β_k, where k indicates the level of an attribute out of a total of K levels). For identification purposes the last level is often normalised to zero, this is also known as the base level. As a result, only three parameters are estimated. For the first K-1 levels the recoded variable is equal to 1 and the value for the first K recoded variable is equal to -1. Given the utility function as defined in formula (3-1) the utility for level 1 of attribute x is:

$$V_{ni} = \beta_1 \times 1 + \beta_2 \times 0 + \beta_3 \times 0 = \beta_1 \tag{4-1}$$

The utility for the third level of attribute x then becomes:

$$V_{ni} = \beta_1 \times -1 + \beta_2 \times -1 + \beta_3 \times 1 = -\beta_1 - \beta_2 \tag{4-2}$$

Note that because the parameter associated with the third level (β_3) is equal to zero it effectively drops out of the equation. The result is then that the utility for the third level is equal to the negative sum of the first two parameters. The result is then that for a variable with K levels, the new recoded variable with an effects coding structure consists of K-1 columns and K rows.

For dummy coding the structure is very similar. The difference is that the base level is represented by a 0 instead of -1. Filling in the formula as shown above the utility for the third level of attribute x would then be 0 which is equal to the grand mean of the utility for that attribute. It is for this reason that effects coding is often preferred over dummy coding (Hensher, Rose, & Greene, 2005).

4.3 Construction of dataset

To research the effect an attribute has on the ranking of a specific choice set the dataset has been constructed in such a way that each of the ranking alternatives was contrasted with the "very unlikely" option. Effectively, a binary choice model is thus estimated for each of the other ranking alternatives. Because each choice set consists of 4 attributes with 3 levels and 4 attributes with 4 levels which have been transformed with the use of effect coding, a comparison with a single choice set would then consist of 20 $[4 \times (3-1) + 4 \times (4-1)]$ columns. To contrast all other four alternatives the dataset thus contains 80 columns in total. With a total of 377 respondents each being tasked with performing 8 evaluations with each having a choice of 5 ranking options the dataset contains 15,080 rows (377×805). An example of the way the dataset is constructed is presented in Table 4-3.

Table 4-3: Example of dataset setup

CSET	ALT	CHO	2AL1	2AL2	3AL1	3AL2	4AL1	4AL2	5AL1	5AL2
1	1	0	0	0	0	0	0	0	0	0
1	2	0	1	0	0	0	0	0	0	0
1	3	1	0	0	1	0	0	0	0	0
1	4	0	0	0	0	0	1	0	0	0
1	5	0	0	0	0	0	0	0	1	0
4	1	0	0	0	0	0	0	0	0	0
4	2	0	0	1	0	0	0	0	0	0
4	3	0	0	0	0	1	0	0	0	0
4	4	1	0	0	0	0	0	1	0	0
4	5	0	0	0	0	0	0	0	0	1
9	1	0	0	0	0	0	0	0	0	0
9	2	1	-1	-1	0	0	0	0	0	0
9	3	0	0	0	-1	-1	0	0	0	0
9	4	0	0	0	0	0	-1	-1	0	0
9	5	0	0	0	0	0	0	0	-1	-1

CSET = choice set
ALT = alternative (1 = very unlikely, …, 5 = very likely)
CHO = alternative chosen (1 if chosen, 0 otherwise)
2A1L1 = attribute 1 with level 1 for alternative 2

In the table above an example is presented with a single attribute containing three levels. Because effect coding was used, the third level is indicated by a -1 in both the first and second column. The attribute level is dependent on the choice profiles the respondent was presented with. Note that the attribute and its levels are left for alternative 1 (very unlikely) as that is set as the profile of the base level to which all other levels are contrasted with. A β- parameter is estimated for each column but only differs from zero if the ranking option was indeed chosen by the respondent. For example, the first choice set contains the first level for the attribute. A β- parameter can only be estimated for the 3rd ranking option because it is the only with a value that differs from zero in the “CHO” column.

4.4 Survey results

An overview of the socio-demographic characteristics of the respondents is shown below in Table 4-4.

Table 4-4: Socio-demographic characteristics of respondents

Total participants:	377		
Gender			
	#	%	
Female	168	44.56%	
Male	209	55.44%	
Age			
Full range	18-75		
	Division in groups	#	%
	18-25	182	48.28%
	26-35	142	37.67%
	36+	35	14.05%
	Mean (arithmetic):	28.29	
Region/country of origin			
	#		*% of total*
EU-citizens	264		70.02%
Belgians	221 (83.71% of EU respondents)		58.62%
Non-EU citizens	113		29.98%
Pakistani	75 (66.37% of non-EU respondents)		19.89%
Educational level			
	#		%
Secondary school	29		7.7%
High school degree	48		12.7%
Bachelor degree	113		30%
Master degree	150		39.8%
PhD degree	37		9.8%

A total of 377 respondents have responded to the survey. All of the participants were 18 years of age or older. The division of groups based on their age was done with the assumption of their different phases of life in mind and therefore have different needs. It is assumed that most of the respondents between the age of 18 and 25 are students or have just graduated and are therefore less likely to own a car or are more likely to use public transport. Respondents between the age of 26 and 35 are more likely to have a job but are also more likely to travel. The last group of respondents that are 36 or older are assumed to have settled down in life and perhaps have more experience regarding parking than younger respondents.

Over 30 different nationalities have taken part in this survey with the vast majority being Belgian (58.6%) which is logical seeing as the student that created this survey graduated from the Hasselt University and the survey was spread there as well. The other somewhat significant nationality was Pakistani (19.9%) as the student that created the survey is likely to have asked his friends and family to help with his survey. The division of EU and non-EU respondents has been done to see whether there is a difference between these two groups in regards to their preferences for a parking facility.

Most participants are or were studying at said university at the time and this is shown in the education level of most of the participants. Participants were also asked about their family situation. Seeing as most of the participants are still students the vast majority do not have any children (78.8%). This might also impact the frequency at which they travel to a city centre for leisure or shopping activities.

In order to gather as much information, each participant was asked about their self-assessed frequency with which they visit the centre of a city or town by car. Unfortunately there is no guideline as to what counts as seldom or frequent thus there might be a discrepancy between various participants. The results are shown in Figure 4.

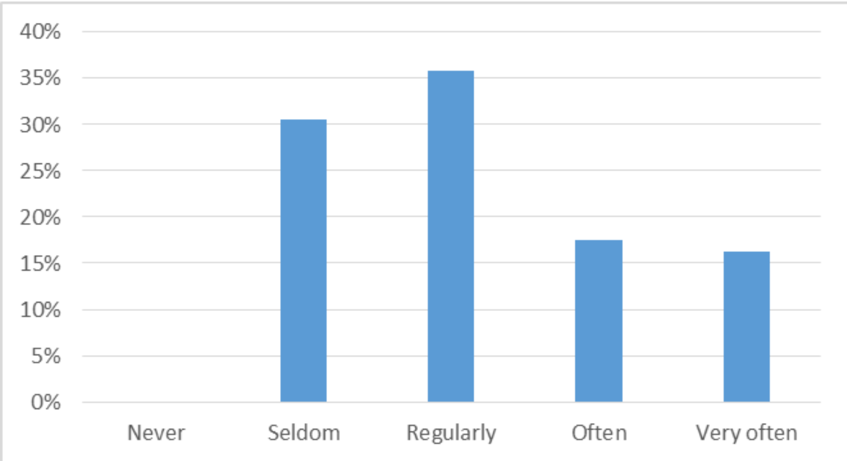

Figure 4: Frequency of using car to drive to the centre of a town or city

Respondents that stated they never used their car for this purpose were immediately taken to the end of the survey as their answers would not be realistic. The same goes for respondents that stated they had no driver's license. As stated before, the vast majority of respondents are students so the relatively high amount of people that seldom use a car to drive to the city centre is not that surprising.

With regards to the use of parking facilities for work/study, shopping and leisure activities, there is a relatively high amount of people that never make use of parking garages for work or study. This is most likely the result of most of the respondents working or studying at the University of Hasselt where no parking garages are present, instead, parking lots are available which would also explain why most respondents stated they make frequent use of them.

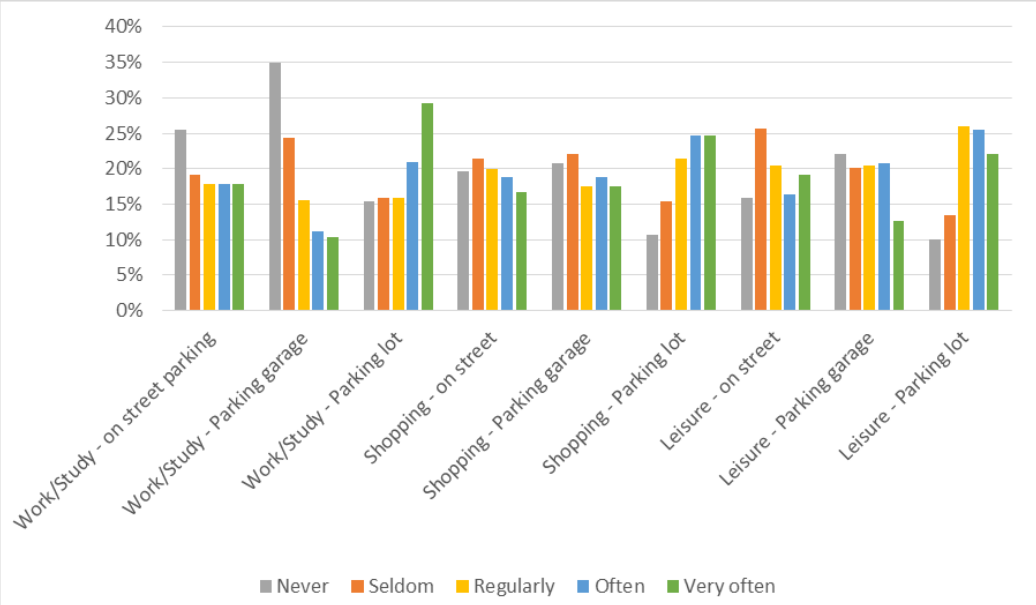

Figure 5: Frequency of using parking facility for work/study, shopping or leisure

4.4.1 Response to social influence

Participants were also asked about the likelihood of listening to advice from four different groups:

- Family members;
- Friends;
- Colleagues;
- Experts (persons with detailed knowledge of travel situation).

In the context of their advice for one of the three following travel related choice decisions

- Choice of travel mode;
- Choice of travel route;
- Choice of parking facility.

Results are shown in Figure 6. Comparing the graphs it is clear that advice from family is most often followed by friends coming in second. This suggests that respondents deem the advice of those closest to them as important. A difference was also found when it comes to advice regarding the travel route where the opinion of experts is more often followed than that of their friends.

In terms of heterogeneity, respondents show a higher variance in their response to the advice of experts as the percentages for each option are closer than that for the advice from family, friends or colleagues. The results suggest that advice from family will play a significant role in the decision of choosing a parking facility.

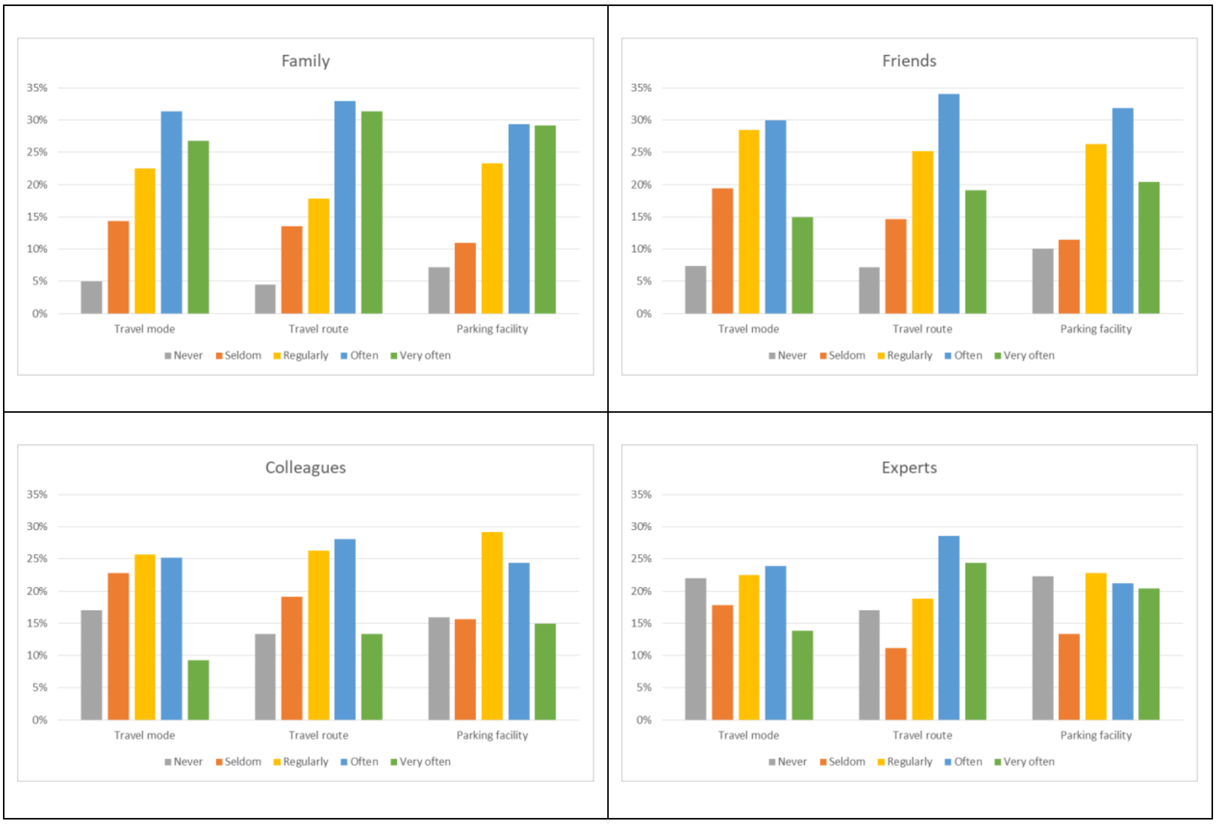

Figure 6: Following advice of one's social circle

Lastly, the results of the choice rankings are shown in Table 4-5.

Table 4-5: Ranking option results

	Frequency	Percentage
Very unlikely	266	8.8%
Unlikely	452	15.0%
Neutral	563	18.7%
Likely	987	32.7%
Very likely	748	24.8%
Total	3016	

As can be seen most participants answered that they were either likely or very likely to choose for the presented parking facility accounting for over half of the given answers. Based on the assumption that the "neutral" option would be the middle ground, the given descriptions of the parking facility have a positive influence on the likelihood of respondents stating they would park at the presented parking facility. Another possibility is that because only one parking facility was presented, there was no alternative it could be compared to. It is thus uncertain whether the presented parking facility was indeed the best option available for the respondent.

5 Model estimation

This chapter describes the estimation results of the different models with the use of NLogit 5.0 (Econometric Software, Inc., 2012). Three models (MNL, LC and ML) as described in chapter 3 were used to derive information present within the data from the survey. Unfortunately, the data did not allow for proper estimation of the LC model. Instead, the MNL model was used to try and find the differences between respondents based on socio-demographic characteristics. For each model the goodness-of-fit methods will be discussed as well as the results.

5.1 Multinomial logit model

To estimate the importance of the attributes the MNL model has been used. The results can be found in Table 5-1. Note that the reference category is the option “very unlikely” and that the other categories are contrasted with this option. A positive parameter then suggests an increased utility of the alternative if it is present and vice versa for a negative parameter. Although parameters are estimated for all attribute levels, only those that are found to be significant can be said to be statistically different from zero with a minimum confidence level of 90% being used in this research. In turn, insignificant parameters of attribute levels cannot be interpreted as having any effect on the decision of the respondents with the same level of certainty.

All attributes have been transformed with the use of effect coding. The base level for each attribute is denoted with a shaded row. The part-worth utility for this attribute level is calculated by summing the part-worth utilities of the other two attributes and multiplying these by -1 as explained by formula (4-1) given in chapter 4.2.3. Note that because utility values are relative, the sum of all part-worth utility values for a single attribute is equal to zero. The output of the MNL model can be found in Appendix I.

Table 5-1: Results for the MNL model (including all variables)

Alternative	Unlikely	Neutral	Likely	Very likely
Constant	***0.6583	***0.9923	***1.5460	***0.9759
Parking tariff €1	-0.2212	**0.2929	***0.7663	***1.2894
Parking tariff €2	***0.3631	***0.4443	***0.3533	0.0876
Parking tariff €3	-0.1419	-0.7372	-1.1196	-1.3770
Walking distance 100m	-0.0836	0.1194	*0.1917	***0.5054
Walking distance 300m	0.0924	0.0106	0.1192	-0.0478
Walking distance 500m	-0.0088	-0.1300	-0.3109	-0.4577
Parking type: on-street	-0.0823	-0.0941	-0.1630	***-0.3107
Parking type: parking garage	-0.0340	-0.0371	-0.0439	0.1235
Parking type: parking lot	0.1163	0.1312	0.2069	0.1872
Security: no security	0.0101	**-0.2622	***-0.5989	***-0.8216
Security: security staff	0.1780	**0.4364	***0.6394	***0.7913
Security: security cameras	-0.1880	-0.1741	-0.0404	0.0303
Family: closest	0.0797	0.1620	-1.4504	0.0842
Family: cheapest	-0.0746	-0.0928	-0.0487	-0.1010
Family: safest	0.1630	0.1843	**0.3103	***0.4796
Family: no opinion	-0.1682	-0.2535	1.1888	-0.4627
Friends: closest	0.0266	0.1650	0.0645	0.0065
Friends: cheapest	-0.1798	-0.2296	**-0.2675	**-0.2829
Friends: safest	-0.0966	-0.1041	0.1474	0.1535
Friends: no opinion	0.2497	0.1687	0.0556	0.1230
Colleagues: closest	0.1744	0.0277	0.0732	-0.1037
Colleagues: cheapest	0.0848	0.1334	0.1974	*0.2702
Colleagues: safest	-0.2958	-0.0917	-0.0998	0.0448
Colleagues: no opinion	0.0366	-0.0694	-0.1708	-0.2113
Experts: closest	0.1529	0.2441	*0.2679	*0.3056
Experts: cheapest	0.1294	0.0558	0.2076	0.2115
Experts: safest	-0.1640	-0.0014	-0.1158	0.0245
Experts: no opinion	-0.1183	-0.2985	-0.3598	-0.5416
Note: ***, **, * indicate significance at 1%, 5%, 10% level				

	Null	Constant	β
Log-likelihood	-4854.0647	-4594.1596	-4223,0139
$\rho^2_{adjusted}$		.0527	.0625
AIC	3.2719	3.1022	2.8561
BIC	3.2719	3.2697	3.0235
LRS (critical χ^2 value)		519.8102 (9.488)	742.2915 (101.897)

5.1.1 Model significance

The goodness-of-fit measures are shown for three different models. The null model is based on equal shares of the choice options and no further information (i.e. zero parameters). The constant model is based on the observed share of choice shares. As only the constants are present as attributes only four parameters can be estimated. The β-column shows the goodness-of-fit measures for the full model in which all attributes are taken into account.

The results of the MNL model show that the log-likelihood increased as more parameters were added indicating a better model fit. The AIC value went down for the constant model (*3.1022*) and for the full-model (*2.8561*) suggesting that the addition of these parameters increase the accuracy of the model. The same goes for the BIC value, going down to (*3.2697*) for the constant model to (*3.0235*) for the full model. The likelihood ratio statistic for the constant model is compared with the null-model and the full model compares the log-likelihoods of the constant and full model. The value between the brackets denote the critical $\chi 2$ value. If the LRS-value is higher than the critical $\chi 2$ value the addition of the extra parameters can be stated to be a significant improvement to the prediction power of the model.

5.1.2 Parameters

The model was estimated with the inclusion of constants which captures the unobserved sources of utility. First thing to note is that the constants are significant for all rankings. As mentioned before, a neutral or positive ranking occurred far more often than a negative ranking which also shows in the utility of the alternative-specific constants (ASC's). Another important aspect of the ASC's is that they capture the average utility of unobserved sources of utility affecting the choice decision of the respondents (Hensher, Rose, & Greene, 2005). That is, the attributes of the parking facility did not fully capture the reasoning behind the decision of the respondent.

The significance of the parameters show that the characteristics of the parking facility are deemed the most important aspect. Because each ranking option is contrasted with the base level separately, the utility values can be compared directly between the different rankings. This shows that a linear relationship is found between a positive valuation for a parking facility and a low parking tariff of €1. The utility for this attribute level is the strongest for the "very likely" option. When the parking tariff was raised to €2, the likelihood of a positive evaluation decreased with the highest utility now being present for the neutral option.

A short walking distance was only deemed significant for a positive evaluation of a parking facility with the utility being strongest for the most positive score whereas a walking distance of 300m was not found to be significant for all rankings. Similarly, the type of parking place was only found to be significant for the highest score where a disutility can be found for on-street parking. This suggests that people prefer parking lots or parking garages although those are not found to be significant. It is possible that there are certain attributes ascribed to on-street parking that are not described in the survey.

The second most important attribute of a parking facility according to the respondents is the issue of security. The presence of security staff was heavily preferred with no security showing a negative part-worth utility for a positive ranking. Security cameras might then be expected to also have a positive utility value for the positive ranking options but this is not the case. This does not mean that security cameras being present at a parking facility is of little importance for a respondent, rather, when given the choice between the three levels specified for the security attribute it is not the most preferred or least preferred option. With the other two levels being of similar importance and the utility value of an attribute always equalling zero the relative importance of security cameras is then negligible compared to the other two levels.

In terms of social influence each attribute is found to be significant although the levels differ for each group that has been defined. It seems that respondents trust their family the most when they claim the parking facility is the safest showing a significant contribution for a positive ranking. The advice of colleagues is taken into account when they claim it is the cheapest and experts are to be believed when they state the parking facility is the closest to the respondent's destination. Peculiar is the negative part-worth utility for the advice of friends stating it is the cheapest parking facility for the positive rankings. Perhaps they are not believed when this claim is made. Although not indicated by the results of the MNL model, this attribute level has a p-value of .1004 for the "neutral" option which is just outside of the 10% significance level. Although the reason behind it is unknown, it does seem to influence the decision of the respondent.

From the results gathered with the MNL model a ranking can be established for the importance of the attributes with the highest utility being assumed to be the most important. Another interesting result is that for each increasingly positive ranking more parameters are deemed to be significant. This suggests that an ordered process is taking place whereby certain conditions need to be met for a particular scoring and additional attributes may then contribute to a more positive score or detract depending on the level of the attribute.

The relative importance of an attribute can be calculated by summing the largest and smallest utility values and dividing it by the total utility of all attributes. Figure 7 shows the relative importance for the MNL model. Note that the solid filled bars indicate an attribute which has at least one significant parameter and the pattern filled bars have zero significant parameters and thus it cannot be stated with certainty that these are their absolute utility values. For all choice rankings, parking tariff was found to be the most important attribute as is also indicated by it being the only attribute with at least one of the levels being significant for all choice rankings. The second most important attribute was the security level being present at the parking facility. In terms of social influence, the opinion of experts and family seem to be of similar importance whereas the opinion of colleagues and friends seems to matter less.

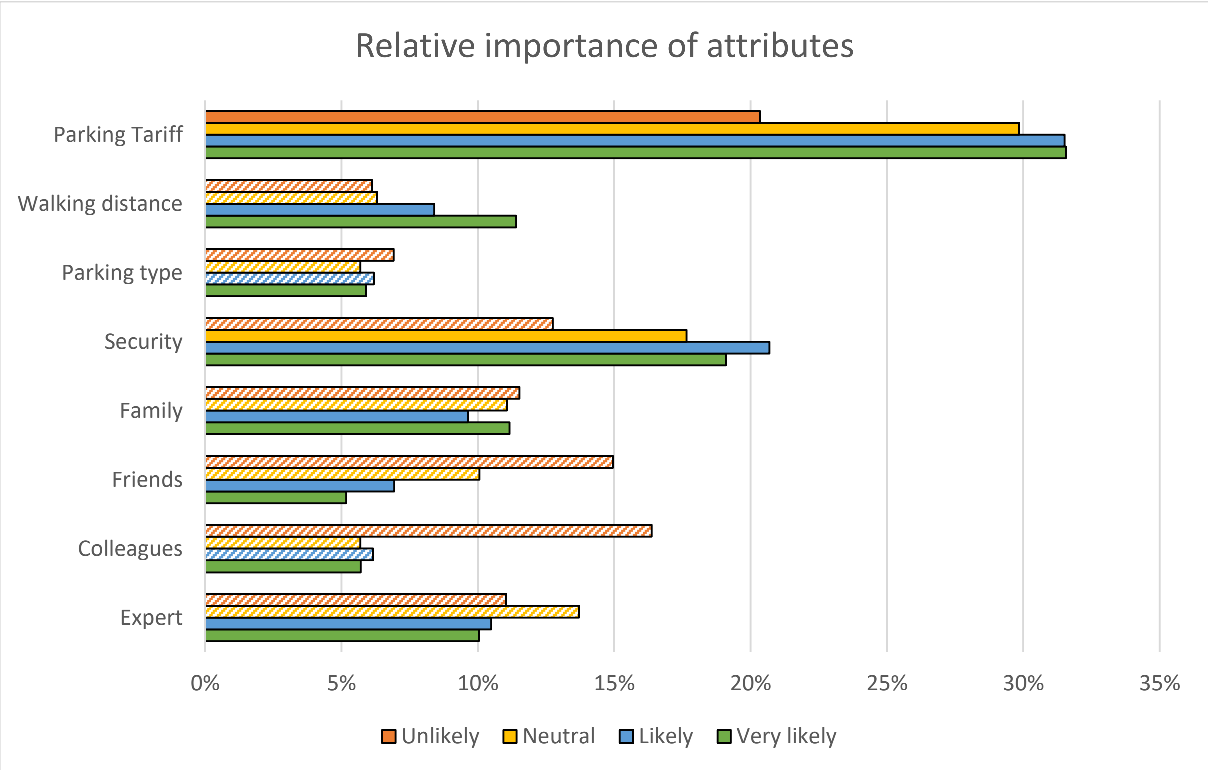

Figure 7: Relative importance of attributes estimated with a MNL model

The relative importances of attributes with at least one significant level are shown in Figure 8. Note that all insignificant attribute levels are shown in grey.

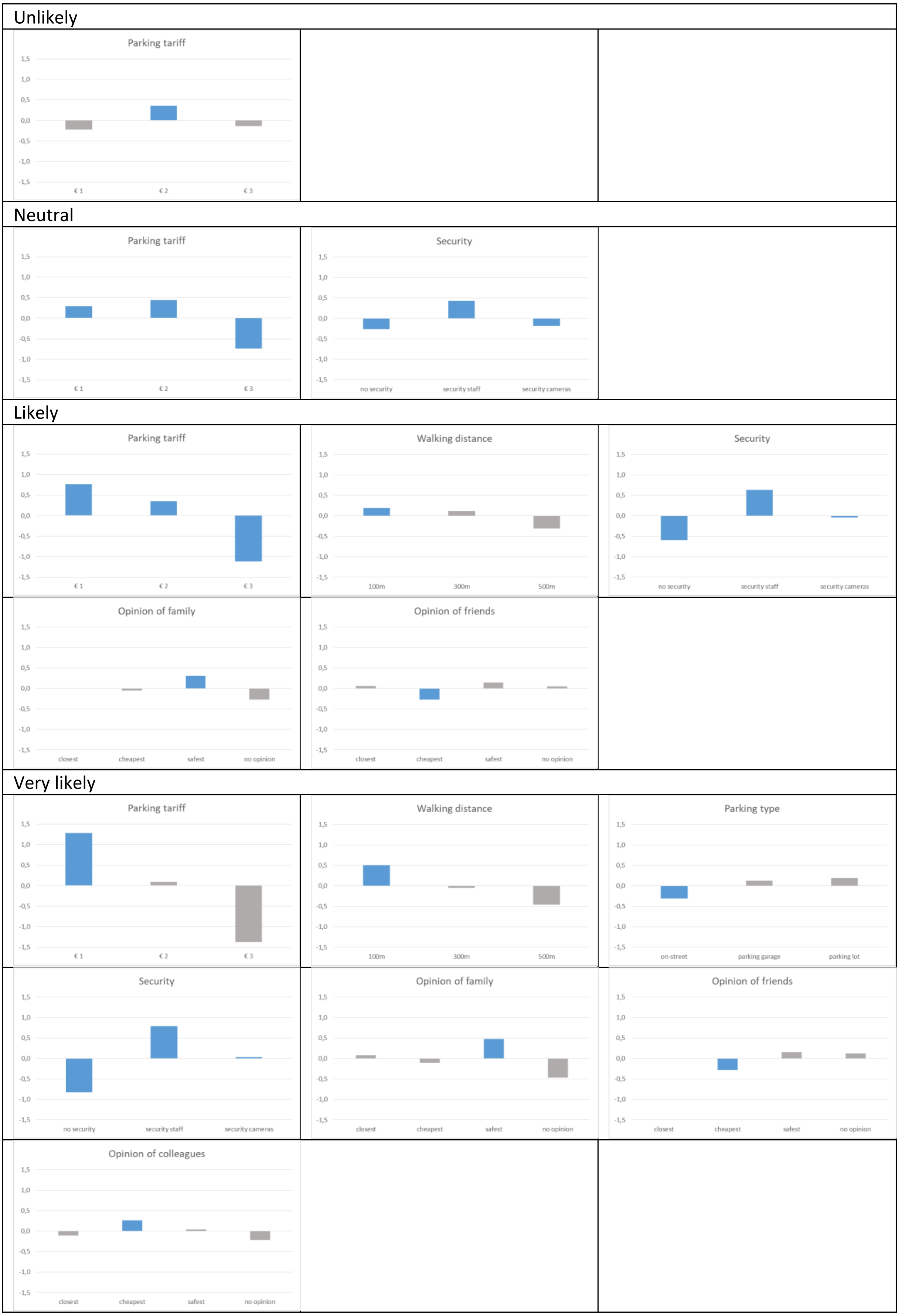

Figure 8: Relative utility of significant attributes for each choice ranking

5.1.3 Example of utility change when a parameter changes

To aid in the interpretation of the numbers, consider the following example of a description for a parking facility a respondent may have come across in the survey as shown in Table 5-2. Note that the shaded rows are inserted to show the change for the choice probabilities when the parking tariff goes from €1 to €2. The estimated utilities are contrasted with the option "very unlikely" which therefore has a fixed β-parameter value of 0 for all attribute levels.

Table 5-2: Example of a choice set from the survey

Proposal 23						
		β-parameter estimate				
Parking facility		Very Unlikely	Unlikely	Neutral	Likely	Very Likely
Parking tariff	€1	0	*-0.2212*	0.2929	0.7663	1.2894
Parking tariff	€2	0	0.3631	0.4443	0.3533	*0.0876*
Walking distance	100m	0	*-0.0836*	*0.1194*	0.1917	0.5054
Social environment						
Opinion family member	safest	0	*0.1630*	*0.1843*	0.3103	0.4796
Opinion friend	safest	0	*-0.0966*	*-0.1041*	*0.1474*	*0.1535*
Opinion colleague	No opinion	0	*0.0366*	*-0.0694*	*-0.1708*	*-0.2113*
Opinion expert	cheapest	0	*0.1294*	*0.0558*	*0.2076*	*0.2115*
Total utility		0	*0*	0.3070	0.6694	2.7853
Total utility		0	0.3631	0.4750	0.2564	-0.1473
Choice probability		4,65%	4.65%	6.32%	9.08%	75,31%
Choice probability		16,12%	23,19%	25,93%	20,84%	13,92%
Italicized numbers were deemed insignificant according to the model and are therefore regarded as equal to zero Shaded row indicates the new numbers with a parking tariff of €2 instead of €1						

The utility for a certain ranking is calculated by summing the part-worth utilities for each attribute level for each ranking option. Note that the insignificant part-worth utilities are considered to be zero as they cannot be statistically proven to be different from zero with a confidence level of 90%. The total utility of a ranking option is calculated with the formula (3-3) for the "neutral" choice the formula becomes:

$$P_i = \frac{e^{0.3070}}{(e^0 + e^0 + e^{0.3070} + e^{0.6694} + e^{2.7853})} = 0.0632$$

Given the current choice set, the probability that the ranking option "unlikely" would be chosen is only 6.32%. By changing one attribute of the situation the difference in choice probabilities can be calculated. The shaded rows show the different part-worth utility for a ranking option for a parking tariff of €2. All else being equal, raising the parking tariff from €1 to €2 significantly changes the utility ascribed to the rankings and thus the choice probabilities as is shown in Figure 9.

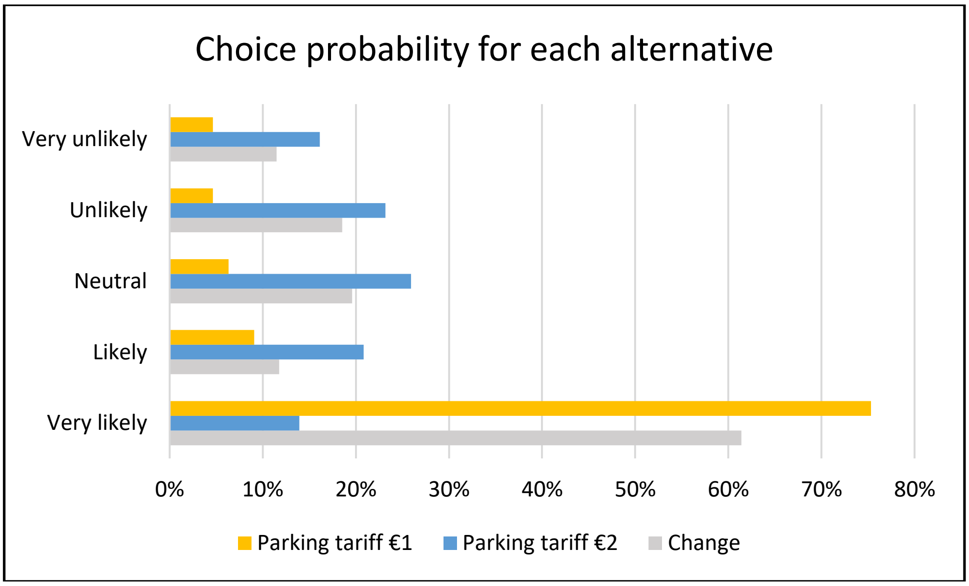

Figure 9: Choice probabilities for two scenarios

5.2 MNL model adjusted

To search for the optimal model, another MNL model was constructed with the insignificant attribute levels being left out to see if the AIC and BIC scores improved. The attribute levels that were not significant in the first run with the MNL model were left out. The result of this second run is shown in Table 5-3, the full output of this model can be found in Appendix II.

Table 5-3: MNL results including significant parameters only

Alternative	Unlikely	Neutral	Likely	Very likely
Constant	***0,6745	***0,9935	***1,5397	***0,9355
Parking tariff €1	-0,1479	***0,2996	***0,7697	***1,3179
Parking tariff €2	**0,3164	***0,4357	***0,3549	0,0430
Parking tariff €3	-0,1684	-0,7353	-1,1246	-1,3609
Walking distance 100m	0,0279	0,1307	***0,2415	***0,5601
Walking distance 300m				
Walking distance 500m	-0,0279	-0,1307	-0,2415	-0,5601
Parking type: on-street	-0,0818	-0,0886	*-0,1773	**-0,2235
Parking type: parking garage				
Parking type: parking lot	0,0818	0,0886	0,1773	0,2235
Security: no security	-0,7370	**-0,2784	***-0,6101	***-0,8734
Security: security staff	0,2309	***0,4402	***0,6387	***0,7752
Security: security cameras	0,5061	-0,1619	-0,0286	0,0982
Family: closest				
Family: cheapest				
Family: safest	0,1295	*0,1882	**0,2602	***0,4397
Family: no opinion	-0,1295	-0,1882	-0,2602	-0,4397
Friends: closest				
Friends: cheapest	-0,1884	-0,1797	-0,1524	-0,1440
Friends: safest				
Friends: no opinion	0,1884	0,1797	0,1524	0,1440
Colleagues: closest				
Colleagues: cheapest	0,0237	0,1051	*0,1867	**0,2467
Colleagues: safest				
Colleagues: no opinion	-0,0237	-0,1051	-0,1867	-0,2467
Experts: closest	*0,2079	***0,3108	***0,3362	***0,4605
Experts: cheapest				
Experts: safest				
Experts: no opinion	-0,2079	-0,3108	-0,3362	-0,4605
*Note: ***, **, * indicate significance at 1%, 5%, 10% level*				
	β (full model)		β (adjusted model)	
Log-likelihood	-4223,0139		-4246.2718	
$\rho^2_{adjusted}$	.1127		.1161	
AIC	2.8561		2.8450	
BIC	3.0235		2.9327	
LRS (critical χ^2 value)	742.2915 (101.897)		46.5158 (55.785)	

Looking at the goodness-of-fit measures the log-likelihood has slightly increased but the AIC and BIC values for the adjusted model which penalise the addition of non-explanatory variables have gone down. Comparing the log-likelihood of the two models is done with the likelihood ratio statistic. In this case the test will determine whether the addition of parameters in the full model will improve the model fit. Using the formula (3-13)**Error! Reference source not found.** the equation becomes:

$$LRS = -2[LL(\beta_{adj}) - LL(\beta_{full})]$$
$$LRS = -2[-4246.3 - (-4223.0)]$$
$$LRS = 46.5$$

With a difference of 40 estimated parameters the critical $\chi 2$ value is 55.785. As the LRS-value is lower, the full model cannot be said to perform better than the adjusted model with less parameters as also indicated by the AIC and BIC value. The adjusted model thus has a slightly better explanation power but the margin is very small.

A final comparison can be made by comparing the contingency tables which show the observed choices made and the predictions based on the probabilities derived from the model. The comparison between the two models is shown in Table 5-4. The two columns for each ranking option show the predicted times a certain option was chosen for the full model in the left column and the adjusted model in the right column indicated by its shaded cells. The rows show the actual observed times a choice was made. The diagonal elements then show the amount of times a choice was correctly predicted. A percentage of correctly predicted choices can then be derived by comparing the predicted choices to the actual observed choices.

Table 5-4: Contingency table comparison of full and adjusted model

Choice	Very unlikely		Unlikely		Neutral		Likely		Very likely		Total
	full	***adj***	full	***adj***	full	***adj***	full	***adj***	full	***adj***	
Very unlikely	65	***57***	74	***63***	25	***52***	42	***51***	60	***43***	266
Unlikely	79	***94***	141	***107***	52	***91***	97	***86***	83	***74***	452
Neutral	75	***99***	88	***110***	101	***108***	146	***128***	153	***118***	563
Likely	77	***149***	125	***157***	88	***172***	309	***248***	388	***261***	987
Very likely	26	***91***	55	***91***	61	***112***	198	***201***	408	***253***	748
Total	322	*489*	483	***528***	327	***536***	792	***714***	1092	***748***	3016
Wrongly predicted	+21.05%	*+83.83%*	+6.86%	*+16,81%*	-44.03%	-4,80%	-19.76%	-27.66%	+39.29%	0%	
correctly estimated (full model): 26.16% *correctly estimated (adj model): 25.63%*											

The results show a marginal greater prediction capability for the full model. However, because the full model also includes more insignificant parameters it is not certain whether the correctly predicted choices are partially based on "random" luck rather than a proper estimate. Concluding, the adjusted model shows an improvement according to goodness-of-fit tests but does not improve the correct amount of predicted choices.

Influence of attributes

The MNL model suggests that the social influence attributes as described in the survey do not play a very big role in the decision making process of the respondents. However, even a reduced model where those attributes were left out did not improve the goodness-of-fit measures despite the model being more parsimonious in theory. Insignificance of parameters can be interpreted in two different ways (Kjær, 2005):

1. The attribute associated with the parameter did not influence the respondents' choices. This implies that the respondents did not deem this attribute with its ascribed level important when making their decision;
2. That preference heterogeneity exists within the sample of respondents. It is possible that an attribute does affect the choice of the respondents but that the preference of the attribute level is different for the respondents. This in turn can off-set the estimation of a significant parameter estimate.

This means that it is possible that the influence of the respondents' social circle is very minimal in the context of parking choice decisions as only one attribute level was found to be significant or that preference heterogeneity exists for the attribute levels. To test this, a latent class model has been run to see if certain social influence attributes now become significant.

5.3 Latent class model

The latent class model is used to investigate whether there are any significant differences in the evaluations for the parking facilities. Running the full model first with a distinction of 2 classes yielded no results indicating that the respondents largely placed the same importance on the same attributes. Dividing the respondents in 3 classes made no difference. Due to the amount of parameters in the model more than 3 classes could not be estimated as the Nlogit 5.0 program gave the following error:

```
"Error   1076: Latent class model has too many paramaters (#C*K)."
```

Therefore, the use of the LC model will be limited with usage of 2 and 3 latent classes. Because no significant results could be found with all parameters included the first step to try and find any results was to run the LC model with only the constants taken into account. This was done with both 2 and 3 classes for which the latter showed no good results. The differences for the two classes are shown in Table 5-5 below.

Table 5-5: Constant only model with 2 latent classes

Attributes \ Class	1		2	
	β	ρ	β	ρ
Unlikely	*1.4128*	*.2799*	0.5104	.0000
Neutral	*2.4047*	*.1134*	0.6895	.0000
Likely	3.6256	.0201	1.1765	.0000
Very likely	4.4869	.0033	0.4842	.0000
Probability (%)	17,14%	.0000	82,86%	.0000

Ignoring the relative value of the part-worth utilities it seems that a difference can be found in the scoring of the alternatives. Respondents in class 1 seem to be more prone to a positive scoring indicating that they rarely chose the very unlikely, unlikely, or neutral option given the description of the parking facility. This subgroup seems to be relatively small however, with only an estimated 17% of the respondents belonging to this group.

Further attempts to discover the presence of heterogeneity that can be grouped into classes did not show any results. Estimation with only the linear effects included and estimation with only the significant attributes derived from the MNL model did not lead to any results. A model could be estimated when leaving out the ASC's but it is unclear how one should interpret these results knowing that the unobserved sources of heterogeneity (which are statistically significant as found with estimation with the MNL model), are then ascribed to the attributes that are included in the model.

Because no results could be derived with the LC model, further research has been done with the MNL model where the influence of socio-demographic characteristics (SDC's) has been estimated by selecting the responses of one group and then comparing it to the opposite group.

5.4 Socio-demographic influence

Because it is not possible to estimate a model with the use of latent classes a manual division can be created with the use of the characteristics of the respondents. As personal information was also gathered during the survey the resulting socio-demographic characteristics will be used to investigate any differences between groups of respondents. As the model is constructed in a way where the attribute levels are equal for each choice alternative (ranking option), socio-demographic characteristics can be entered into the model as additional attributes. They have been coded in such a way that the influence of the characteristic can be estimated separately for each ranking option allowing for better insight in the differences for the different groups. The following characteristics have been taken into account:

1. Age;
2. Gender;
3. Education;
4. Nationality;
5. Offspring (children: yes or no)

Table 5-6 shows the significant parameter differences for the entered socio-demographics. Because age did not show any significant differences it was left out. Because the SDC's were added to the model as ASC's the β-parameters are the utility values related to the choice rankings

Table 5-6: Estimated beta-parameters for socio-demographic characteristics

	Unlikely	Neutral	Likely	Very likely
Gender			*0.1344	**0.2007
Education (HS)		**-0.4384		*-.3386
Education (Master)		.5635***		***0.4231
Region	***0.1862	***0.3654	***0.4060	***0.5680
Children			*0.2030	**0.3040
*Note: ***, **, * indicate significance at 1%, 5%, 10% level*				

For the gender characteristic, males were coded as the base level. Women were found to have a higher utility for the two most positive choices "likely" and "very likely" indicating they are more likely to choose these ranking options compared to men given the same description for a parking facility. A similar effect was found for evaluations when considering the difference between EU-citizens and non-EU citizens. Contrasted with the latter, EU-citizens ascribe a higher utility to all options indicating that they were more likely to give a higher ranking to a parking facility than non-EU citizens. Lastly, a significant difference was found for respondents that have children which, similar to the gender differences, described a higher utility to the two most positive ranking options for a given choice set, i.e. they were more likely to give that parking facility a higher score. An interesting finding was for the education people have received. Contrasted to those with a PhD, respondents who had only finished secondary school were much less likely to give a positive score to a parking facility whereas those with a master's degree show the exact opposite reaction. It must be stated however, that the amount of respondents with only a high school degree is very low and therefore it is not certain whether this result is representative for a broader population sample

As region and gender seem to have the biggest differences, these two characteristics have been further investigated in more detail.

5.4.1 Gender differences

To investigate the differences between the genders an MNL model was run twice. Once with data containing only answers of female respondents and once with data containing only male respondents. Unfortunately, an MNL model could not be estimated when using female respondents only. A model with male respondents only did show a result with significant parameters. The error lies with the attribute level of the expert opinion stating the parking facility is the closest. Further investigation as to why this is the case did not result in an answer yet. However, because this attribute level was found to be insignificant in both the model for males only and the full model it is assumed that it can be left out without any consequences. Full results of the male and female only models can be found in Appendix III and IV. A comparison of the results is given in Table 5-7 with only significant parameters being shown.

Table 5-7: Difference in significant parameters – female only model and male only model

	Female (N=168 - 1344 observations)			Male (N=209 - 1672 observations)		
Unlikely						
	Parking tariff: €1	-0.5743	*			
	Parking tariff: €2	0.6518	***	Parking tariff: €2	0.2924	*
				Security: security staff	0.4126	*
Neutral						
	Parking tariff: €2	0.4097	*	Parking tariff: €2	0.5055	***
				Walking distance: 100m	0.3557	**
				Parking type: on-street	-0.2704	*
				Security: no security	-0.3104	**
				Security: security staff	0.8095	***
				Family: parking facility is the closest	0.3212	*
Likely						
	Parking tariff: €1	0.9782	***	Parking tariff €1	0.6704	***
	Parking tariff: €2	0.5445	**			
				Walking distance: 100m	0.3798	**
				Parking type: on-street	-0.3256	**
	Security: no security	-0.7474	***	Security: no security	-0.6454	***
				Security: security staff	0.9172	***
				Experts: parking facility is the cheapest	0.3431	*
Very likely						
	Parking tariff: €1	1.4280	***	Parking tariff: €1	1.2666	***
				Walking distance: 100m	0.6767	***
				Parking type: on-street	-0.4172	***
	Security: no-security	-0.9611	***	Security: no security	-0.8975	***
				Security: security staff	1.0105	***
				Family: parking facility is the safest	0.5453	**
				Friends: parking facility is the cheapest	-0.3532	*
				Experts: parking facility is the cheapest	0.4099	*
	Expert: parking facility is the safest	0.4465	**			
*Note: ***, **, * indicate significance at 1%, 5%, 10% level*						

Differences in the significant parameters indicate that men and women place a higher or lower utility on different attribute levels. For example, the male only model shows that the opinion of experts when stating the parking facility was the cheapest became significant for the utility of both the likely and very likely choice. Comparing the attribute levels regarding social influence is difficult due to the trade-off that is made when making a decision. A respondent may highly prefer a low parking tariff and a short walking distance to his final destination but it is difficult to assess whether he would prefer his social circle to state whether it is the cheapest or closest and what influence it could have on his choice for a certain alternative. Less attributes were found to be significant for the female only model indicating that they either placed more importance on the attributes that were significant or that heterogeneity is more present within the group of female respondents.

The results of the two models show that men seem to put a higher importance on security as the attribute level security staff is significant for all four ranking options. On-street parking also seems to have a negative contribution to positive rankings for male respondents whereas female respondents do not seem to place much importance on the type of parking facility.

Advice from one's social circle seemingly does not play a very big role in the decision of a parking facility for the female respondents. Only one advice as found to be significant which was the experts stating the parking facility is the safest for the "very likely" option. Male respondents on the other hand seem to put more importance on the advice of their social circle or they are more homogeneous in their preferred type of advice given. Note that the advice of colleagues which was found to be significant in the full model is now insignificant for both the male and female only model. This indicates that there is a group of respondents which does put a certain importance on their advice but that said group is divided over male and female respondents. A comparison of the relative importance of the attributes per choice ranking can be found in Figure 10.

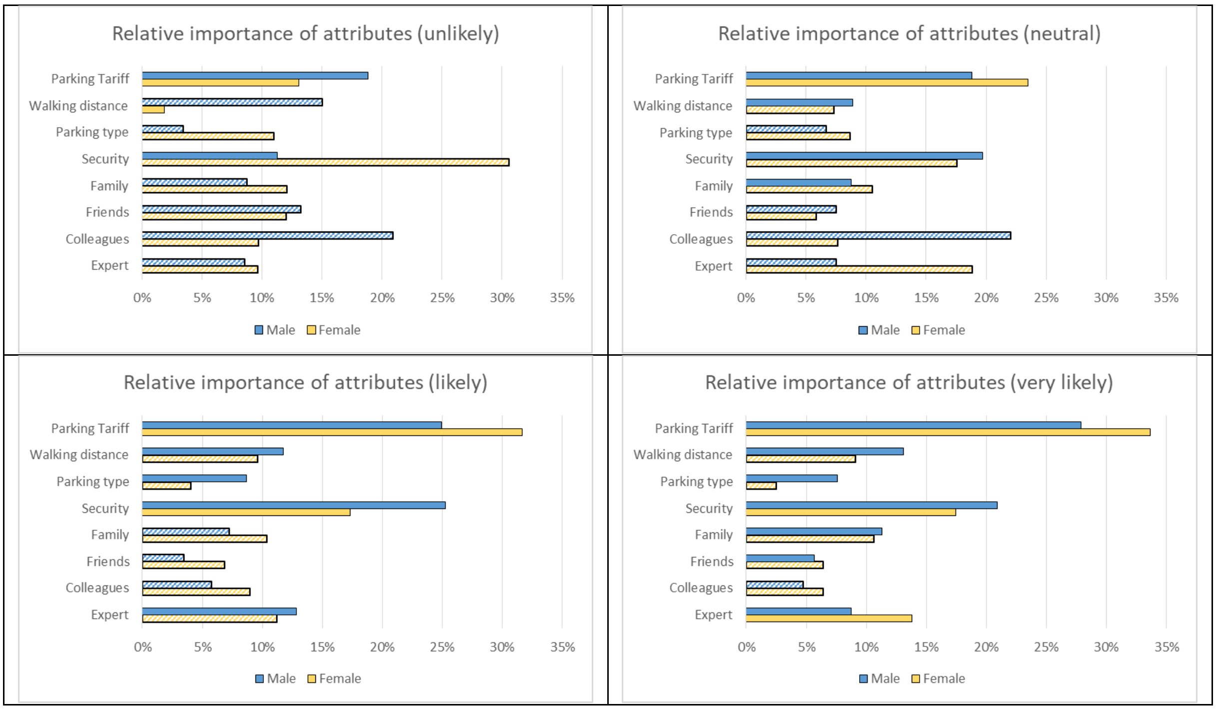

Figure 10: Gender differences in relative importance of attributes

5.4.2 Regional differences

To see whether there was any difference between EU-citizens and non-EU citizens the same setup as for the genders has been used. Although respondents are grouped into EU and non-EU classes respectively, the majority of the EU group has the Belgian nationality whereas the majority of the non-EU group is from Pakistan. This time, an MNL model was able to be estimated for both groups. The full results of the models are shown in Appendix V and VI. The parameters that were deemed significant by one group but not the other are shown in Table 5-8.

Table 5-8: Comparison between EU and non-EU citizens

	EU-citizen (N=264 > 2112 observations)			Non-EU (N=113 > 904 observations)		
Unlikely						
	Parking tariff: €2	0,3742	*			
Neutral						
	Parking tariff: €1	0.6238	***			
	Parking tariff: €2	0.3210	*	Parking tariff: €2	0.5420	***
				Parking type: on-street parking	-0.3030	*
				Security: no security	-0.4201	**
	Security: security staff	0.6748	*	Security: security staff	0.5743	**
	Friends: parking facility is the closest	0.4611	*			
Likely						
	Parking tariff: €1	1.2041	***	Parking tariff: €1	0.4565	***
	Security: no security	-0.6427	***	Security: no security	-0.7926	***
	Security: security staff	.8840	**	Security: security staff	0.7997	***
				Family: parking facility is the closest	0.3996	*
	Friends: parking facility is the cheapest	-.3660	*			
	Colleagues: parking facility is the cheapest	.44367	*			
				Experts: parking facility is the closest	0.4585	**
Very likely						
	Parking tariff: €1	1.8515	***	Parking tariff: €1	0.6802	***
	Walking distance: 100m	0.5924	***			
				Parking type: on-street	-0.3480	*
	Security: no security	-0.9381	***	Security: no security	-0.9610	***
	Security: security staff	1.1637	***	Security: security staff	0.6906	***
	Family: parking facility is the safest	0.4787	***	Family: parking facility is the safest	0.4361	*
	Friends: parking facility is the cheapest	-0.3658	*			
	Colleagues: parking facility is the cheapest	0.6014	**			
	Experts: parking facility is the closest	0.5129	**			

First thing to notice is that those from outside the EU seem to place less importance on the parking tariffs as the parking tariff of €1 has a lower utility compared to EU-citizens.

Another significant attribute seems to be on-street parking. Non-EU citizens seem to dislike on-street parking more compared to EU-citizens. It is possible that people from within the EU regard the streets as a relatively safe space to park whereas non-EU citizens see on-street parking as a major disadvantage as they may return to a damaged car to different infrastructures or carelessness from other drivers.

In terms of social influence it seems that non-EU citizens are more reliant on the advice given by their family members. As stated before, the order in which the attributes are given may also influence the decision process. Still, EU-citizens seem to consider more opinions from different groups indicating that they are more likely to seek advice outside of their own family. The attribute importance for the ranking options are shown in Figure 11. A striped bar indicates that no significant parameter was estimated for that attribute. The solid coloured bars indicate that at least one estimated part-worth utility of the attribute was found to be significant.

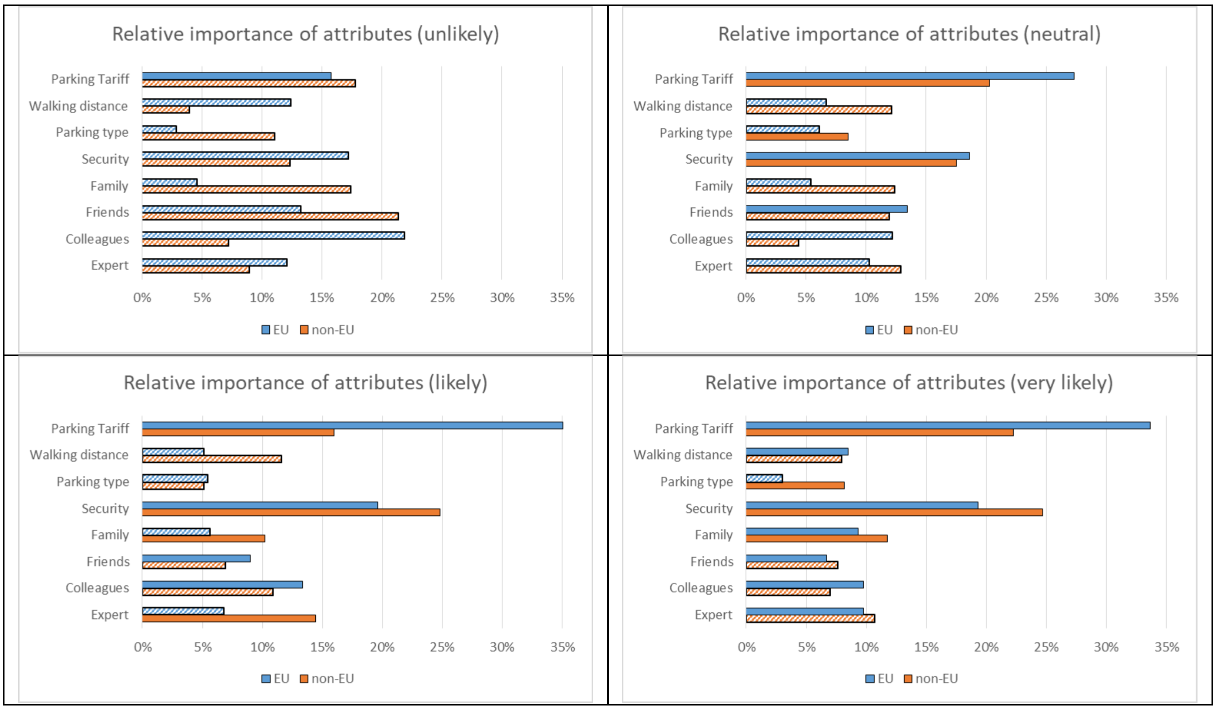

Figure 11: Regional differences of importance of attributes

5.5 Mixed logit model

As indicated by the results of the MNL model heterogeneity seems to be present within the sample. Therefore, the average of the attribute's utility would not be a good representation for all individuals within the sample. A mixed logit model was used to test for individual heterogeneity for all attributes. Each attribute has been introduced to the model with a normal distribution. Not all attributes could be estimated simultaneously thus the estimates of the utilities may differ somewhat for the attributes. However, the first runs are only used to see what attributes have a significant standard deviation. To find what parameters are significant an iterative process was done whereby the model was re-estimated with only the parameters that showed a significant standard deviation. A final model was then run with a 1000 draws. The full model results can be found in Appendix VIII.

Interestingly, a few attributes show a significant standard deviation from the mean but the mean itself is statistically not different from zero. This indicates that there's an opposite reaction to certain attribute levels within the response group which causes the utility function to be close to zero on average. Most of these attributes are related to the social influence.

Despite not being able to gain much information using the LC model, ASC's did show a significant distribution between respondents suggesting that unobserved heterogeneity was present. The ML model confirms this finding based on the significant deviation of the ASC's.

All attribute levels regarding the parking tariff showed significant estimates for the standard deviation parameters indicating that people placed different utility on the price of a parking facility. Walking distance was only found to have significant deviations for the "unlikely", "likely" and "very likely" ranking with the first two concerning the walking distance of 300 metres and the last the a walking distance of 100 metres. This indicates that some people did not find walking distance to their final destination an important attribute whereas others show a high preference for a short walking distance. On-street parking and the absence of security showed significant deviation for both the ranking option of "unlikely" and "very likely" with the latter also being significant for the "neutral" option. Attributes concerning social influence showed no significant deviation except for the opinion of experts stating that the parking facility was the safest for the ranking “neutral”. As other attributes were found to have no significant deviation, they were not included in the final model.

Iteratively running the model with the exclusion of parameters that were found to have insignificant random parameters resulted in the following parameters being included as random parameters in the final model as shown in Table 5-9.

Table 5-9: Attribute levels with significant standard deviation according to the ML model

	Unlikely	Neutral	Likely	Very likely
Constant	***0.7827	***0.6266	***0.9041	***2.1372
Parking tariff €1			***0.7881	***1.4541
Parking tariff €2		***0.9002		
Walking distance: 100m				***0.8099
Parking type: on-street parking	***0.5638			***0.7981
Security: no security				***1.1813

Values in the cells denote the standard deviation from the parameter estimate

	MNL	ML
# Parameters	84	95
Log-likelihood	-4223,0139	-3930.1123
AIC	2.8561	2.6692
BIC	3.0235	2.8585
LRS (critical χ^2 value)	742.2915 (101.897)	585.8030 (19.675)

The ML model shows an improvement over the full MNL model in all goodness-of-fit measures suggesting that it has more explanation power in comparison. The AIC (2.6692) and BIC (2.8585) value have gone down compared to the MNL model suggesting that the added random parameters give more information. This is confirmed by the decreased log-likelihood of -3930.11 and the likelihood ratio statistic confirming that the log-likelihood is statistically closer to zero thus confirming a better model fit.

The attributes with a significant standard deviation are shown in Figure 12 for each ranking option. Table 5-10 shows the results of the ML model with only significant parameters for the standard deviation being shown as range.

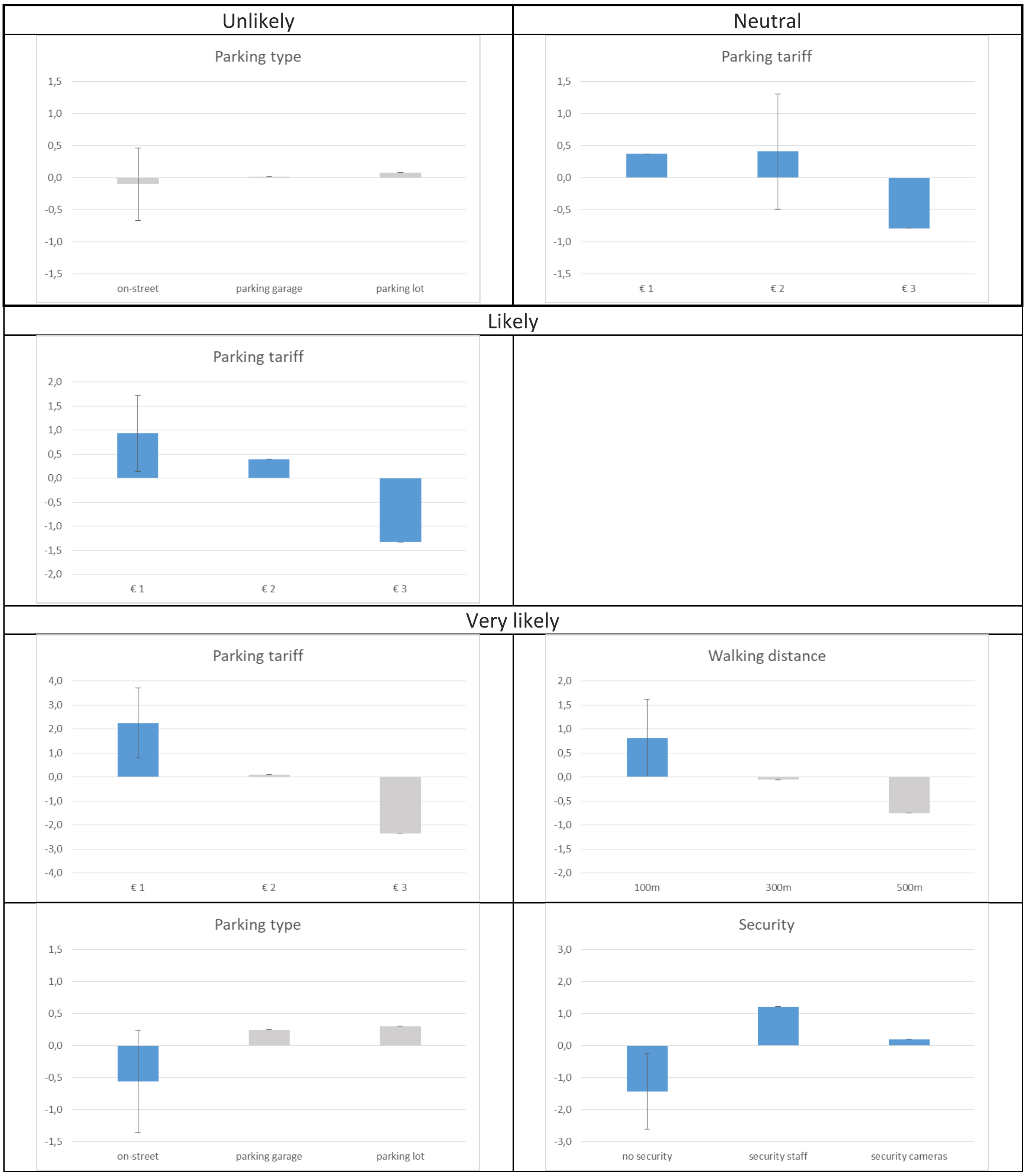

Figure 12: Attributes with a significant standard deviation according to the ML model

Table 5-10: Comparison of MNL and ML models (white rows = MNL; shaded columns = ML)

	Unlikely		Neutral		Likely		Very likely	
	β	Std. dev	β	Std. dev	β	Std. dev	β	Std dev.
Constant	***0.6583		***0.9923		***1.5460		***0.9759	
	**-0,3090	0.7827	***0.4230	0.6266	***1.5165	0.9041	-0.2540	2.1372
Parking tariff €1	-0.2212		**0.2929		***0.7663		***1.2894	
	**-0.3090		***0.3749		***0.9311	0.7881	***2.2448	1.4541
Parking tariff €2	***0.3631		***0.4443		***0.3533		0.0876	
	0.3605		***0.4100	0.9002	***0.3934		0.0929	
Parking tariff €3	-0.1419		-0.7372		-1.1196		-1.3770	
	-0.0515		-0.7849		-1.3246		-2.3378	
Walking distance 100m	-0.0836		0.1194		*0.1917		***0.5054	0.8099
	0.1051		0.1255		*0.2189		***0.8095	
Walking distance 300m	0.0924		0.0106		0.1192		-0.0478	
	0.1009		0.0119		0.1031		-0.0577	
Walking distance 500m	-0.0088		-0.1300		-0.3109		-0.4577	
	0.0042		-0.1374		-0.3220		-0.7518	
Parking type: on-street	-0.0823		-0.0941		-0.1630		***-0.3107	
	-0.0979	0.5638	**-0.0977		*-0.1864		***-0.5574	0.7981
Parking type: parking garage	-0.0340		-0.0371		-0.0439		0.1235	
	0.0160		**-0.0299		0.0364		0.2514	
Parking type: parking lot	0.1163		0.1312		0.2069		0.1872	
	0.0819		0.1276		0.1500		0.3060	
Security: no security	0.0101		**-0.2622		***-0.5989		***-0.8216	
	0.0476		**0.2660		***-0.7218		***-1.4268	1.1813
Security: security staff	0.1780		**0.4364		***0.6394		***0.7913	
	0.1905		**0.4523		***0.6903		***1.2221	
Security: security cameras	-0.1880		-0.1741		-0.0404		0.0303	
	-0.2380		-0.7183		0.0316		0.2047	
Family: closest	0.0797		0.1620		-1.4504		0.0842	
	0.0754		0.1493		0.0046		0.1061	
Family: cheapest	-0.0746		-0.0928		-0.0487		-0.1010	
	-0.0809		-0.0877		-0.0482		-0.1105	
Family: safest	0.1630		0.1843		**0.3103		***0.4796	
	0.1579		0.1932		***0.3064		***0.6381	
Family: no opinion	-0.1682		-0.2535		1.1888		-0.4627	
	-0.1524		-0.2548		-0.2628		-0.6337	
Friends: closest	0.0266		0.1650		0.0645		0.0065	
	0.0266		0.1175		0.0590		-0.1636	
Friends: cheapest	-0.1798		-0.2296		**-0.2675		**-0.2829	
	-0.1665		*-0.2485		*-0.2530		-0.1940	
Friends: safest	-0.0966		-0.1041		0.1474		0.1535	
	-0.1187		-0.1175		0.1463		0.2565	
Friends: no opinion	0.2497		0.1687		0.0556		0.1230	
	0.2585		0.2458		0.0476		0.1011	
Colleagues: closest	0.1744		0.0277		0.0732		-0.1037	
	0.1913		0.0488		0.0909		-0.1822	
Colleagues: cheapest	0.0848		0.1334		0.1974		*0.2702	
	0.0460		0.1042		0.1888		0.2753	
Colleagues: safest	-0.2958		-0.0917		-0.0998		0.0448	
	-0.2802		-0.0863		-0.0511		0.2181	
Colleagues: no opinion	0.0366		-0.0694		-0.1708		-0.2113	
	0.0429		-0.0667		-0.2286		-0.3113	
Experts: closest	0.1529		0.2441		*0.2679		*0.3056	
	0.1649		0.2307		0.2440		**0.4193	
Experts: cheapest	0.1294		0.0558		0.2076		0.2115	
	0.0958		0.0752		0.2294		0.2081	
Experts: safest	-0.1640		-0.0014		-0.1158		0.0245	
	-0.1524		-0.0289		-0.1331		0.1674	
Experts: no opinion	-0.1183		-0.2985		-0.3598		-0.5416	
	-0.1084		-0.2770		-0.3403		-0.9021	

The next step of the research then was to search for any possible explanations of this heterogeneity. This is done by through the interaction of each random parameter with other attributes that may explain the sources of heterogeneity derived from the ML model. The following socio-demographic characteristics of respondents have been used to see whether the heterogeneity could be explained simply because this is the information that is available from the dataset:

- Gender;
- Nationality;
- Education;
- Offspring.

The results show that nationality is the biggest source of heterogeneity between the respondents accounting for 5 of the 8 significant values. Other differences were accounted for by gender, education and offspring. The significant results are shown in Table 5-11.

Table 5-11: Significant parameters for estimated heterogeneity in the mean with SDC's

	Unlikely	Neutral	Likely	Very likely
Gender (base category = male)				
Constant				**0.3620
Regional (base category = non-EU)				
Constant		***0.4971	***0.4979	
Parking tariff €1			***0.3358	***0.8122
Walking distance 100m				***0.3992
Education – (base category = up to high-school diploma)				
Constant			***0.3742	
Offspring (base category = no children)				
Constant				***0.4942
*Note: ***, **, * indicate significance at 1%, 5%, 10% level*				

Although strictly not within the 10% confidence interval, two parameters were very close to the 10% significance level. The constant for the "likely" choice ranking for respondents with children had a p-value of 0.1025 and the constant for the EU-citizens had a p-value of 0.1062. It is possible that these parameters would become significant if more draws were being done during the simulation process. The significances of the constants show that there are still unobserved sources of utility that are not captured with the attributes used in the model. The model shows that heterogeneity exists for the choice rankings and that it can be related to certain characteristics of respondents but that still does not explain as to why this difference exists.

Differences for a low parking tariff and a short walking distance are the only parameters that are not directly related to the ranking options. As was previously found when using the MNL model with a modified dataset EU-citizens show a much stronger preference for a low parking tariff and short walking distance resulting in a higher utility for the "likely" and "very likely" option.

Table 5-12: Comparison of goodness-of-fit for the ML models

	ML	ML with SDC's
Number of parameters	95	139
Log-likelihood	-3930.1123	-3863.6821
AIC	2.6692	2.6543
BIC	2.8585	2.9314
LRS (critical χ^2 value)		132.8604 (60.481)

The model has log-likelihood of -3863.6821 but also an additional 55 parameters. Based on the BIC, the model including SDC's is less likely to generate the observed data indicated by its higher BIC value.

The AIC value on the other hand shows a slight improvement over the model without SDC's. The deviance per observation is thus smaller but in general the model is less likely to give the same outcome as the observed data. The LRS has a value of 132.8604 with 44 degrees of freedom. With a critical χ^2 value of 60.481 which it exceeds, the log-likelihood is statistically closer to zero indicating a better model fit.

Concluding whether the added parameters are significant is a question of whether one would prefer a more parsimonious model that is able to better predict the outcomes with the least amount of parameters or a more informative model that can give more information. In other words, the model with the addition of SDC's will give more information for this particular dataset but is less likely to predict the correct outcome if a different dataset were to be used.

5.6 Conclusion

A low parking tariff is the most important attribute of a parking facility according to the parameters estimated with both the MNL and ML model. This particular attribute was found to have the highest relative attribute importance for all choice rankings but the ML model showed that not all respondents deemed this attribute very important. This may be due to the parking tariffs given in the survey being perceived as moderate or low for some respondents or that they simply placed much more importance on another attribute. The second most important attribute was the security level being present at the parking facility. Security staff seems to be a good predictor for a positive evaluation of a parking facility. Although one may expect that security cameras would also increase the probability of a positive ranking option this was not found in the model results. This may be due to the fact that it was taken as the base level and that the parameters of the other two attribute levels -no security and security staff- should be viewed as relative to the presence of security cameras. Because these two attributes show a similar effect on a choice ranking albeit in opposite directions, the estimated parameter of the base level is then almost equal to zero.

Differences based on gender showed that men are more likely to prefer a short walking distance and put more importance on the presence of security staff compared to women. Regional differences showed that EU-citizens are much more price-conscious and more likely to take the advice of their social circle into account as it was found that those attributes were significant for the EU-only model.

Social influence does seem to play a role in the decision for a parking facility according to the MNL model. However, these were only found to be significant for the most positive evaluations. This may be due to the fact that the type of advice given in the survey was either a positive trait of the parking facility or neutral (no opinion). It is therefore unlikely that a description of a positive trait would result in a higher utility for a negative evaluation of a parking facility.

The ML model showed that heterogeneity is present for several attributes and two of those could be related to socio-demographic characteristics of the respondents. It confirms the findings of the estimations done with the MNL model. Although the added parameters do add up to a better model fit there was very little extra information that could be derived from it compared to the separate MNL models.

6 Conclusion

The extent to which social influence impacts the decision making process of individuals is a well-researched subject within the field of social psychology. Numerous studies have found that opinions or behaviour may change due to the actions of actors around an individual. In the context of decision making regarding parking the impact of social influence in research is very limited (Sunitiyoso, Avineri, & Chatterjee, 2011). Part of the reason being that it is hard to quantify to what extent social influence is present and how it can be researched. The aim of the current study was to research the impact of social influence in the decision for choosing for a certain parking facility. Results show that it is indeed present but subordinate to the characteristics of the parking facility itself. That is, it is unlikely that when social influence is taken into account when modelling parking behaviour it will significantly improve models which only take attributes specifically related to the parking facility into account. Rather, this study suggests that social influence is an extra tiny piece of the puzzle in correctly predicting the behaviour of car drivers' decision on where to park their car.

Of the four groups used in the survey, it was found that advice from family was the most influential and in particular, the advice concerning safety showed the highest part-worth utility values for that attribute. It seems that there is a connection between the preference of advice from family and the attribute level concerning the safety of the parking facility. The preferred advice from other groups mentioned in the study was found to differ depending on what model was used indicating that although of importance no connection as with family and safety exists for the other groups.

6.1 Model comparison

The three models used in this study showed similar results for the parameters that could be estimated. The LC model where a result was gotten when including ASC's only cannot be compared in this instance due to this limitation. The MNL and ML models both have their advantages and disadvantages. The MNL model allowed for relative easy interpretation of the estimated parameters and can be quickly estimated with the use of computer software. The drawback is that heterogeneity remains unobserved. It is possible to determine differences between respondents when the researcher assigns them to a group manually. It is then important that a sufficient number of respondents is available for each group which requires a larger sample size but it also may not lead to significant results which might be uncovered when using the LC model. Excluding insignificant parameters in the MNL model lead to a better model fit according to the goodness-of-fit tests theoretically giving a more parsimonious model which is often preferred. However, in terms of deriving information from the model, the exclusion of insignificant parameters did not lead to any new insights.

The ML models showed an improved model fit due to the addition of extra parameters. As continuous heterogeneity per attribute can be estimated with the ML model it offers a higher potential to uncover more information compared to the MNL model. A major drawback is the time it takes to compute the model as well as the added complication of the need to determine the distribution type of the unobserved heterogeneity beforehand. This makes it more difficult to interpret the results of the model as it requires a better understanding of the underlying process of the model.

For this study neither of the models can be said to be better than the other, rather, each has their own use and using both models will most likely give the researcher a better picture of the situation then specifically using one of these models and neglecting the use of the other.

6.2 Managerial implications

The MNL model confirmed that the attributes included in the study regarding the characteristics of the parking facility play a role in the decision making process of a car driver that wants to park his car. The significant parameters estimates for the ASC's also showed that heterogeneity was present and it would be insufficient to implement policies based on the results of the MNL model alone.

The application of the ML model is context specific. The need for individual differences to be uncovered for this research is limited. After all, policies implemented to influence parking behaviour of car drivers are not yet aimed at a single individual but rather all car drivers looking for a parking space. The results of the ML do show that when determining what factors are needed to be considered in a policy to change the parking behaviour of car drivers that there is no one-size-fits-all policy that will influence all car drivers as it was shown that individuals placed different values on certain attributes and deemed one more important than the other.

6.3 Limitations and considerations

The decision to choose a certain parking facility is dependent on a host of factors of which some are more often included in models than others. The four attributes related to the characteristics of a parking facility -being parking tariff, walking distance to final destination, the type of parking, and security level- in this study were also found to be most frequently considered and used in models in other research regarding parking preferences. However, it was also found that these four attributes did not fully capture the factors that influence the decision of a car driver to choose where to park his car. In other words, it was observed that there are other sources of influence that were not included in the model. The addition of advice from one's social circle did prove to be significant for positive ranking options but did not show to be a determinant factor in the sense that it proved to be a critical factor

The sample of respondents was mostly limited to students from the University of Hasselt which may skew the results towards a particular outcome. It is unclear whether the results from this study are applicable to a larger group of people. A larger and more diverse respondent sample may show different results. The survey design was limited to estimate main effects only. Considering that the advice of the four groups is directly related to three of the four characteristics of the parking facility it may be worth setting up a survey design where interaction effects can be taken into account. For example, consider the walking distance attribute used in this study. It is possible that the perceived part-worth utility of the farthest distance (500 metres) would change when someone from the respondent's social circle mentions it is the closest parking facility to his final destination. This would also require a larger respondent sample however, so the researcher would need to consider whether this is possible for his own research.

6.4 Discussion

This study has researched the influence of advice given by family, friends, colleagues and experts in the context of choosing for a certain parking facility. Social influence is most often researched with the use of experiments that give revealed preferences rather than using stated preference methods where hypothetical situations are presented. This is due to the fact that discrepancies are often found between hypothesised behaviour and actual behaviour. Furthermore, social influence was limited to positive or no advice regarding the parking facility. This may explain why the advice of these four groups was only found to be significant for positive ranking options. Further research may be needed to investigate the effect of negative advice on the likelihood of choosing for a certain parking facility.

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Appendices

Appendix I: Full results of the MNL model

Discrete choice (multinomial logit) model			
Dependent variable	Choice		
Log likelihood function	-4223.68851		
Estimation based on N = 3016, K = 84			
Inf.Cr.AIC = 8615.4 AIC/N = 2.857			
R2=1-LogL/LogL*	Log-L fncn	R-sqrd	R2Adj
Constants only	-4594.1596	.0806	.0742
Response data are given as ind. choices			
Number of obs.= 3016, skipped 0 obs			

CHOICE	*Coefficient*	*Standard Error*	*z*	*Prob. |z|>Z**	*95% Confidence Interval*	
CS2	.65855***	.11405	5.77	.0000	.43501	.88208
CS3	.99250***	.10615	9.35	.0000	.78444	1.20.055
CS4	1.54616***	.10089	15.32	.0000	1.34841	1.74391
CS5	.97606***	.10934	8.93	.0000	.76175	1.19036
IPT1	-.22081	.14059	-1.57	.1163	-.49637	.05475
IPT2	.36247***	.13616	2.66	.0078	.09560	.62933
IWD1	-.08435	.13922	-.61	.5446	-.35721	.18851
IWD2	.09362	.15487	.60	.5455	-.20991	.39716
ITY1	-.08258	.11814	-.70	.4846	-.31412	.14897
ITY2	-.03489	.13769	-.25	.8000	-.30475	.23497
ISE1	.00994	.13911	.07	.9430	-.26271	.28259
ISE2	.17733	.19591	.91	.3654	-.20664	.56130
IFM1	.08579	.15031	.57	.5682	-.20881	.38039
IFM2	-.07623	.14588	-.52	.6013	-.36215	.20969
IFM3	.16031	.16692	.96	.3369	-.16685	.48746
IFR1	.02701	.15769	.17	.8640	-.28207	.33608
IFR2	-.17999	.14880	-1.21	.2264	-.47163	.11164
IFR3	-.09665	.15906	-.61	.5435	-.40841	.21511
ICO1	.17364	.16049	1.08	.2793	-.14091	.48819
ICO2	.08467	.17763	.48	.6336	-.26348	.43283
ICO3	-.29612	.21656	-1.37	.1715	-.72058	.12833
IEX1	.15293	.17217	.89	.3744	-.18452	.49038
IEX2	.12931	.16995	.76	.4467	-.20378	.46240
IEX3	-.16477	.16578	-.99	.3203	-.48969	.16015
JPT1	.29340**	.12476	2.35	.0187	.04888	.53792
JPT2	.44356***	.12832	3.46	.0005	.19206	.69506
JWD1	.11873	.12360	.96	.3368	-.12352	.36098
JWD2	.01177	.14429	.08	.9350	-.27104	.29457
JTY1	-.09449	.11186	-.84	.3983	-.31373	.12476
JTY2	-.03778	.13070	-.29	.7725	-.29395	.21839
JSE1	-.26234**	.12310	-2.13	.0331	-.50361	-.02108
JSE2	.43581**	.17255	2.53	.0115	.09762	.77400
JFM1	.16823	.14269	1.18	.2384	-.11144	.44791
JFM2	-.09454	.13942	-.68	.4977	-.36779	.17872
JFM3	.18122	.16049	1.13	.2588	-.13334	.49578
JFR1	.16573	.14734	1.12	.2607	-.12305	.45452
JFR2	-.23013	.14009	-1.64	.1004	-.50471	.04445
JFR3	-.10400	.14901	-.70	.4852	-.39606	.18807
JCO1	.02701	.14886	.18	.8560	-.26474	.31876
JCO2	.13317	.16073	.83	.4074	-.18187	.44820
JCO3	-.09207	.18061	-.51	.6102	-.44607	.26192
JEX1	.24417	.15715	1.55	.1203	-.06384	.55218
JEX2	.05596	.15703	.36	.7216	-.25182	.36374
JEX3	-.00227	.14903	-.02	.9879	-.29436	.28983
KPT1	.76597***	.11819	6.48	.0000	.53431	.99763
KPT2	.35167***	.12382	2.84	.0045	.10898	.59435
KWD1	.19131	.11691	1.64	.1018	-.03784	.42045
KWD2	.12075	.13646	.88	.3762	-.14671	.38821
KTY1	-.16119	.10604	-1.52	.1285	-.36904	.04665
KTY2	-.04479	.12351	-.36	.7169	-.28686	.19728
KSE1	-.59673***	.11656	-5.12	.0000	-.82519	-.36827
KSE2	.63709***	.16326	3.90	.0001	.31710	.95708
KFM1	.00520	.13773	.04	.9699	-.26475	.27515
CHOICE	*Coefficient*	*Standard Error*	*z*	*Prob. |z|>Z**	*95% Confidence Interval*	

KFM2	-.05174	.13224	-.39	.6956	-.31094	.20745
KFM3	.30614**	.15298	2.00	.0454	.00631	.60598
KFR1	.06679	.14111	.47	.6360	-.20978	.34337
KFR2	-.26866**	.13220	-2.03	.0421	-.52776	-.00955
KFR3	.14503	.13957	1.04	.2988	-.12853	.41859
KCO1	.07152	.14041	.51	.6105	-.20368	.34672
KCO2	.19490	.15170	1.28	.1989	-.10243	.49223
KCO3	-.09818	.17139	-.57	.5668	-.43410	.23775
KEX1	.26714*	.14968	1.78	.0743	-.02623	.56051
KEX2	.20940	.14774	1.42	.1564	-.08016	.49895
KEX3	-.11755	.14205	-.83	.4080	-.39596	.16087
LPT1	1.28991***	.12539	10.29	.0000	1.04415	1.53568
LPT2	.08702	.13659	.64	.5241	-.18070	.35474
LWD1	.50477***	.12394	4.07	.0000	.26185	.74768
LWD2	-.04656	.14946	-.31	.7554	-.33949	.24638
LTY1	-.31110***	.11361	-2.74	.0062	-.53376	-.08843
LTY2	.12299	.12900	.95	.3404	-.12985	.37583
LSE1	-.82162***	.12393	-6.63	.0000	-1.06452	-.57872
LSE2	.79085***	.16759	4.72	.0000	.46239	111.932
LFM1	.09080	.14492	.63	.5309	-.19323	.37484
LFM2	-.10328	.14078	-.73	.4632	-.37921	.17264
LFM3	.47606***	.15821	3.01	.0026	.16597	.78614
LFR1	.00756	.15023	.05	.9599	-.28690	.30201
LFR2	-.28388**	.14027	-2.02	.0430	-.55881	-.00896
LFR3	.15383	.14730	1.04	.2963	-.13487	.44253
LCO1	-.10445	.14997	-.70	.4862	-.39839	.18950
LCO2	.26986*	.15868	1.70	.0890	-.04115	.58087
LCO3	.04435	.18334	.24	.8089	-.31498	.40368
LEX1	.30563*	.15740	1.94	.0522	-.00287	.61412
LEX2	.21213	.15451	1.37	.1698	-.09070	.51496
LEX3	.02344	.14958	.16	.8755	-.26974	.31662
*Note: ***, **, * indicate significance at 1%, 5%, 10% level*						

Appendix II: Full results of the adjusted MNL model

Discrete choice (multinomial logit) model						
Dependent variable			Choice			
Log likelihood function			-4246.27177			
Estimation based on N = 3016, K = 44						
Inf.Cr.AIC = 8580.5 AIC/N = 2.845						
R2=1-LogL/LogL*		Log-L fncn	R-sqrd	R2Adj		
Constants only		-4594.1596	.0757	.0723		
Response data are given as ind. choices						
Number of obs.= 3016, skipped 0 obs						
CHOICE	*Coefficient*	*Standard Error*	*z*	*Prob. |z|>Z**	*95% Confidence Interval*	
CS2	.67451***	.10387	6.49	.0000	.47093	.87809
CS3	.99353***	.09865	10.07	.0000	.80018	1.18688
CS4	1.53974***	.09353	16.46	.0000	1.35643	1.72304
CS5	.93550***	.10311	9.07	.0000	.73340	1.13760
IPT1	-.14794	.12120	-1.22	.2222	-.38548	.08961
IPT2	.31638**	.12815	2.47	.0136	.06520	.56755
IWD1	.02789	.09815	.28	.7763	-.16449	.22026
ITY1	-.08178	.10296	-.79	.4270	-.28357	.12001
ISE1	-.07370	.11854	-.62	.5341	-.30603	.15863
ISE2	.23092	.15460	1.49	.1352	-.07208	.53392
IFM3	.12950	.11361	1.14	.2543	-.09317	.35218
IFR2	-.18447	.11616	-1.59	.1123	-.41214	.04320
ICO2	.02369	.12488	.19	.8495	-.22106	.26845
IEX1	.20792*	.11235	1.85	.0642	-.01228	.42811
JPT1	.29959***	.11268	2.66	.0078	.07874	.52044
JPT2	.43574***	.12242	3.56	.0004	.19580	.67568
JWD1	.13068	.09309	1.40	.1604	-.05177	.31312
JTY1	-.08858	.09883	-.90	.3701	-.28228	.10512
JSE1	-.27836**	.11188	-2.49	.0128	-.49763	-.05908
JSE2	.44023***	.14698	3.00	.0027	.15215	.72831
JFM3	.18822*	.11070	1.70	.0891	-.02875	.40519
JFR2	-.17973	.11165	-1.61	.1075	-.39856	.03910
JCO2	.10513	.11606	.91	.3650	-.12234	.33260
JEX1	.31078***	.10937	2.84	.0045	.09642	.52513
KPT1	.76966***	.10679	7.21	.0000	.56036	.97896
KPT2	.35492***	.11801	3.01	.0026	.12364	.58621
KWD1	.24152***	.08820	2.74	.0062	.06865	.41438
KTY1	-.17732*	.09369	-1.89	.0584	-.36095	.00630
KSE1	-.61818***	.10606	-5.83	.0000	-.82605	-.41031
KSE2	.63866***	.13911	4.59	.0000	.36602	.91130
KFM3	.26020**	.10540	2.47	.0136	.05362	.46677
KFR2	-.15244	.10605	-1.44	.1506	-.36028	.05541
KCO2	.18671*	.10927	1.71	.0875	-.02746	.40088
KEX1	.33617***	.10409	3.23	.0012	.13216	.54017
LPT1	1.31791***	.11388	11.57	.0000	1.09471	1.54112
LPT2	.04300	.13085	.33	.7425	-.21346	.29946
LWD1	.56009***	.09622	5.82	.0000	.37151	.74868
LTY1	-.22347**	.09903	-2.26	.0240	-.41758	-.02937
LSE1	-.87338***	.11238	-7.77	.0000	-1.09364	-.65311
LSE2	.77518***	.14352	5.40	.0000	.49389	1.05646
LFM3	.43974***	.11157	3.94	.0001	.22107	.65840
LFR2	-.14403	.11210	-1.28	.1988	-.36374	.07568
LCO2	.24668**	.11605	2.13	.0335	.01923	.47412
LEX1	.46045***	.11039	4.17	.0000	.24409	.67680
*Note: ***, **, * indicate significance at 1%, 5%, 10% level*						

Appendix III: Full results of the male only MNL model

Discrete choice (multinomial logit) model						
Dependent variable			Choice			
Log likelihood function			-2366.53369			
Estimation based on N = 1672, K = 83						
Inf.Cr.AIC = 4899.1 AIC/N = 2.930						
R2=1-LogL/LogL*	Log-L fncn	R-sqrd	R2Adj			
Constants only	-2591.7515	.0869	.0754			
Response data are given as ind. choices						
Number of obs.= 1672, skipped 0 obs						
CHOICE	*Coefficient*	*Standard Error*	*z*	*Prob. |z|>Z**	*95% Confidence Interval*	
CS2	.72558***	.14452	5.02	.0000	.44233	1.00883
CS3	1.01914***	.13745	7.41	.0000	.74973	1.28854
CS4	1.40518***	.13229	10.62	.0000	1.14589	1.66446
CS5	.68625***	.14977	4.58	.0000	.39272	.97979
IPT1	-.17380	.17249	-1.01	.3136	-.51187	.16427
IPT2	.29242*	.17385	1.68	.0926	-.04832	.63317
IWD1	.08483	.17134	.50	.6205	-.25098	.42064
IWD2	-.10220	.18431	-.55	.5792	-.46344	.25904
ITY1	-.23966	.14970	-1.60	.1094	-.53306	.05373
ITY2	.08710	.18701	.47	.6414	-.27943	.45362
ISE1	-.06796	.17098	-.40	.6910	-.40308	.26717
ISE2	.41256*	.23958	1.72	.0851	-.05701	.88213
IFM1	.04819	.19308	.25	.8029	-.33024	.42663
IFM2	-.16475	.18416	-.89	.3710	-.52569	.19619
IFM3	.26805	.21995	1.22	.2230	-.16304	.69914
IFR1	-.01925	.19662	-.10	.9220	-.40462	.36612
IFR2	.02779	.18432	.15	.8801	-.33346	.38905
IFR3	-.21932	.19470	-1.13	.2600	-.60093	.16228
ICO1	.21362	.21057	1.01	.3103	-.19909	.62634
ICO2	.04769	.20927	.23	.8197	-.36246	.45785
ICO3	-.13439	.24809	-.54	.5880	-.62063	.35185
IEX1	.11690	.20568	.57	.5698	-.28622	.52002
IEX2	.11120	.21797	.51	.6100	-.31603	.53842
JPT1	.24137	.15860	1.52	.1280	-.06948	.55222
JPT2	.50547***	.16472	3.07	.0021	.18263	.82831
JWD1	.35573**	.15888	2.24	.0252	.04433	.66713
JWD2	-.11189	.17373	-.64	.5196	-.45239	.22862
JTY1	-.27035*	.14263	-1.90	.0580	-.54990	.00920
JTY2	.17359	.17823	.97	.3301	-.17574	.52292
JSE1	-.31037**	.15708	-1.98	.0482	-.61823	-.00250
JSE2	.80953***	.22297	3.63	.0003	.37251	1.24655
JFM1	.32117*	.18175	1.77	.0772	-.03506	.67740
JFM2	-.21233	.17713	-1.20	.2306	-.55950	.13483
JFM3	.15309	.21484	.71	.4761	-.26799	.57417
JFR1	.17257	.18660	.92	.3551	-.19317	.53831
JFR2	-.17680	.18047	-.98	.3272	-.53051	.17691
JFR3	-.24792	.18781	-1.32	.1868	-.61602	.12019
JCO1	.08152	.20042	.41	.6842	-.31129	.47433
JCO2	.01898	.19644	.10	.9230	-.36603	.40398
JCO3	-.07832	.22473	-.35	.7275	-.51878	.36214
JEX1	.10770	.19766	.54	.5858	-.27970	.49510
JEX2	.18140	.21013	.86	.3880	-.23045	.59325
JEX3	.02946	.13414	.22	.8262	-.23345	.29236
KPT1	.67037***	.15328	4.37	.0000	.36994	.97080
KPT2	.20025	.16337	1.23	.2203	-.11995	.52045
KWD1	.37976**	.15314	2.48	.0131	.07961	.67990
KWD2	-.03248	.16566	-.20	.8446	-.35717	.29221
KTY1	-.32560**	.13723	-2.37	.0177	-.59457	-.05664
KTY2	.11346	.17279	.66	.5114	-.22521	.45213
KSE1	-.64539***	.15132	-4.27	.0000	-.94197	-.34881
KSE2	.91721***	.21441	4.28	.0000	.49698	1.33744
KFM1	.09685	.17907	.54	.5886	-.25413	.44783
KFM2	-.19141	.17087	-1.12	.2626	-.52632	.14349
KFM3	.25607	.20673	1.24	.2155	-.14912	.66126
KFR1	.10378	.18073	.57	.5658	-.25044	.45801
KFR2	-.11169	.17150	-.65	.5149	-.44782	.22444

CHOICE	*Coefficient*	*Standard Error*	*z*	*Prob. |z|>Z**	*95% Confidence Interval*	
KFR3	-.02213	.17810	-.12	.9011	-.37120	.32693
KCO1	.16953	.19186	.88	.3769	-.20651	.54558
KCO2	.04297	.18742	.23	.8187	-.32438	.41032
KCO3	-.18659	.21803	-.86	.3921	-.61393	.24074
KEX1	.26358	.18925	1.39	.1637	-.10735	.63451
KEX2	.34310*	.20066	1.71	.0873	-.05018	.73638
KEX3	-.15590	.12735	-1.22	.2209	-.40551	.09371
LPT1	1.26657***	.16747	7.56	.0000	.93833	159.481
LPT2	.00773	.18653	.04	.9669	-.35785	.37332
LWD1	.67674***	.16724	4.05	.0001	.34895	100.453
LWD2	-.15904	.19067	-.83	.4042	-.53275	.21468
LTY1	-.41716***	.15172	-2.75	.0060	-.71453	-.11978
LTY2	.27454	.18452	1.49	.1368	-.08711	.63619
LSE1	-.89749***	.16629	-5.40	.0000	-1.22342	-.57157
LSE2	1.01051***	.22547	4.48	.0000	.56861	1.45241
LFM1	.18800	.19255	.98	.3289	-.18939	.56539
LFM2	-.24920	.18644	-1.34	.1813	-.61462	.11622
LFM3	.54532**	.21512	2.54	.0112	.12370	.96695
LFR1	.16172	.19613	.82	.4096	-.22270	.54614
LFR2	-.35323*	.19114	-1.85	.0646	-.72787	.02140
LFR3	.16599	.19082	.87	.3844	-.20802	.54000
LCO1	.04504	.20849	.22	.8290	-.36360	.45368
LCO2	.14798	.20354	.73	.4672	-.25095	.54692
LCO3	.09280	.24006	.39	.6991	-.37772	.56331
LEX1	.25042	.20605	1.22	.2242	-.15343	.65426
LEX2	.40992*	.21218	1.93	.0534	-.00595	.82579
LEX3	-.02712	.15108	-.18	.8575	-.32324	.26899
*Note: ***, **, * indicate significance at 1%, 5%, 10% level*						

Appendix IV: Full results of the female only MNL model

Discrete choice (multinomial logit) model						
Dependent variable			Choice			
Log likelihood function			-1785.15032			
Estimation based on N = 1344, K = 83						
Inf.Cr.AIC = 3736.3 AIC/N = 2.780						
R2=1-LogL/LogL*	Log-L fncn	R-sqrd	R2Adj			
Constants only	-1982.1335	.0994	.0853			
Response data are given as ind. choices						
Number of obs.= 1344, skipped 0 obs						
CHOICE	*Coefficient*	*Standard Error*	*z*	*Prob. |z|>Z**	*95% Confidence Interval*	
CS2	.58746**	.24789	2.37	.0178	.10161	1.07331
CS3	1.12955***	.20423	5.53	.0000	.72926	1.52985
CS4	1.93095***	.19403	9.95	.0000	1.55066	2.31124
CS5	1.50967***	.20012	7.54	.0000	1.11745	1.90189
IPT1	-.57429*	.34106	-1.68	.0922	-1.24275	.09418
IPT2	.65182**	.27260	2.39	.0168	.11754	1.18610
IWD1	-.42912	.31270	-1.37	.1700	-1.04199	.18376
IWD2	.54873*	.31926	1.72	.0857	-.07701	1.17446
ITY1	.14700	.21199	.69	.4880	-.26849	.56249
ITY2	-.06976	.22387	-.31	.7553	-.50855	.36902
ISE1	.20981	.34348	.61	.5413	-.46340	.88303
ISE2	-.47128	.40785	-1.16	.2479	-1.27065	.32809
IFM1	.24665	.26134	.94	.3453	-.26556	.75886
IFM2	.08737	.25841	.34	.7353	-.41911	.59385
IFM3	-.00968	.27520	-.04	.9719	-.54906	.52971
IFR1	-.04166	.29561	-.14	.8879	-.62105	.53772
IFR2	-.32244	.26324	-1.22	.2206	-.83838	.19351
IFR3	-.17216	.28141	-.61	.5407	-.72373	.37940
ICO1	.39017	.33372	1.17	.2424	-.26392	1.04425
ICO2	.07727	.35821	.22	.8292	-.62481	.77935
ICO3	-.91371	.58029	-1.57	.1154	-2.05106	.22363
IEX1	-.18247	.38461	-.47	.6352	-.93629	.57135
IEX2	.36885	.34448	1.07	.2843	-.30631	1.04402
JPT1	.38413	.23952	1.60	.1088	-.08532	.85359
JPT2	.40969*	.23783	1.72	.0850	-.05646	.87584
JWD1	-.16283	.23111	-.70	.4811	-.61580	.29014
JWD2	.21286	.28455	.75	.4544	-.34484	.77056
JTY1	.18060	.19914	.91	.3645	-.20971	.57091
JTY2	-.26418	.21414	-1.23	.2173	-.68388	.15552
JSE1	-.33738	.24107	-1.40	.1617	-.80987	.13511
JSE2	-.22489	.28557	-.79	.4310	-.78460	.33481
JFM1	.06940	.25300	.27	.7839	-.42648	.56528
JFM2	.10372	.24647	.42	.6739	-.37935	.58679
JFM3	.18334	.26419	.69	.4877	-.33446	.70114
JFR1	.09442	.26182	.36	.7184	-.41874	.60757
JFR2	-.12280	.23365	-.53	.5992	-.58074	.33515
JFR3	-.13596	.25834	-.53	.5987	-.64231	.37038
JCO1	.03605	.26608	.14	.8922	-.48546	.55755
JCO2	.19244	.30010	.64	.5213	-.39574	.78063
JCO3	-.03013	.35633	-.08	.9326	-.72853	.66827
JEX1	.28136	.27191	1.03	.3008	-.25156	.81429
JEX2	-.03970	.27194	-.15	.8839	-.57269	.49329
JEX3	.36155	.23626	1.53	.1259	-.10151	.82460
KPT1	.97819***	.22522	4.34	.0000	.53676	1.41962
KPT2	.54453**	.22569	2.41	.0158	.10218	.98687
KWD1	.00440	.21566	.02	.9837	-.41828	.42708
KWD2	.37822	.26978	1.40	.1609	-.15055	.90698
KTY1	.12077	.18707	.65	.5185	-.24588	.48742
KTY2	-.19798	.19770	-1.00	.3166	-.58546	.18951
KSE1	-.74737***	.22732	-3.29	.0010	-1.19291	-.30183
KSE2	.12719	.26243	.48	.6279	-.38715	.64154
KFM1	-.01799	.23979	-.08	.9402	-.48798	.45200
KFM2	.20968	.23109	.91	.3642	-.24324	.66261
KFM3	.31451	.24943	1.26	.2073	-.17436	.80338
KFR1	-.05754	.24881	-.23	.8171	-.54519	.43012
KFR2	-.30211	.21962	-1.38	.1689	-.73256	.12834

CHOICE	*Coefficient*	*Standard Error*	*z*	*Prob. |z|>Z**	*95% Confidence Interval*	
KFR3	.12135	.23994	.51	.6130	-.34893	.59164
KCO1	.00148	.24983	.01	.9953	-.48818	.49113
KCO2	.29640	.28161	1.05	.2925	-.25554	.84835
KCO3	.11393	.33258	.34	.7319	-.53791	.76576
KEX1	.15272	.25635	.60	.5513	-.34971	.65515
KEX2	.14777	.25337	.58	.5598	-.34883	.64437
KEX3	.29206	.22032	1.33	.1850	-.13976	.72388
LPT1	1.42803***	.23102	6.18	.0000	.97524	1.88081
LPT2	.18270	.23726	.77	.4413	-.28232	.64771
LWD1	.33838	.22176	1.53	.1270	-.09626	.77303
LWD2	.14658	.28185	.52	.6030	-.40583	.69899
LTY1	-.10956	.19381	-.57	.5719	-.48943	.27030
LTY2	-.00604	.20127	-.03	.9761	-.40053	.38844
LSE1	-.96113***	.23328	-4.12	.0000	-1.41835	-.50390
LSE2	.34928	.26453	1.32	.1867	-.16919	.86774
LFM1	.09057	.24638	.37	.7132	-.39232	.57346
LFM2	.12330	.23915	.52	.6061	-.34543	.59203
LFM3	.37285	.25618	1.46	.1456	-.12925	.87495
LFR1	-.20371	.25857	-.79	.4308	-.71050	.30308
LFR2	-.13865	.22596	-.61	.5395	-.58153	.30423
LFR3	-.03378	.24890	-.14	.8920	-.52161	.45405
LCO1	-.20324	.25847	-.79	.4317	-.70983	.30335
LCO2	.32820	.28708	1.14	.2529	-.23446	.89086
LCO3	.12693	.34259	.37	.7110	-.54453	.79839
LEX1	.24578	.26201	.94	.3482	-.26774	.75931
LEX2	.10603	.26070	.41	.6842	-.40492	.61699
LEX3	.44652**	.22679	1.97	.0490	.00201	.89102
*Note: ***, **, * indicate significance at 1%, 5%, 10% level*						

Appendix V: Full results of EU-citizens only MNL model

Discrete choice (multinomial logit) model						
Dependent variable			Choice			
Log likelihood function			-2804.03312			
Estimation based on N = 2112, K = 84						
Inf.Cr.AIC = 5776.1 AIC/N = 2.735						
R2=1-LogL/LogL*	Log-L fncn	R-sqrd	R2Adj			
Constants only	-3155.0410	.1113	.1023			
Response data are given as ind. choices						
Number of obs.= 2112, skipped 0 obs						
CHOICE	*Coefficient*	*Standard Error*	*z*	*Prob. |z|>Z**	*95% Confidence Interval*	
CS2	.80584***	.19088	4.22 .	.0000	.43172	1.17996
CS3	1.28766***	.17421	7.39	.0000	.94622	1.62910
CS4	1.87231***	.16956	11.04	.0000	1.53999	2.20463
CS5	1.28027***	.17835	7.18	.0000	.93071	1.62982
IPT1	-.15166	.25717	-.59	.5554	-.65571	.35239
IPT2	.37424*	.19909	1.88	.0601	-.01598	.76446
IWD1	-.23837	.22420	-1.06	.2877	-.67779	.20106
IWD2	-.00835	.22573	-.04	.9705	-.45078	.43408
ITY1	.06724	.17033	.39	.6930	-.26660	.40107
ITY2	-.04124	.18360	-.22	.8223	-.40108	.31861
ISE1	.06460	.25768	.25	.8020	-.44044	.56963
ISE2	.29383	.40673	.72	.4700	-.50335	1.09101
IFM1	.08395	.20798	.40	.6865	-.32368	.49158
IFM2	-.09090	.20061	-.45	.6505	-.48409	.30229
IFM3	.04530	.23064	.20	.8443	-.40675	.49734
IFR1	.24290	.25371	.96	.3384	-.25436	.74017
IFR2	-.25681	.23752	-1.08	.2796	-.72235	.20873
IFR3	.09138	.24987	.37	.7146	-.39835	.58112
ICO1	.27188	.26111	1.04	.2978	-.23989	.78365
ICO2	.37801	.30541	1.24	.2158	-.22058	.97661
ICO3	-.45014	.39270	-1.15	.2517	-1.21981	.31954
IEX1	.17024	.28374	.60	.5485	-.38587	.72636
IEX2	.07593	.27241	.28	.7805	-.45799	.60984
IEX3	-.28651	.26810	-1.07	.2852	-.81198	.23896
JPT1	.62383***	.22248	2.80	.0050	.18777	1.05989
JPT2	.32097*	.18399	1.74	.0811	-.03964	.68158
JWD1	-.02957	.18643	-.16	.8740	-.39497	.33582
JWD2	-.17787	.20552	-.87	.3868	-.58068	.22494
JTY1	.12822	.16046	.80	.4242	-.18627	.44271
JTY2	-.22149	.17502	-1.27	.2057	-.56452	.12155
JSE1	-.27977	.22277	-1.26	.2092	-.71639	.15686
JSE2	.67483*	.36867	1.83	.0672	-.04774	1.39740
JFM1	.15104	.19830	.76	.4462	-.23761	.53970
JFM2	-.15071	.19084	-.79	.4297	-.52475	.22332
JFM3	.15472	.22006	.70	.4820	-.27660	.58604
JFR1	.46106*	.23705	1.94	.0518	-.00356	.92567
JFR2	-.31028	.22182	-1.40	.1619	-.74504	.12448
JFR3	.03515	.23514	.15	.8812	-.42571	.49602
JCO1	.09791	.23573	.42	.6779	-.36412	.55993
JCO2	.37140	.27435	1.35	.1758	-.16631	.90912
JCO3	-.14022	.30141	-.47	.6418	-.73097	.45053
JEX1	.39848	.25493	1.56	.1180	-.10118	.89814
JEX2	-.10598	.24509	-.43	.6654	-.58634	.37438
JEX3	-.19003	.23531	-.81	.4193	-.65123	.27117
KPT1	1.20411***	.21581	5.58	.0000	.78113	1.62709
KPT2	.32286*	.17852	1.81	.0705	-.02703	.67274
KWD1	.17490	.17828	.98	.3265	-.17451	.52432
KWD2	-.07660	.19700	-.39	.6974	-.46271	.30950
KTY1	.02564	.15441	.17	.8681	-.27700	.32828
KTY2	-.22476	.16699	-1.35	.1783	-.55206	.10255
KSE1	-.64266***	.21614	-2.97	.0029	-1.06629	-.21904
KSE2	.88398**	.36103	2.45	.0143	.17638	1.59159
KFM1	-.01672	.19359	-.09	.9312	-.39614	.36271
KFM2	.00603	.18204	.03	.9736	-.35076	.36283
KFM3	.27065	.21320	1.27	.2043	-.14721	.68851
KFR1	.33321	.23141	1.44	.1499	-.12034	.78676

CHOICE	*Coefficient*	*Standard Error*	*z*	*Prob. |z|>Z**	*95% Confidence Interval*	
KFR2	-.36603*	.21453	-1.71	.0880	-.78651	.05445
KFR3	.29645	.22590	1.31	.1894	-.14630	.73920
KCO1	.11724	.22710	.52	.6057	-.32785	.56234
KCO2	.44367*	.26482	1.68	.0939	-.07536	.96270
KCO3	.03519	.28766	.12	.9026	-.52860	.59899
KEX1	.30155	.24905	1.21	.2260	-.18658	.78969
KEX2	.14738	.23429	.63	.5293	-.31182	.60658
KEX3	-.22140	.22620	-.98	.3277	-.66474	.22193
LPT1	1.85153***	.22320	8.30	.0000	1.41407	2.28898
LPT2	-.04201	.19357	-.22	.8282	-.42140	.33738
LWD1	.59237***	.18664	3.17	.0015	.22655	.95819
LWD2	-.33476	.21538	-1.55	.1201	-.75690	.08737
LTY1	-.16080	.16346	-.98	.3253	-.48118	.15958
LTY2	-.00509	.17249	-.03	.9765	-.34316	.33298
LSE1	-.93813***	.22344	-4.20	.0000	-1.37607	-.50019
LSE2	1.16372***	.36377	3.20	.0014	.45075	1.87670
LFM1	.04168	.20268	.21	.8371	-.35556	.43892
LFM2	.01272	.19191	.07	.9471	-.36342	.38886
LFM3	.47867**	.21917	2.18	.0290	.04911	.90824
LFR1	.17729	.24180	.73	.4634	-.29663	.65122
LFR2	-.36579*	.22192	-1.65	.0993	-.80073	.06916
LFR3	.36581	.23399	1.56	.1180	-.09280	.82443
LCO1	-.11397	.23709	-.48	.6307	-.57866	.35072
LCO2	.60141**	.26997	2.23	.0259	.07229	1.13054
LCO3	-.02813	.30559	-.09	.9267	-.62706	.57081
LEX1	.51288**	.25566	2.01	.0448	.01181	1.01396
LEX2	.06867	.24117	.28	.7759	-.40402	.54136
LEX3	-.02939	.23325	-.13	.8997	-.48655	.42777
*Note: ***, **, * indicate significance at 1%, 5%, 10% level*						

Appendix VII: Full results of the non-EU citizens MNL model

Discrete choice (multinomial logit) model						
Dependent variable			Choice			
Log likelihood function			-1323.34799			
Estimation based on N = 904, K = 84						
Inf.Cr.AIC = 2814.7 AIC/N = 3.114						
R2=1-LogL/LogL*		Log-L fncn	R-sqrd	R2Adj		
Constants only		-1416.6511	.0659	.0436		
Response data are given as ind. choices						
Number of obs.= 904, skipped 0 obs						
CHOICE	*Coefficient*	*Standard Error*	*z*	*Prob. |z|>Z**	*95% Confidence Interval*	
CS2	.55781***	.18001	3.10	.0019	.20499	.91062
CS3	.71301***	.17545	4.06	.0000	.36913	1.05689
CS4	1.16940***	.16604	7.04	.0000	.84398	1.49483
CS5	.64414***	.17872	3.60	.0003	.29384	.99443
IPT1	-.16987	.19798	-.86	.3909	-.55791	.21816
IPT2	.29871	.21736	1.37	.1694	-.12731	.72473
IWD1	-.05992	.19940	-.30	.7638	-.45073	.33089
IWD2	.11148	.23607	.47	.6368	-.35120	.57416
ITY1	-.15316	.18183	-.84	.3996	-.50953	.20322
ITY2	-.16146	.23191	-.70	.4863	-.61599	.29307
ISE1	-.17605	.19335	-.91	.3625	-.55502	.20291
ISE2	.35428	.26971	1.31	.1890	-.17434	.88291
IFM1	-.00082	.23449	.00	.9972	-.46041	.45878
IFM2	.00974	.22143	.04	.9649	-.42425	.44374
IFM3	.37159	.26131	1.42	.1550	-.14057	.88375
IFR1	-.14651	.23606	-.62	.5348	-.60918	.31616
IFR2	-.07388	.22541	-.33	.7431	-.51567	.36791
IFR3	-.35039	.24057	-1.46	.1453	-.82190	.12112
ICO1	.12403	.24498	.51	.6126	-.35612	.60419
ICO2	-.18799	.24386	-.77	.4408	-.66595	.28997
ICO3	-.25095	.28208	-.89	.3737	-.80382	.30193
IEX1	.20181	.24593	.82	.4119	-.28020	.68382
IEX2	.12028	.25657	.47	.6392	-.38258	.62315
IEX3	-.13820	.24646	-.56	.5750	-.62125	.34485
JPT1	.06376	.18697	.34	.7331	-.30269	.43021
JPT2	.54197***	.20822	2.60	.0092	.13386	.95008
JWD1	.29587	.18822	1.57	.1160	-.07302	.66477
JWD2	.09452	.23010	.41	.6812	-.35646	.54551
JTY1	-.30295*	.17693	-1.71	.0868	-.64972	.04382
JTY2	.17826	.21622	.82	.4097	-.24552	.60205
JSE1	-.42012**	.18327	-2.29	.0219	-.77933	-.06092
JSE2	.57431**	.25086	2.29	.0221	.08263	1.06599
JFM1	.17345	.22329	.78	.4373	-.26418	.61109
JFM2	.02385	.21688	.11	.9124	-.40123	.44893
JFM3	.25214	.25813	.98	.3287	-.25380	.75807
JFR1	-.07998	.22762	-.35	.7253	-.52611	.36615
JFR2	-.20033	.22367	-.90	.3705	-.63871	.23806
JFR3	-.19468	.22447	-.87	.3858	-.63463	.24527
JCO1	-.04995	.23973	-.21	.8350	-.51981	.41992
JCO2	-.10212	.23301	-.44	.6612	-.55882	.35458
JCO3	.00625	.25288	.02	.9803	-.48938	.50187
JEX1	.12920	.23569	.55	.5836	-.33275	.59115
JEX2	.16907	.24584	.69	.4916	-.31278	.65091
JEX3	.21684	.22801	.95	.3416	-.23006	.66373
KPT1	.45648***	.17665	2.58	.0098	.11026	.80271
KPT2	.11223	.20807	.54	.5896	-.29559	.52004
KWD1	.16563	.17809	.93	.3524	-.18342	.51467
KWD2	.28873	.21347	1.35	.1762	-.12967	.70713
KTY1	-.21246	.16607	-1.28	.2008	-.53794	.11303
KTY2	.11544	.20689	.56	.5769	-.29006	.52095
KSE1	-.79264***	.17243	-4.60	.0000	-1.13060	-.45467
KSE2	.79974***	.23341	3.43	.0006	.34227	1.25721
KFM1	.02612	.21472	.12	.9032	-.39472	.44696
KFM2	-.16832	.20877	-.81	.4201	-.57751	.24086
KFM3	.39956*	.24175	1.65	.0984	-.07426	.87337
KFR1	-.14248	.21546	-.66	.5084	-.56477	.27982

CHOICE	*Coefficient*	*Standard Error*	*z*	*Prob. |z|>Z**	*95% Confidence Interval*	
KFR2	-.12936	.20612	-.63	.5303	-.53335	.27462
KFR3	-.02834	.20990	-.14	.8926	-.43973	.38305
KCO1	.01151	.22424	.05	.9591	-.42799	.45101
KCO2	-.05976	.21446	-.28	.7805	-.48009	.36057
KCO3	-.31287	.24738	-1.26	.2060	-.79772	.17198
KEX1	.45847**	.21751	2.11	.0350	.03217	.88478
KEX2	.08077	.23325	.35	.7291	-.37640	.53794
KEX3	-.07027	.22089	-.32	.7504	-.50322	.36267
LPT1	.68020***	.19248	3.53	.0004	.30295	1.05745
LPT2	.13017	.22665	.57	.5657	-.31405	.57439
LWD1	.18589	.19350	.96	.3367	-.19337	.56514
LWD2	.16020	.23219	.69	.4902	-.29489	.61529
LTY1	-.34797*	.18047	-1.93	.0538	-.70168	.00574
LTY2	.15037	.22184	.68	.4979	-.28444	.58517
LSE1	-.96104***	.18886	-5.09	.0000	-1.33119	-.59089
LSE2	.69056***	.24795	2.79	.0054	.20460	1.17653
LFM1	.18620	.22966	.81	.4175	-.26393	.63632
LFM2	-.26830	.22927	-1.17	.2419	-.71765	.18105
LFM3	.43607*	.25725	1.70	.0901	-.06814	.94028
LFR1	-.03767	.23173	-.16	.8709	-.49186	.41651
LFR2	-.29422	.23104	-1.27	.2029	-.74705	.15862
LFR3	-.04160	.22841	-.18	.8555	-.48927	.40608
LCO1	.00728	.24284	.03	.9761	-.46868	.48323
LCO2	-.18685	.24426	-.76	.4443	-.66559	.29189
LCO3	.28000	.25511	1.10	.2724	-.22001	.78001
LEX1	.16375	.24291	.67	.5002	-.31235	.63985
LEX2	.26982	.24766	1.09	.2759	-.21559	.75522
LEX3	.01174	.24029	.05	.9610	-.45921	.48270
*Note: ***, **, * indicate significance at 1%, 5%, 10% level*						

Appendix VIII: Full results of the mixed logit model

Discrete choice (multinomial logit) model						
Dependent variable	Choice					
Log likelihood function	-3930.11234					
Restricted log likelihood	-4854.06474					
Chi squared [95 d.f.]	1847.90482					
Significance level	.00000					
McFadden Pseudo R-squared	.1903461					
Estimation based on N = 3016, K = 95						
Inf.Cr.AIC = 8050.2 AIC/N = 2.669						
R2=1-LogL/LogL*	Log-L fncn	R-sqrd	R2Adj			
No coefficients	--4854.0647	.1903	.1839			
Constants only	-4594.1596	.1445	.1378			
At start values	-4223.6885	.0695	.0621			
Response data are given as ind. choices						
Fixed number of obsrvs./group= 8						
Number of obs.= 3016, skipped 0 obs						
CHOICE	*Coefficient*	*Standard Error*	*z*	*Prob. |z|>Z**	*95% Confidence Interval*	
	Random parameters in utility functions					
CS2	.42299***	.13858	3.05	.0023	.15137	.69460
CS3	.84022***	.12164	6.91	.0000	.60182	1.07862
CS4	1.51647***	.11703	12.96	.0000	1.28710	1.74584
CS5	-.25396	.23131	-1.10	.2722	-.70732	.19940
JPT2	.41003***	.14370	2.85	.0043	.12837	.69168
KPT1	.93114***	.13410	6.94	.0000	.66832	1.19397
LPT1	2.24482***	.20550	10.92	.0000	1.84205	2.64758
LWD1	.80952***	.15926	5.08	.0000	.49738	1.12166
ITY1	-.09790	.12851	-.76	.4462	-.34977	.15397
LTY1	-.55737***	.15318	-3.64	.0003	-.85759	-.25715
LSE1	-1.42677***	.17675	-8.07	.0000	-1.77320	-1.08034
	Nonrandom parameters in utility functions					
IPT1	-.30898**	.14845	-2.08 .	374	-.59995	-.01802
IPT2	.36048**	.14243	2.53	.0114	.08132	.63965
IWD	-.10512	.14463	-.73	.4673	-.38859	.17834
IWD2	.10094	.16101	.63	.5307	-.21463	.41650
ITY2	.01604	.14648	.11	.9128	-.27106	.30314
ISE1	.04756	.14499	.33	.7429	-.23662	.33173
ISE2	.19047	.20228	.94	.3464	-.20600	.58693
IFM1	.07540	.15798	.48	.6332	-.23424	.38503
IFM2	-.08090	.15348	-.53	.5981	-.38170	.21991
IFM3	.15792	.17407	.91	.3643	-.18325	.49909
IFR1	.01652	.16498	.10	.9202	-.30683	.33988
IFR2	-.16647	.15601	-1.07	.2860	-.47225	.13931
IFR3	-.11867	.16558	-.72	.4736	-.44320	.20586
ICO1	.19134	.16762	1.14	.2537	-.13719	.51988
ICO2	.04601	.18369	.25	.8022	-.31401	.40603
ICO3	-.28024	.22408	-1.25	.2111	-.71943	.15895
IEX1	.16491	.18116	.91	.3627	-.19016	.51999
IEX2	.09581	.17853	.54	.5915	-.25410	.44572
IEX3	-.15236	.17150	-.89	.3743	-.48850	.18378
JPT1	.37487***	.13186	2.84	.0045	.11642	.63331
JWD1	.12551	.12823	.98	.3277	-.12581	.37682
JWD2	.01185	.14951	.08	.9369	-.28119	.30488
JTY1	-.09766	.11717	-.83	.4046	-.32731	.13200
JTY2	-.02991	.13738	-.22	.8276	-.29918	.23935
JSE1	-.26600**	.12733	-2.09	.0367	-.51556	-.01644
JSE2	.45228**	.17712	2.55	.0107	.10514	.79943
JFM1	.14932	.15004	1.00	.3196	-.14475	.44339
JFM2	-.08769	.14586	-.60	.5477	-.37358	.19819
JFM3	.19315	.16788	1.15	.2499	-.13589	.52220
JFR1	.17765	.15415	1.15	.2491	-.12448	.47978
JFR2	-.24845*	.14657	-1.70	.0901	-.53572	.03883
JFR3	-.11752	.15500	-.76	.4483	-.42132	.18628
JCO1	.04881	.15525	.31	.7532	-.25548	.35311
JCO2	.10424	.16609	.63	.5303	-.22129	.42977
JCO3	-.08632	.18628	-.46	.6431	-.45143	.27878
JEX1	.23067	.16461	1.40	.1611	-.09196	.55331

CHOICE	*Coefficient*	*Standard Error*	*z*	*Prob. |z|>Z**	*95% Confidence Interval*	
JEX2	.07520	.16418	.46	.6469	-.24658	.39698
JEX3	-.00289	.15493	-.02	.9851	-.30655	.30076
KPT2	.39343***	.13070	3.01	.0026	.13726	.64960
KWD1	.21891*	.12340	1.77	.0761	-.02296	.46078
KWD2	.10310	.14381	.72	.4734	-.17877	.38496
KTY1	-.18635*	.11299	-1.65	.0991	-.40781	.03511
KTY2	-.03636	.13151	-.28	.7822	-.29412	.22141
KSE1	-.72183***	.12384	-5.83	.0000	-.96455	-.47910
KSE2	.69025***	.16997	4.06	.0000	.35711	1.02339
KFM1	.00459	.14661	.03	.9750	-.28277	.29194
KFM2	-.04819	.14059	-.34	.7318	-.32374	.22737
KFM3	.30635*	.16145	1.90	.0578	-.01008	.62279
KFR1	.05902	.14991	.39	.6938	-.23479	.35283
KFR2	-.25296*	.14071	-1.80	.0722	-.52875	.02282
KFR3	.14633	.14700	1.00	.3195	-.14180	.43445
KCO1	.09091	.14956	.61	.5433	-.20222	.38405
KCO2	.18882	.15960	1.18	.2368	-.12399	.50163
KCO3	-.05111	.18021	-.28	.7767	-.40432	.30210
KEX1	.24398	.15861	1.54	.1240	-.06688	.55485
KEX2	.22937	.15682	1.46	.1436	-.07798	.53673
KEX3	-.13305	.14993	-.89	.3749	-.42691	.16081
LPT2	.09294	.17410	.53	.5935	-.24830	.43417
LWD2	-.05772	.18562	-.31	.7558	-.42153	.30609
LTY2	.25140	.16386	1.53	.1250	-.06976	.57256
LSE2	1.22205***	.19843	6.16	.0000	.83315	161.096
LFM1	.10606	.18169	.58	.5594	-.25005	.46217
LFM2	-.11047	.17653	-.63	.5315	-.45647	.23553
LFM3	.63809***	.19135	3.33	.0009	.26305	1.01312
LFR1	-.16361	.18857	-.87	.3856	-.53321	.20598
LFR2	-.19395	.17683	-1.10	.2727	-.54052	.15263
LFR3	.25647	.18054	1.42	.1554	-.09738	.61032
LCO1	-.18218	.18709	-.97	.3302	-.54886	.18450
LCO2	.27533	.19274	1.43	.1531	-.10242	.65309
LCO3	.21812	.22305	.98	.3281	-.21905	.65530
LEX1	.41933**	.19302	2.17	.0298	.04102	.79764
LEX2	.20814	.18907	1.10	.2710	-.16244	.57871
LEX3	.16737	.18495	.90	.3655	-.19513	.52987
	Distns. of RPs. Std.Devs or limits of triangular					
NsCS2	.78268***	.11786	6.64	.0000	.55168	1.01368
NsCS3	.62662***	.11821	5.30	.0000	.39493	.85831
NsCS4	.90405***	.09420	9.60	.0000	.71941	1.08868
NsCS5	2.13722***	.18529	11.53	.0000	1.77406	2.50037
NsJPT2	.90020***	.14441	6.23	.0000	.61717	1.18323
NsKPT1	.78812***	.11426	6.90	.0000	.56416	1.01207
NsLPT1	1.45414***	.20817	6.99	.0000	1.04613	1.86214
NsLWD1	.80985***	.18942	4.28	.0000	.43860	1.18110
NsITY1	.56375***	.14459	3.90	.0001	.28036	.84714
NsLTY1	.79806***	.19214	4.15	.0000	.42148	1.17464
NsLSE1	1.18126***	.17682	6.68	.0000	.83470	1.52783
*Note: ***, **, * indicate significance at 1%, 5%, 10% level*						

Appendix VIII: Full results of the mixed logit model including SDC's

Discrete choice (multinomial logit) model	
Dependent variable	Choice
Log likelihood function	-3863.68214
Restricted log likelihood	-4854.06474
Chi squared [95 d.f.]	980.76522
Significance level	.00000
McFadden Pseudo R-squared	.2040316
Estimation based on N = 3016, K = 139	
Inf.Cr.AIC = 8005.4 AIC/N = 2.654	

R2=1-LogL/LogL*	Log-L fncn	R-sqrd	R2Adj
No coefficients	--4854.0647	.2040	.1948
Constants only	-4594.1596	.1590	.1492
At start values	-4223.6885	.0852	.0746

Response data are given as ind. choices
Replications for simulated probs. =1000
Used Halton sequences in simulations.
RPL model with panel has 377 groups
Fixed number of obsrvs./group= 8
Number of obs.= 3016, skipped 0 obs

CHOICE	*Coefficient*	*Standard Error*	*z*	*Prob. |z|>Z**	*95% Confidence Interval*	
	Random parameters in utility functions					
CS2	.36978*	.19730	1.87	.0609	-.01692	.75647
CS3	.66536***	.18105	3.68	.0002	.31051	1.02020
CS4	1.26335***	.17853	7.08	.0000	.91343	1.61326
CS5	.42148	.27056	1.56	.1193	-.10880	.95176
IPT1	-.39131*	.21636	-1.81	.0705	-.81537	.03276
JPT1	.59226***	.20485	2.89	.0038	.19077	.99375
JPT2	.45636**	.20032	2.28	.0227	.06375	.84898
KPT1	1.22528***	.20280	6.04	.0000	.82781	1.62276
KPT2	.18716	.19096	.98	.3270	-.18712	.56145
LPT1	1.69303***	.24492	6.91	.0000	1.21300	2.17306
LWD1	.66526***	.19007	3.50	.0005	.29273	1.03780
	Nonrandom parameters in utility functions					
IPT1	.40736***	.14656	2.78 .	54	.12011	.69461
IPT2	-.09164	.14421	-.64	.5251	-.37427	.19100
IWD	.09822	.16037	.61	.5403	-.21610	.41254
IWD2	-.07438	.12388	-.60	.5483	-.31718	.16842
ITY2	-.04779	.14475	-.33	.7413	-.33149	.23591
ISE1	.03169	.14421	.22	.8261	-.25097	.31434
ISE2	.20306	.20158	1.01	.3138	-.19202	.59815
IFM1	.07105	.15734	.45	.6516	-.23733	.37943
IFM2	-.08955	.15246	-.59	.5570	-.38837	.20927
IFM3	.17023	.17494	.97	.3305	-.17263	.51310
IFR1	.01213	.16440	.07	.9412	-.31008	.33435
IFR2	-.17208	.15588	-1.10	.2696	-.47759	.13343
IFR3	-.11550	.16479	-.70	.4834	-.43848	.20748
ICO1	.20117	.16779	1.20	.2306	-.12769	.53002
ICO2	.05132	.18286	.28	.7790	-.30707	.40972
ICO3	-.29611	.22345	-1.33	.1851	-.73406	.14185
IEX1	.19482	.18010	1.08	.2794	-.15816	.54780
IEX2	.09457	.17775	.53	.5947	-.25382	.44297
IEX3	-.18837	.17120	-1.10	.2712	-.52391	.14717
JPT1	.15686	.12970	1.21	.2265	-.09735	.41107
JWD1	-.00564	.15085	-.04	.9702	-.30130	.29003
JWD2	-.08009	.11853	-.68	.4992	-.31239	.15222
JTY1	-.05080	.13883	-.37	.7144	-.32291	.22131
JTY2	-.29342**	.12891	-2.28	.0228	-.54608	-.04075
JSE1	.46839***	.17886	2.62	.0088	.11783	.81895
JSE2	.16370	.15100	1.08	.2783	-.13226	.45965
JFM1	-.08916	.14693	-.61	.5440	-.37713	.19882
JFM2	.19890	.16981	1.17	.2415	-.13393	.53173
JFM3	.18342	.15546	1.18	.2381	-.12128	.48812
JFR1	-.27072*	.14836	-1.82	.0680	-.56149	.02006
JFR2	-.10938	.15645	-.70	.4845	-.41602	.19727
JFR3	.03496	.15744	.22	.8243	-.27362	.34354
JCO1	.08297	.16785	.49	.6211	-.24600	.41195

CHOICE	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
JCO2	-.05453	.18877	-.29	.7727	-.42451	.31545
JCO3	.24321	.16598	1.47	.1428	-.08211	.56854
JEX1	.06396	.16539	.39	.6989	-.26020	.38812
JEX2	.02091	.15626	.13	.8935	-.28536	.32719
JEX3	.28051**	.12517	2.24	.0250	.03518	.52584
KPT2	.11041	.14523	.76	.4471	-.17423	.39504
KWD1	-.16645	.11445	-1.45	.1458	-.39076	.05786
KWD2	-.06285	.13345	-.47	.6377	-.32442	.19871
KTY1	-.75265***	.12505	-6.02	.0000	-.99775	-.50756
KTY2	.71081***	.17134	4.15	.0000	.37499	1.04662
KSE1	.02943	.14797	.20	.8424	-.26059	.31945
KSE2	-.05642	.14210	-.40	.6913	-.33493	.22208
KFM1	.30973*	.16403	1.89	.0590	-.01177	.63123
KFM2	.07028	.15158	.46	.6429	-.22682	.36738
KFM3	-.26291*	.14249	-1.85	.0650	-.54220	.01637
KFR1	.16724	.14902	1.12	.2618	-.12484	.45932
KFR2	.08740	.15187	.58	.5649	-.21025	.38505
KFR3	.15155	.16107	.94	.3467	-.16413	.46723
KCO1	-.02582	.18236	-.14	.8874	-.38325	.33161
KCO2	.29648*	.16000	1.85	.0639	-.01711	.61007
KCO3	.23392	.15818	1.48	.1392	-.07612	.54395
KEX1	-.15133	.15161	-1.00	.3182	-.44849	.14583
KEX2	.08106	.16548	.49	.6242	-.24327	.40539
KEX3	-.04640	.17464	-.27	.7905	-.38869	.29589
LPT2	-.44141***	.13550	-3.26	.0011	-.70699	-.17582
LWD2	.14062	.15203	.92	.3550	-.15735	.43860
LTY2	-1.27439***	.14795	-8.61	.0000	-1.56437	-.98442
LSE2	1.07762***	.18676	5.77	.0000	.71157	1.44367
LFM1	.14539	.16931	.86	.3905	-.18646	.47724
LFM2	-.09000	.16445	-.55	.5842	-.41233	.23232
LFM3	.58572***	.18124	3.23	.0012	.23049	.94094
LFR1	-.06968	.17560	-.40	.6915	-.41385	.27449
LFR2	-.25072	.16508	-1.52	.1288	-.57427	.07283
LFR3	.25635	.17001	1.51	.1316	-.07686	.58957
LCO1	-.13408	.17525	-.77	.4442	-.47756	.20940
LCO2	.24683	.18124	1.36	.1732	-.10839	.60204
LCO3	.20712	.21201	.98	.3286	-.20842	.62265
LEX1	.45331**	.18131	2.50	.0124	.09794	.80868
LEX2	.21318	.17834	1.20	.2319	-.13636	.56271
LEX3	.05895	.17313	.34	.7335	-.28038	.3982
	Heterogeneity in mean, Parameter:Variable					
CS2:GEN	-.05976	.10723	-.56	.5773	-.26992	.15040
CS2:NAT	.16779	.11388	1.47	.1407	-.05541	.39099
CS2:EDU	-.02772	.12823	-.22	.8289	-.27905	.22361
CS2:CHI	-.09532	.13553	-.70	.4818	-.36095	.17031
CS3:GEN	-.13106	.10075	-1.30	.1933	-.32852	.06640
CS3:NAT	.44713***	.10725	4.17	.0000	.23692	.65734
CS3:EDU	.10990	.11996	.92	.3596	-.12522	.34502
CS3:CHI	.04202	.12263	.34	.7319	-.19833	.28238
CS4:GEN	.11443	.10163	1.13	.2602	-.08475	.31361
CS4:NAT	.49786***	.10926	4.56	.0000	.28370	.71201
CS4:EDU	.37421***	.12750	2.94	.0033	.12432	.62410
CS4:CHI	.19973	.12231	1.63	.1025	-.04000	.43946
CS5:GEN	.36202**	.16046	2.26	.0241	.04752	.67651
CS5:NAT	.28505	.17646	1.62	.1062	-.06081	.63091
CS5:EDU	.12188	.19643	.62	.5349	-.26312	.50688
CS5:CHI	.49417***	.18428	2.68	.0073	.13298	.85536
IPT1:GEN	-.03865	.11389	-.34	.7343	-.26187	.18456
IPT1:NAT	.00239	.12009	.02	.9842	-.23299	.23776
IPT1:EDU	-.00097	.13594	-.01	.9943	-.26740	.26546
IPT1:CHI	-.15488	.14364	-1.08	.2809	-.43642	.12665
JPT1:GEN	.00978	.12046	.08	.9353	-.22632	.24589
JPT1:NAT	.17010	.12747	1.33	.1821	-.07973	.41994
JPT1:EDU	-.12105	.14335	-.84	.3984	-.40202	.15992
JPT1:CHI	.20278	.14434	1.40	.1601	-.08012	.48568
JPT2:GEN	-.16376	.10880	-1.51	.1323	-.37700	.04948
JPT2:NAT	-.01019	.11822	-.09	.9313	-.24190	.22152

CHOICE	*Coefficient*	*Standard Error*	*z*	*Prob. |z|>Z**	*95% Confidence Interval*	
JPT2:EDU	.00674	.12722	.05	.9578	-.24261	.25609
JPT2:CHI	.10670	.13051	.82	.4136	-.14909	.36250
KPT1:GEN	.00969	.11645	.08	.9337	-.21856	.23793
KPT1:NAT	.33578***	.12472	2.69	.0071	.09134	.58022
KPT1:EDU	-.23189	.14563	-1.59	.1113	-.51732	.05354
KPT1:CHI	.18188	.13905	1.31	.1909	-.09066	.45441
KPT2:GEN	.10248	.09739	1.05	.2927	-.08841	.29336
KPT2:NAT	.12094	.10950	1.10	.2694	-.09368	.33556
KPT2:EDU	.10465	.12289	.85	.3944	-.13620	.34550
KPT2:CHI	-.07141	.11674	-.61	.5407	-.30022	.15740
LPT1:GEN	-.16388	.14699	-1.11	.2649	-.45198	.12422
LPT1:NAT	.81218***	.16121	5.04	.0000	.49621	1.12814
LPT1:EDU	.12626	.17935	.70	.4814	-.22526	.47778
LPT1:CHI	.03124	.16814	.19	.8526	-.29832	.36080
LWD1:GEN	-.09800	.09470	-1.03	.3007	-.28360	.08760
LWD1:NAT	.39922***	.10764	3.71	.0002	.18824	.61019
LWD1:EDU	-.00804	.12032	-.07	.9468	-.24386	.22779
LWD1:CHI	.07137	.10656	.67	.5030	-.13748	.28023
	Distns. of RPs. Std.Devs or limits of triangular					
NsCS2	.78317***	.11765	6.66	.0000	.55258	1.01376
NsCS3	.63084***	.12058	5.23	.0000	.39451	.86717
NsCS4	.80744***	.09278	8.70	.0000	.62559	.98928
NsCS5	1.78601***	.14662	1.218	.0000	1.49864	2.07339
NsIPT1	.37375*	.21737	1.72	.0855	-.05229	.79979
NsJPT1	.37639**	.17829	2.11	.0348	.02694	.72584
NsJPT2	.76854***	.16390	4.69	.0000	.44730	1.08978
NsKPT1	.65237***	.12846	5.08	.0000	.40060	.90414
NsKPT2	.65325***	.17063	3.83	.0001	.31882	.98768
NsLPT1	1.07767***	.16088	6.70	.0000	.76234	1.39300
NsLWD1	.62853***	.16216	3.88	.0001	.31070	.94637
*Note: ***, **, * indicate significance at 1%, 5%, 10% level*						

Parameter Matrix for Heterogeneity in Means.				
	1	2	3	4
1	-.0597565	.167788	-.0277181	-.0953203
2	-.131058	.447132	.109899	.0420217
3	.114427	.497857	.374208	.199730
4	.362016	.285050	.121881	.494168
5	-.0386515	.00238510	-.971051E-03	-.154882
6	.00978204	.170102	-.121052	.202781
7	-.163761	-.0101870	.00673785	.106704
8	.00968718	.335777	-.231886	.181875
9	.102476	.120941	.104648	-.0714082
10	-.163879	.812177	.126261	.0312398
11	-.0979965	.399216	-.00803601	.0713743