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Modeling parking choices considering user heterogeneity

Bachelor Thesis

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Abstract. The examination of car driver behavior deciding which parking space to choose. The application of various logit models has led to an insight of selecting between the available alternatives: free on-street parking, paid on-street parking and parking in an underground car park. Several logit models allowing for correlation between random taste parameters calculate coefficients using stated choice data. The main purpose of this paper is to extend a Mixed Multinomial Logit (M-MNL) model to similar models which can also implement the correlation between random parameters. This leads to the following: Nested Logit (NL), Nested Generalized Extreme Value (NGEV), Cross-Nested Logit (CNL) and Mixed-Mixed Multinomial Logit (MM-MNL) models to approach modeling parking choice models. The estimated coefficients are used to compute subjective-value of time (SVT) when looking for a parking space.

Keywords: Stated preference, Heterogeneity, Mixed Multinomial Logit, Mixed-Mixed Multinomial Logit, Nested Logit, Willingness-to-pay

I. Introduction

One of the most urgent problems in cities is the shortage of parking spaces. The rapidly growing number of vehicles and limited parking space results in the reality of difficult parking and disorganized parking. Growth is beneficial economic situation however there must be enough parking space to provide inhabitants and also their visitors. The population is discouraged to come to the city, because it is impossible to find a place to park or the parking fee is too high. Not only its own residents will be unsatisfied however also people who come in their leisure time will not come back. This will affect the economy in a city and that creates a negative sentiment to a city. Residents must have enough parking space for their car nearby their house or workplace. Constructing car parks is the main approach. These are cost-intensive projects. Therefore it is necessary to have an insight in the need and willingness to manage such projects even profitable. That is why parking policy is an important component of management policies. To obtain more success on a certain parking policy, it is essential to comprehend the factors and variables in influencing parking type choices. These factors will construct an indicator: willingness-to-pay (WTP). With this indicator and the estimation of demand an evaluation will be computed.

To capture an adequate method, knowledge is required of the needs and choices from drivers. The objective is to construct a suitable model which can define the behavior of future car drivers where they want to park and against which costs. The focus will be on the construction of the idea from a local authority to build an underground car park.

Model introduction

This paper reports results of an analysis of parking choice behavior, based on a stated choice dataset collected in one city. This data will be used to formulate several discrete choice models. Initially, a mixed multinomial logit model (M-MNL) with error components and incorporating correlation between random taste parameters will be computed as a base model on which different logit models will be compared. To achieve various formulations of the influence factor, several logit models with various assumptions will estimate according the collected data.

There will be two different point of views regarding the data. First assumption will be the existence of a certain relation between the alternatives, this assumption leads to a nested logit model (NL). Third model, the mixed-mixed multinomial logit model (MM-MNL) will be a extension of the M-MNL, however the difference will lie in the assumption of continuous or discrete distribution. With the computed factors, the influence of user behavior, and the characteristics of potential car park drivers will be determined.

Another indicator will be calculated, subjective values of time (SVT); willingness-to-pay in order to save time looking for a place to park and for reaching the final destination. [Ibeas et al. 2013] The main aim of this paper is to find significant factors for parking needs with heterogeneity and gain more knowledge in affecting the WTP for different logit models.

Research question

Is it possible to gain insight into parking choices considering user heterogeneity with various logit models?

The paper has the following set up: the next section will review relevant literature based on the topic of parking choices, especially work that utilizes discrete choice models from survey choice or preference data. Section 3 will report the characteristics of the collected data, section 4 will give a methodology for the various models used for this data set collected for this particularly city. Section 5 illustrates the results of the model. All significant coefficients and WTP for different models will be presented. Section 6 will give the main conclusions and formulates different findings regarding the difference between the various logit models.

II. Literature

The topic of parking choice has already been investigated by a multiple researchers. These studies use several discrete choice models to estimate model characteristics. This paper bases on the estimation of a discrete choice model of a mixed logit model with error components and incorporated correlation between their random taste parameters. [Ibeas et al. 2013] They conclude that vehicle age was key when choosing where to park and the perception of parking charge was fairly heterogeneous. Another study reports the results of an analysis of parking choice behavior, based on a stated preference (SP) dataset, collected in various city center locations in the UK. This analysis uses a mixed multinomial logit (M-MNL) model for studying behavior of car drivers in a similar way, the results of the analysis indicate that taste heterogeneity is a major factor in parking type choice. [Hess et al. 2009]. All these papers use the mixed multinomial logit model, in addition to M-MNL. The following paper describes the estimation of a nested logit model (NL) of parking location choice using revealed preference data. These data concerned the behavior of drivers going to work in a central business district. They consider a variety of attributes other than money cost and separation of different time coefficients for the model's utility functions. They state that this proposed nested structure with the inclusion of measures representing various attributes other these components than money and time are found to be appropriate. [Hunt and Teply. 1993]

Although this presented nested logit model is appropriate to estimate for that particular study, the collected data for this paper consist heterogeneity. To adjust to this addition, they consider a cross-nested logit model. [Hess et al. 2012], this study is not based on parking choice, however they use a choice stated experiment concerning the demand for alternative fuel vehicles. The study recognizes the fact that choice process potentially has correlation which can be a problem for MNL or NL model as a result. The hypothesis of a Cross-Nested Logit structure is studied to capture more of the correlation than the standard Nested Logit model in such a choice process. With some analysis and forecasting an evidence is produced to support these assumptions. Finally, an extension states that further gains can be made by using mixed GEV structures, allowing for random heterogeneity in addition to correlation. This mixed GEV structure is examined in the following paper of [Hess et al. 2005]. In this article, a model of mixed Generalized Extreme Value (GEV) is investigated as potential model to simultaneously account for several phenomena, using a stated preference (SP) dataset for mode-choice in Switzerland. The use of mixed GEV models on this dataset leads to important insights on performance in contrast of MNL. However, in addition the results show that, by simultaneously accounting for correlation and random taste heterogeneity, it is problematic to retrieve a specific explanation on correlation or heterogeneity. This study shows that this problem of vague clarification on one of the two phenomena can lead to false conclusions about the existence of the other phenomenon. This is a strong indication that the use of this mixed GEV models should be examined in the future. It will not be able to explain random taste heterogeneity and correlation in current models. Therefore the use of GEV should be encouraged in the case where the nature of the error structure is not clear. Moreover, it is possible to only use a multinomial logit model (MNL). On the basis of the survey about the choice behavior of drivers in the shopping mall, utilization of a MNL model to analyze the preferences which has significant impacts on the choice behavior. As conclusion, they state that not only the social attributes but in addition the driving attributes and consuming ones have impact on the individual's parking choice. [Liang et al. 2016] Because of the unobserved preference heterogeneity, there has to be some representation and this can be achieved with a latent class (LC) discrete choice model. This model offers an alternative to M-MNL by replacing the continuous distribution assumption with a discrete distribution in which preference heterogeneity is captured in distinct classes [Boxall and Adamowicz 2002]. If the assumption of preference homogeneity holds within segments latent class-specific multinomial logit (LC-MNL) could be useful. In a LC-MNL, all individuals in a given class have the same parameters, however the parameters vary across segments. A Bayesian setting model is capable of cal-

culating these various parameters. [Allenby and McCulloch. 2005]. In later studies, a model has been derived with discrete-continuous mixing distributions of unobserved heterogeneity in the form of a mixture of normal distributions. [Greene and Hensher. 2013] This model is also known as mixed-mixed multinomial logit (MM-MNL). [Keane and Wasi. 2013]. The MM-MNL model essentially incorporates M-MNL with LC models and minimizes the disadvantages of each. Recent studies have started to question whether the specification of M-MNL with a multivariate normal (MVN) mixing distribution is adequate for explaining key features of stated preference data. It is argued that the major source of heterogeneity in choice data comes from scale heterogeneity. They state that this means in general that scaling the attribute weights as opposed to the random coefficients specification of M-MNL. Specifying the mixing distribution of M-MNL with MVN is actually equivalent to extending LC models to incorporate unobserved heterogeneity within class.
In conclusion, there are numerous logit models to utilize stated choice surveys. The main focus through all these studies is that the model should capture the concept of heterogeneity in combination with a logit model. This will be achieved with a multinomial logit or nested logit. These two distinctive models will be used in this paper. By an evaluation of the data, a correct model can be created by carefully selecting the significant variables and making the right assumptions about the data.

III. Data evaluation

Data collected of user behavior for a stated choice survey conducted in 2007 to resident and non-resident drivers in Santoña with 10.000 inhabitants in Cantabria, Spain. The survey consisted of eight choice scenarios based on the following three alternatives.

- Free on-street Parking (FSP),
- Paid on-street parking (PSP) and
- Paid parking in an underground car park (PUP).

The sample size is 200 respondents after the design of the survey. [Rose and Bliemer. (2009)] Respondents are contacted on the streets of the study area when they are involved with parking activities with a response rate of 90%. The number of responses (observations) is 1576. It was designed to be random among the individuals who parked in the study area. The experimental design considered the following three variables.

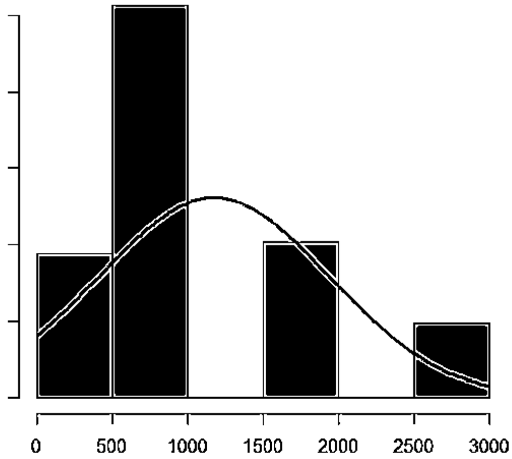

Figure 1: Histogram for Income level (monthly, in euros).

- Access time to parking (AR): the time a user takes once arriving to the parking area, to find an empty space and park.
- Access time to destination (TD): the time a user takes from the parking space to the real destination.
- Parking fee (FEE): the amount paid for parking, either in the street of in the underground car park.

So combining the alternatives with the variables, the following scenarios are presented in table (2.a). There are eight responses per individual, each associated with a different scenario. The number of scenarios is carefully picked as the number of scenarios must be equal to or greater than the degrees of freedom of the design. [Rose and Bliemer. 2009] To gain more insight into the respondents, table (2.b) presents the sample composition of the data. To comprehend the circumstances of the parking stay, table (2.c) presents the purposes of visitors and residents of Santoña. It can be seen that heterogeneity is present between these two groups.

	FSP			PSP			PUP		
Scenario	AT	TD	FEE	AT	TD	FEE	AT	TD	FEE
1	10	10	0	10	10	0.6	5	10	0.8
2	10	15	0	10	15	0.6	5	10	0.8
3	15	15	0	10	10	0.8	5	10	0.8
4	15	10	0	10	15	0.8	5	10	0.8
5	15	15	0	10	10	0.6	5	10	1.5
6	15	10	0	10	15	0.6	5	10	1.5
7	10	10	0	10	10	0.8	5	10	1.5
8	10	15	0	10	15	0.8	5	10	1.5

Attribute		**%**	**Attribute**		**%**
Gender			Place of residence		
	Male	73.10		Santoña	53.30
	Female	26.90		Outside Santoña	46.70
Age			Income level		
	<24	11.68		<600 €	20.22
	25-34	30.46		600-1500 €	55.19
	35-44	20.81		1500-2500 €	21.86
	45-54	16.75		>2500 €	2.73
	55-64	13.71			
	>65	6.60	Sample size		197

Purposes	Residents of Santoña	Visitors of Santoña
Home	24.76	9.78
Work	33.33	35.87
Shopping	9.52	17.39
Leisure	14.29	26.09
Other purposes	18.10	10.87

Alternative	Times chosen	Percentage
FSP	839	0,53
PUP	666	0,42
PSP	71	0,05

Table 2: Tables from top to bottom. First table (a) shows the scenarios based on the AT, TD and FEE variables. second table (b) presents the purposes of stay among residents and visitors. Third table (c) shows the ample composition. Last table (d) indicates the percentage of each alternative.

In table (3), descriptive statistics for some of the variables are shown. It is detectable from this table that the data consist a remarkable quantity of dummy variables containing only the values 0/1. The data collected for income varies over the various values which are presented in figure (1). It is not clear which distribution the variable income per month follows. It is uncertain because the presented histogram only has four different values. It is detected that the mean of INCM: 763 is left-shifted in contrast to the normal distribution which is also displayed in the graph.

To gain some insight into the behavior of the applicants. For every alternative the chosen percentage is presented in table (2.d) with the eight given scenarios. It is noticeable that the respondents prefer FSP and PUP alternative over PSP. It looks like when people are willing-to-pay a fee for parking, it is only for an underground parking. If they have to choice between paid parking and free parking, they are indifferent.

Variables	Mean	Std. Dev	Minimum	Maximum
Choice	1,89	0,97	1	3
Gender	0,27	0,44	0	1
Age≤20	0,05	0,22	0	1
21<Age≤30	0,25	0,43	0	1
31<Age ≤40	0,25	0,43	0	1
41<Age ≤50	0,19	0,39	0	1
51<Age≤60	0,15	0,36	0	1
Age>61	0,07	0,25	0	1
Resident	0,53	0,50	0	1
Origin Internal	0,45	0,50	0	1
Destination Internal	0,84	0,37	0	1
Origin/Destination Internal	0,31	0,46	0	1
Age Vehicle < 3 years	0,38	0,48	0	1
Age Vehicle < 2 years	0,27	0,45	0	1
Income per Month	1172,59	763,61	300	3000
Income per Hour	4619,57	1661,17	1875	5625
Low Income	0,70	0,46	0	1
Middle Income	0,20	0,40	0	1
High Income	0,10	0,30	0	1

Table 3: Descriptive statistics of parking stated choice.

IV. Methodology

The collected data will be modeled using different approaches. The first model is a base model of a mixed multinomial logit model. The second model is in another direction. First model assumes that the distribution of the coefficients in the model are continuous. The coefficients may indeed be discrete. This leads to the latent class model. The third model consists nests. With these nests several different models will be produced. This model is divided into different models based on a nested logit model. After correcting the model by eliminating redundant variables. Willingness-to-pay will be estimated with the parameter estimations for all models with correlation between choice alternatives included interactions between variables and socio-economic characteristics.

Mixed Multinomial Logit

This model generalizes the multinomial model by allowing the preference or taste parameters to be different for each individual [McFadden and Train. 2000] [Train. 2009]. Mixed multinomial logit (M-MNL) is basically a random parameter logit model with continuous heterogeneity distributions. The random utility of person i for alternative j for choice occasion t is:

$$U_{ijt} = x_{ijt}^T \beta_i + \epsilon_{ijt},$$
$$i = 1, ..., N, \quad j = 1, ..., J, \quad t = 1, ..., T.$$

Allowing the coefficients to vary implies the existence of different decision makers. This allows these decision makers to have different preferences. The formula is based on alternative-specific variables with a generic coefficient and individual - specific variables with an alternative specific coefficient. The mixed logit choice probability is given by:

$$P_{ni} = \int \frac{exp(x_{nj}\beta)}{\sum_{j=1}^{J} exp(x_{nj}\beta)} f(\beta|\theta) d\beta$$

where $f(\beta|\theta)$ is the density function of β. The θ parameters can be estimated by maximizing the simulated log-likelihood function (SML),

$$S_n = \sum_{n=1}^{N} ln \left\{ \frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T} \prod_{j=1}^{J} \left| \frac{exp(x_{njt}\beta)}{\sum_{j=1}^{J} exp(x_{njt}\beta)} \right| \right\}.$$

For this simulation, 200 Halton draws per individual will be used to obtain probabilities. The Hal-

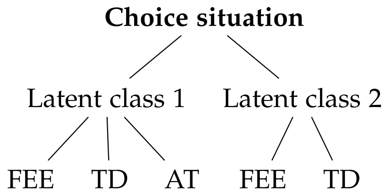

Figure 2: Representation of latent/mix-mixed logit model.

ton sequence is constructed based on a deterministic method that uses prime numbers as its base. [Sarrias. 2016]. Normally simulations use independent random draws, however with this Halton method the computation time could be reduced. By advancing the selection of evaluation points more systematically. Through this better selection a finer inclusion of the integration is established which shortens the computation time of the presented SML. [Sándor and Train. 2004] The number of draws used in the simulation is important in order to have a valuable approximation of the log-likelihood.

It is practical to extent this model to allow and incorporate correlated coefficients. Without this inclusion an inappropriate model would be created. In this case of parking choice discrete model is suitable to apply L as lower triangular matrix (Cholesky matrix), which produces the covariance matrix of the random parameters, $LL^T = \Sigma$. Furthermore, with the observed heterogeneity in the collected data. In addition, this can be accommodated by allowing the parameter heterogeneity to be partly systematic in terms of observed variables. [Sarrias. 2016] Also considering the possibility of interactions between various attributes with socio-economic variables mentioned in tables (2.b) and (2.c).

Latent Class and Mixed-Mixed Multinomial Logit

Discrete mixing distributions is popular especially in psychology and marketing. This leads to the latent class model. Each respondent is assumed to belong to a class q, where preferences vary across, however not within classes. The log-likelihood for this model is

$$S_n = ln\left\{\sum_{q=1}^{Q} w_{iq} \prod_{t=1}^{T}\prod_{j=1}^{J}\left[\frac{exp(x_{njt}\beta)}{\sum_{j=1}^{J} exp(x_{njt}\beta)}\right]^{y_{njt}}\right\}.$$

The number of latent classes needs to be specified prior to estimating the latent class (LC) model. To take advantage of the benefits of both M-MNL and LC-MNL, a new method is created: this double-mixture is known as the mixed-mixed logit model (MM-MNL). This extension is a LC model which allows random parameters within each class. Note that the MM-MNL with only one class is equivalent to the M-MNL model. The choice probabilities for the MM-MNL are given by:

$$P_i(\theta) = \sum_{q=1}^{Q} w_{iq} \int \left\{\prod_{t=1}^{T}\prod_{j=1}^{J}\left[\frac{exp(x_{njt}\beta)}{\sum_{j=1}^{J} exp(x_{njt}\beta)}\right]^{y_{ijt}}\right\} \cdot f(\beta|\theta) d\beta.$$

Let $y_{ijt} = 1$ if individual i chooses j on occasion t, and 0 otherwise. [Sarrias and Daziano. 2017] Individual i belongs to class q with probability w_{iq}. The most common formulation for w_{iq} is the semi-parametric multinomial logit format. [Greene and Hensher. 2003]
This formulation is given as:

$$w_{iq} = \frac{exp(h_i^T \gamma_q)}{\sum_{q=1}^{Q} exp(h_i^T \gamma_q)}, \quad q = 1, ..., Q, \quad \gamma_1 = 0$$

where h_i denotes a set of the incorporated socio-economic characteristics. With additional assumptions and formulations γ_q is a constant [Scarpa and Thiene. 2005]. Figure (2) shows a simple representation of latent class model for $Q = 2$.

(a) Nests are divided based on money. (b) Nests are divided based on area.

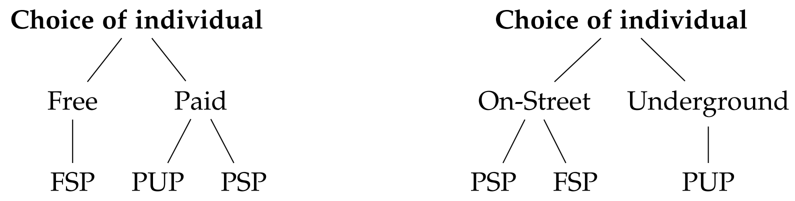

Figure 3: Representation of nested model.

Latent class 1 uses the base utility function and this also shows that the MM-MNL with only one class is equivalent to the M-MNL model. Latent class 2 uses only the FEE and TD coefficients and is designed to exclude the coefficient AT. Due to the complex expression of the probability, the best manner to implement this model is with the maximum likelihood estimator for the MM-MNL parameters with the Monte Carlo approximation of this choice probability and the analytical expression of the gradient. [Keane and Wasi. 2013] [Sarias. 2016] An error component is defined, which is normally distributed, designed to be used for Monte-Carlo simulation. Note that draws are generated for individuals and are similar for all observations of the same individuals. MM-MNL models are implemented using a Bayes estimator, this adds the assumption of correlated parameters. This is typically used in Bayesian treatments.

Nested Logit Model

Nested Logit Model, allowing correlation between some choices through nesting with the use of random utility theory. The choices are correlated inside the nest but with independence between the nests. Preferences are the same as before, individuals choosing the option with the highest utility, where the utility of choice j in dataset for individual n is

$$U_{ijt} = x_{ijt}^T \beta_i + Z_s \alpha + \epsilon_{ijt},$$

where Z_s represents characteristics of the nests and ϵ follows a generalized extreme value (GEV). Within the sets the correlation coefficient for the ϵ_{ijt} is approximately equal to $1 - \lambda$. The parameter λ in this equation has to be interpreted according to [Ben-Akiva and Lerman. 1985] if $0 < \lambda < 1$ is not violated then this indicates consistency with random utility maximization for NL model. [McFadden and Manski. 1981] This leads to the assumption that λ can be considered as a measure of the discrepancy among alternatives. Error terms in the utility function are independently and identically distributed for all the alternatives. Error terms are applied separately to different groups of alternatives that have more similar error terms. Between the sets, choices i & j are independent. The key in this model is the nest construction. Different nest structures will produce different results. In general, the nested structure of an NL model is not limited to either just two levels or just two groups on a level.

Similar choices are clustered in nests or branches as presented in figure (3.a). This is a representation of the relation between the presented parking alternatives when the variable paid is considered as a nest. Figure (3.b) is the representation of a relation between the presented parking alternatives when the variable On-street is considered as a nest. It is possible to estimate these nested models separate. These figures simply represent nesting patterns and structure of system of logit models. Then the probabilities can be presented as

$$P_n = \frac{exp(\alpha Z_n + \lambda_m \, ln \sum_{j \in n} exp(x_{nj}\beta))}{\sum_{j \in m} exp(\alpha Z_n + \lambda_j \, ln \sum_{j \in n} exp(x_{nj}\beta))}$$

with Z_n are variables that vary within nests which represents characteristics of the nests. α and β are estimated coefficients. λ_m is the estimated coefficient corresponding to the utility function. Figure

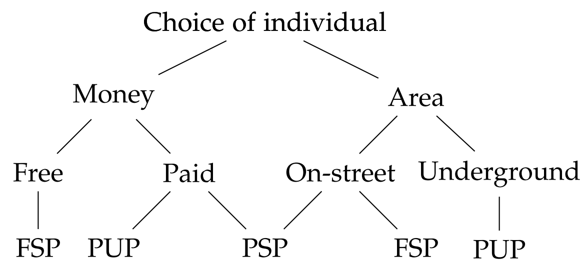

Figure 4: Representation of the cross-nested model.

(3.a) shows Z_{Money} with corresponding λ_{Free} and λ_{Paid}. Figure (3.b) shows Z_{Area} with corresponding $\lambda_{On-street}$ and $\lambda_{Underground}$.
There is a method to combine these nests into a full model as figure (4) shows, the relation between the presented parking alternatives when the variable paid and area are considered as nests together. This displays that a cross-nested logit might be a suitable model to calculate the parameters for the parking choice data set. [Hunt and Tely. 1993]

Cross-nested logit

The cross-nested logit (CNL) model is almost identical to the Ordered GEV model proposed by [Small. 1987] [Bierlaire 2001]. This model has the ability to control a wide variety of correlation which is desirable for this data set.
In this specific application, the CNL structure allows the model to jointly accommodate the correlation between alternatives sharing the same money type and the correlation between alternatives sharing the same area type. Unlike a two-level NL structure, there is no need to make an ordering condition. [Papola. 2000] shows that a special CNL model can be derived for any given homoscedastic variance-covariance matrix. The general specification given in [Train. 2003] is used. Using different nests, α_{im} describing the allocation of alternative j to nest m, this gives

$$P_n = \sum_{m=1}^{M} \frac{\sum_{i \in S_M} (V_{jm})^{\lambda_m} V_{im})}{\sum_{l=1}^{M} (\sum_{j \in S_l} (V_{jl}))^{\lambda_l} \sum_{j=1}^{J} V_{jm}}$$

with V_{jm} as $\alpha_{jm} exp(U_{ij})^{(1/\lambda_m)}$.
This formulation with the extra summation in comparison with the NL formula ensures that each alternative can belong to each nest. In this stated formulation, two conditions exist for the allocation parameters, namely $0 \leq \alpha_{jm} \leq 1, \forall j, m$ and $\sum_{m=1}^{M} \alpha_{jm} = 1, \forall j$ [Hess et al. 2012]. According figure (4) the model estimates λ_m: λ_{Area}, and λ_{Money}, and α_{jm}: α_{Area} and α_{Money}.
First reason to use models such as NL and CNL is because these models are easy to use and additionally significantly reducing estimation cost. [Hess et al. 2012] Second reason is that the regular MNL model is limited to independence-of-irrelevant alternatives (IIA) property. This will overestimate the choice probabilities of the related alternatives and underestimate the probabilities of unrelated alternatives. [Qin et al. (2017)]

Appendix A shows an synopsis of all presented models with according equations and explanations. The table shows the model application with the corresponding parking choice model. With the use of M-MNL, Nested Logit with the focus on money or area, CNL and MM-MNL, parameters will be estimated. This is the first aim of a parking policy, to search for significant variables considering making a parking choice. Second objective is to calculate a certain subjective value of time for on-street parking or underground car parking.

Willingness-to-pay

If the model contains a cost or price variable, it is possible to analyze the trade-off between any variable and money. This reflects the willingness of the decision maker to pay for a modification of another variable of the model. Typical for parking choices is the value of time, which is the amount of money a traveler is willing-to-pay in order to decrease her travel time.

Let FEE_{ij} be the cost of alternative i for individual j. Let AT_{ij} and TD_{ij} be the values of the other variables of the model. Let $U_{ij}(FEE_{ij}, AT_{ij})$ and $U_{in}(FEE_{ij}, TD_{ij})$ be the values of the utility functions. Considered a scenario where the variable of interest takes the value $AT_{ij} + \delta_{ij}^{AT}$. Denoted by δ_{FEE} the additional cost that would achieve the same utility, that is

$$U_{ij}(FEE_{ij},AT_{ij}) = U_{ij}(FEE_{ij} + \delta_{ij}^{FEE}, AT_{ij} + \delta_{ij}^{AT})$$
$$U_{ij}(FEE_{ij},TD_{ij}) = U_{ij}(FEE_{ij} + \delta_{ij}^{FEE}, TD_{ij} + \delta_{ij}^{TD})$$

The willingness-to-pay, the increase the value of AT_{ij} and TD_{ij} is defined as the additional cost per unit of AT or TD, that is

$$\frac{\delta_{ij}^{FEE}}{\delta_{ij}^{AT}} \quad \text{and} \quad \frac{\delta_{ij}^{FEE}}{\delta_{ij}^{TD}}$$

Therefore after the calculation of the value of time, WTP corresponds to:

$$\frac{\delta_{ij}^{FEE}}{\delta_{ij}^{AT}} = \frac{\partial U_{ijt}/\partial AT_{ij}(FEE_{ijt}, AT_{ij})}{\partial U_{ijt}/\partial FEE_{ij}(FEE_{ijt}, AT_{ij})} = \frac{\beta_{AT}}{\beta_{FEE}}$$
$$\frac{\delta_{ij}^{FEE}}{\delta_{ij}^{TD}} = \frac{\partial U_{ijt}/\partial TD_{ij}(FEE_{ijt}, TD_{ij})}{\partial U_{ijt}/\partial FEE_{ij}(FEE_{ijt}, TD_{ij})} = \frac{\beta_{TD}}{\beta_{FEE}}$$

giving the marginal utilities of increases by one unit in access-time, destination time and fee cost respectively. Estimates of these marginal utilities are produced by formulating the model with the correct variables on the choice data used in the estimation. Important note is that both attributes used in the calculation should be statistically significant, otherwise an irrelevant WTP measure is calculated.

Because data consist heterogeneity, it is incompetent to calculate the WTP by using the earlier mentioned formulation. The WTP is extended to willingness -to-pay space model, such that the parameters are the marginal WTP for each attribute rather than the marginal utility. [Train and Weeks. 2005] [Sonnier, Ainslie, and Otter. 2007] The WTP-space allows random parameters. This WTP-space approach is useful for the parking choice model because it allows an estimation of the WTP heterogeneity distribution directly. Within this method, random draws for each parameter are taken from its distribution and their ratio is computed by simulation. By simulation the mean is founded. Usage of 100 correlated simulations of 10.000 draws. A key component of this method is that there are no assumptions required about the distribution of the parameter ratios. In particular, the ratio of two normally distributed variables may turn out to be an unstable distribution.

V. Model estimation

Using the estimation software BIOGEME [Bierlaire. 2003], using Windows 10, various models were estimated on the simulated choice data.[1] The following models are created: M-MNL model, two variants of the NL model, NGEV model, CNL model and the MM-MNL model. The M-MNL model is estimated to illustrate the effect of the other models in contrast to this base model. All models use the same distribution assumptions to estimate. The coefficients β_{AT} and β_{TD} are found to follow a Normal distribution. (Appendix B) Utilize the general-to-specific method, all models include the following variables.

- AT: access time to parking space.
- TD: access time to destination from parking space.
- FEE: parking fee.
- FEE(Low Income): interaction of socio-economic variable Low Income with the variable FEE (generated for PSP and PUP).
- FEE(Resident): interaction of the socio-economic variable Resident of the town with the variable FEE (generated for PSP and PUP).
- Age Vehicle ≤ 3: dummy variable with age of the vehicle is three year or less.

[1]Note that versions of Biogeme running on Windows may be slow. For models requiring a significant computational effort, it is recommended to use Mac OS X or Linux. (Bierlaire)

Table 4: Coefficients and statistical test for the M-MNL, NL, CNL and MM-MNL model.

	M-MNL model	NL-model Money	NL-model Area	NGEV model	CNL model	MM-MNL model
	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
Random parameters						
AT	-0.666* (-3.12)	-0.218* (-3.77)	-0.182* (-4.40)	-0.218* (-3.77)	-0.211* (-4.02)	-1.40* (-5.37)
FEE	-30.9* (-5.98)	-12.4* (-7.15)	-7.87* (-17.36)	-6.77* (-14.68)	-6.74* (-14.75)	-57.2* (-9.43)
Non-random parameters						
TD	-0.442* (-3.47)	-0.140* (-3.64)	-0.0592* (-2.99)	-0.140* (-3.64)	-0.091* (-3.23)	-0.953* (-5.45)
$Age_{Vehicle \leq 3}$	5.47* (3.82)	1.18* (5.01)	1.30* (4.17)	1.18* (5.01)	0.825* (3.64)	9.79* (2.87)
$Origin_{Internal(FSP)}$	-3.84* (-3.26)	-1.42* (-4.12)	-0.506* (-2.55)	-1.42* (-4.12)	-0.863* (-2.41)	-8.94* (-2.37)
β_{PSP}	16.3* (4.48)	2.73* (6.51)	3.56* (9.96)	2.73* (6.51)	4.15* (11.16)	20.7* (5.62)
β_{PUP}	33.6* (5.09)	7.42* (9.92)	8.70* (12.57)	7.42* (9.92)	7.56* (10.96)	62.5* (7.99)
Interaction terms [a]						
$FEE_{PSP(LowIncome)}$	-6.66* (-5.67)	-6.77* (-14.68)	-2.52* (-3.24)	-11.6* (-5.94)	-9.63* (-4.47)	-6.64* (-3.70)
$FEE_{PSP(Resident)}$	-10.9* (-7.61)	-11.6* (-5.94)	-10.5* (-7.68)	-12.7* (-7.84)	-11.7* (-6.99)	-11.4* (-6.04)
$FEE_{PUP(LowIncome)}$	-6.38* (-5.03)	-12.7* (-7.84)	-2.99* (-3.26)	-11.8* (-5.80)	-9.55* (-4.92)	-7.96* (-3.51)
$FEE_{PUP(Resident)}$	-9.06* (-6.55)	-11.8* (-5.80)	-8.31* (-6.31)	-12.4* (-7.15)	-10.8* (-6.37)	-9.81* (-4.95)
Standard deviations of parameter [b]						
$\sigma : AT$	1.95* (4.57)			0.0106 (0.05)		0.565* (2.10)
$\sigma : FEE$	6.32* (4.27)			0.0298 (0.05)		13.0* (2.48)
Specific NL-model parameter						
λ_{Paid}		2.98* (6.58)		2.98* (6.58)		
λ_{Street}			4.49* (5.44)			
λ_{Area}					5.28* (4.24)	
λ_{Money}					3.73* (3.39)	
α_{Money}					0.093* (5.23)	
Specific MM-MNL-model parameter						
w_{iq}						9.994* (5.20)
Standard deviations of latent random effects						
$\sigma : FSP$						9.83* (6.64)
$\sigma : PSP$						1.11*** (1.42)
$\sigma : PUP$						8.45* (8.27)
$Initital - loglikelihood :$	-1.731,41	-1.731,41	-1.731,41	-1.731,41	-1.731,41	-1.245,90
$Final - loglikelihood :$	-1.012,78	-1.012,54	-1.012,79	-1.012,54	-1.002,57	-446,04
$Likelihoodratio - test$	1.437,27	1.437,74	1.437,25	1.437,74	1.457,68	1.599,73
R^2	0.415	0.415	0.415	0.415	0.421	0.642
$Pseudo - R^2 :$	0.408	0.408	0.408	0.408	0.413	0.630
$Iterations :$	24	13	13	43	40	102
$Iteration\ time :$	17:46	01:06	01:07	11h 26:18	03:58	14h 33:38

[a] Interaction terms of random parameters in the utility function with socio-economic variables.
[b] The mixing distribution was Normal for all coefficients.
[*] All coefficients are tested for significance at the 5% level.
[**] All coefficients are tested for significance at the 10% level.
[***] All coefficients are tested for significance at the 20% level

- Origin (Internal FSP): dummy variable if the journey is internal or external to town, affects the free street parking choice.

To see differences between the various models. The variables are kept fixed among the different models. By default, the alternative-specific constants (ASC) for each alternative are included. Since the ASC's are always the first variables entering the model and only $J - 1 = 2$ ASC's are created. Alternative FSP is constant with all the generated estimations. For model MM-MNL several estimation runs were performed until a stable solution is found with all the parameters. For this particular simulation of the MM-MNL model 1.000 Halton draws are used.

The purpose of this research is to understand individual choices. To distinguish the elements of picking a certain parking choice. With these understandings a policy can be made to make efficient use of the limited space. Models are created to make a certain willingness to pay or in this case subjective value of time (SVT). As it was defined in the introduction, SVT is saving time in looking for a place to park and reaching the final destination. Various logit models will only use significant parameters. Detailed estimation results for all models are given in table (4).

First the main findings will be presented then the estimations per model will be analyzed separately. The analysis of the coefficients of the logit models provides the overall revealing results. The only variables presenting random variability are AT and FEE. This reveals that the population has a heterogeneous perception of the importance of both access time and fee charged. Note, every parameter is scaled across individuals. Second overall finding is that the variable with the most influential utility is FEE when choosing among the different available options: free on-street parking, paid on-street parking and underground multistory parking. In a preliminary estimation the mixing on several socio-economic variables were insignificant. Therefore some of these variables are disregarded in all logit models. The random parameter FEE has significant interactions with a few socio-economic variables. As a result the model can estimate the interaction terms with Low-income level and whether an individual is a resident of the study area. The models consist entirely of significant coefficients with the expected negative signs except the significant variable Age Vehicle ≤ 3.

If looked at the significant variable of the interaction between non-random and interaction variables. The variable considering when the journey is internal/ external to town in the free on-street parking (FSP) has a negative sign. This indicates that when the origin of the journey is within the area, it has a negative effect of the utility regarding FSP in comparison of PSP and PUP. Hence by moving the car, it creates a negative feeling to not be able to park the car at the same parking space. Second case, the age of the vehicle is regarded as a major feature in choosing a parking space. So the general age of the car in the area should be considered for creating a policy. Most vehicles are new (age ≤ 3), drivers are more willing to choose paid parking than drivers with older vehicles. Standard deviations of latent random effects are also significant.

Next part is looking at the coefficients at a deeper level. Observing differences between the base model M-MNL and various models with different assumptions. At first can be noted that all coefficients have the same sign but a different magnitude. The variable Age of Vehicle has a smaller value for models with the existence of nests, it is still significant however the effect is in multiple occasions smaller if compared to the MNL models. The same effect is for the variable Origin of journey FSP. For that reason these two socio-economic variables have some effect on the parking choice. However it is considerably smaller than the situation when the parking choice is estimated with a M-MNL model.

Second noticeable fact is that for all NL models the estimated λ are significant. Coefficient $alpha_{Money}$ with corresponding t-value 0.093 (5.23) for model CNL is presented in table (4). This creates the conclusion that the existence of nests is an assumption that might be of use for this particular data choice set. However, table (4) shows in addition to this conclusion that all estimated λ are out of range of the stated restriction of consistency $0 < \lambda < 1$. This means that the use of NL or CNL is inconsistent and might produce unreliable SVT. As justification for only computing the model of NGEV for the model NL-Money is that this model has a substantial computation time and similar conclusions are drawn. In addition, the interpretation of the estimates is questionable. [Hess et al. 2005] Even though the coefficients have other values the interrelation stays similar. Variable FEE stays the variable with the most influential effect among the alternative specific variables. In addition the ratio between the constant β_{PSP} and β_{PUP} are relatively the same.

Examining the test statistics rather than evaluating the coefficients. It is clear that for the models M-MNL, NL, NGEV, CNL the final log-likelihood and R^2 are relatively similar. This may conclude the fact that these models preform worse than the base model. However after examining the MM-

	PSP - AT (min)	PSP - AT: Value of time (FEE/hour)	PSP - AT: Value of time (FEE/hour): 90% CI		PSP - FEE (min)	PSP - TD: Value of time (FEE/hour)	PSP - TD: Value of time (FEE/hour): 90% CI	
WTP_{MMNL}	10,00	6,382	5,492	8,020	12,50	4.467	2,717	7.738
$WTP_{NL_{Area}}$	10,00	1,385	0,974	1,917	12,50	0,451	0,166	0,706
$WTP_{NL_{MONEY}}$	10,00	1,931	0,105	3,040	12,50	1,242	0,620	1,805
WTP_{NGEV}	10,00	1,845	0,611	3,245	12,50	5,158	2,491	7,367
WTP_{CNL}	10,00	1,876	1,200	2,819	12,50	0,814	0,399	1,292
WTP_{MM-MNL}	10,00	5.156	3.933	7.980	12,50	2.606	1.971	4.004

Table 5: Value of time (€/h) to access a parking space (AT) and to destination from parking space (TD) for various models for paid-street parking

	PUP - AT (min)	PUP - AT: Value of time (FEE/hour)	PUP - AT: Value of time (FEE/hour): 90% CI		PUP - FEE (min)	PUP - TD: Value of time (FEE/hour)	PUP - TD: Value of time (FEE/hour): 90% CI	
WTP_{MMNL}	5,00	6,063	5,218	7,619	10,00	4,244	2,578	7,352
$WTP_{NL_{Area}}$	5,00	1,316	0,926	1,821	10,00	0,429	0,157	0,671
$WTP_{NL_{MONEY}}$	5,00	1,835	0,995	2,888	10,00	1,180	0,589	1,715
WTP_{NGEV}	5,00	1,753	0,580	3,082	10,00	4,900	2,366	6,999
WTP_{CNL}	5,00	1,783	1,140	2,679	10,00	0,773	0,379	1,227
WTP_{MM-MNL}	5,00	5,070	3,868	7,847	10,00	2,476	1,873	3,804

Table 6: Value of time (€/h) to access a parking space (AT) and to destination from parking space (TD) for various models for paid-underground parking

MNL model other conclusions are formulated. Using this model improves the R^2, which is a measure of how well observed outcomes are replicated by the model based on the proportion of total variation of outcomes explained by the model. The M-MNL:R^2 was 0.415 and the MM-MNL:R^2 is 0.642, so this MM-MNL has a better fit for this particular data set.
Second, the most remarkable difference between M-MNL and MM-MNL is the drop of log-likelihood of the MM-MNL. It is significantly lower than the base model M-MNL. M-MNL: log-likelihood was -1.012,78 and M-MNL: log-likelihood is -446,04. Coefficient w_{iq} with corresponding t-value: 9.994 (5.20) for model MM-MNL is presented in table (6). The coefficient is significant for this data set. This indicates that the assumption of discrete variables explains a large part of unobserved heterogeneity.

Willingness-to-pay estimations

As stated in the paper, the second aim of this paper is calculating the subjective values of time (SVT). Interpreted in this case as users' willingness-to-pay (WTP) in order to save time looking for a place to park and for reaching the final destination. Table (5) and table (6) show the mean WTP evaluated for the models M-MNL, NGEV, CNL and MM-MNL with 95% -confidence intervals of the mean estimate. All calculations are divided into SVT for paid on-street parking and SVT for paid underground parking. The values depend on significant variables affecting SVT and computed by simulation. Using all the available information about the distribution of the time and cost parameters which are estimated by the models. For every model, the estimates presented in table (4) are used for the simulations.
Examining the WTP, all models have the similar pattern except the NGEV model. The order in every model is approximately $WTP_{AT} > WTP_{TD}$ only for NGEV model seems that this order is $WTP_{AT} < WTP_{TD}$ which is unexpected. This can be an outcome of the inconsistency of the λ created in the model. A substantial difference is the size of the coefficient between the models. It is

clear that M-MNL estimates are larger than all other estimates if it is only examined for WTP_{AT}. Important note is that models NL and CNL are created without random parameter which is only created in NGEV. There also exists a small difference between the WTP_{PSP} and WTP_{PUP} but this is difference is limited and not significant.
Although, NL, CNL and NGEV models have approximately the same log-likelihood and R^2, these models have different WTP estimates. This can be linked to multiple facts: existence of nests can drop estimations, scaling of certain parameters in the model, and the inconsistency of the λ. All these estimations depend on the same data but with different model specifications.

VI. Conclusion

The aim of this paper is to gain knowledge and understanding in the requirements of drivers. It is important to know the choice of a car driver to propose an efficient parking policy. For a certain parking policy to be more successful. It is essential to fully comprehend the factors influencing parking type choices. Creating of parking parks whether it is on the street or underground is a highly expensive plan. However, due to the growing number of car drivers it is necessary to create more space. An issue arises with the limited area space in certain cities. Multiple models were created based on the assumption of a logit model. The results shed a light on the importance of the parking fee and the time usage to discover where to park or to access the desired destination. To obtain these results, a survey is conducted to bring all socio-economic characteristics of drivers into account. With the models derived from the collected data for the case of the Spanish coastal town of Santoña, this city has the need of new parking space. Two main directions of conclusions are formulated. First conclusions are derived from the overall coefficients created by the models. Second part of the conclusion consists the discussion whether the presented logit models are useful to predict the willingness-to-pay for this particular data set. Third part is remarks and work that can be done in the future. After calibrations of the models, random parameters are defined for the variables parking fee and access time to the parking space. This assumption gives the model significant taste variations which suggests that these two coefficients are independent. This can be concluded after the impact of an individual is examined. This variation between fee and access time creates the possibility to establish subjective value of time (willingness-to-pay). Examining the coefficients that were estimated by all the models. Two concepts can be found, first the marginal utility of the access time to the parking space and destination time ratio are relatively equivalent for all models. Which means that drivers place the same importance on time finding a parking space for their car and the time it takes from a parking space to the destination. However, the main finding after estimations of the subjective values is that drivers are less likely to pay for destination time. For that reason it can be stated that time required for parking space searching appears to be more important than time required to reach the final destination.
Second main finding is that owners of new vehicles prefer paid parking space. This variable is significant for every models. Therefore, to create a viable plan of creating car parking the age of cars should be included. Once the driver makes the decision to choose for a paid parking space. It appears that drivers prefer to pay more for street parking even it is only a tiny difference. So eventually more money could be asked for parking on street if ceteris-paribus assumption holds.
Second part of this study is based on the fact that the M-MNL model is considered as the base model. All created models are tested on this base model and attempt to recreate or attain coefficient estimates in a model with a better fit. Eventually six different models are created: M-MNL, NL(Area), NL(Money), CNL, NGEV and MM-MNL. All these models have different assumptions. MM-MNL is the only model that is able to improve the fit of the model. Thus the assumption of discrete mixing distribution of unobserved heterogeneity is considered significant. This model has the same outcomes as the M-MNL model, yet with higher estimates.

Conclusion remarks

This study is based a stated choice set which is conducted at recession time in Spain. This could lower the willingness-to-pay, which questions the created subject value of time of its liability. To test the created model of correctness, the same model should be used on a different data set from different cities and different time areas. The overall model used for this study is based on a logit model. With some modifications eventually a set of seven models is created. For future works it is advised to create a model with a different perspective. A model could be created with a Probit model or with a Poisson model. This could be tested in the future. Simulations created for this study are established with a statistical program, Biogeme. This model in combination with Windows generates large computation time. This concluded that some models have the restriction of a maximum iteration number or computation time. Other programs could be used to create the same models with different stopping conditions. This could change the outcome of the model.

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Appendix A

Model	Equations	Explanation
M-MNL	$U_{ijt} = x_{ijt}^T \beta_i + \epsilon_{ijt}$	Utility of parking choice of car driver i alternatives j: FSP, PSP or PUP. x_{ijt} contains alternative specific variables with interaction with socio-economic variables. $t = 1$
	$P_{ni} = \int \frac{exp(x_{ni}\beta)}{\sum_{j=1}^{J} exp(x_{nj}\beta)} f(\beta\|\theta) d\beta$	Mixed logit choice probability where $f(\beta\|\theta)$ is the density function of β.
	$S_n = \sum_{n=1}^{N} ln \left\{ \frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T} \prod_{j=1}^{J} \left\| \frac{exp(x_{njt}\beta)}{\sum_{j=1}^{J} exp(x_{njt}\beta)} \right\| \right\}$	Simulated maximum log-likelihood function where R = number of Halton draws.
MM-MNL	$S_n = ln \left\{ \sum_{q=1}^{Q} w_{iq} \prod_{t=1}^{T} \prod_{j=1}^{J} \left[\frac{exp(x_{njt}\beta)}{\sum_{j=1}^{J} exp(x_{njt}\beta)} \right]^{y_{njt}} \right\}.$	The log-likelihood and probability with $Q = 2$. Latent class 1 uses the base utility function. Latent class 2 uses only the FEE and TD coefficients and is designed to exclude the coefficient AT. Car driver i belongs to class q with probability w_{iq}. h_i denotes a set of the incorporated socio-economic characteristics.
	$P_i(\theta) = \sum_{q=1}^{Q} w_{iq} \int \left\{ \prod_{t=1}^{T} \prod_{j=1}^{J} \left[\frac{exp(x_{njt}\beta)}{\sum_{j=1}^{J} exp(x_{njt}\beta)} \right]^{y_{ijt}} \right\} \cdot f(\beta\|\theta) d\beta.$	
	$w_{iq} = \frac{exp(h_i^T \gamma_q)}{\sum_{q=1}^{Q} exp(h_i^T \gamma_q)}$	
NL	$U_{ijt} = x_{ijt}^T \beta_i + Z_s \alpha + \epsilon_{ijt}$	α are estimated coefficients of Z_n nests. Z_{Money} with corresponding λ_{Free} and λ_{Paid}. Z_{Area} with corresponding $\lambda_{On-street}$ and $\lambda_{Underground}$. $t = 1$
	$P_n = \frac{exp(\alpha Z_n + \lambda_m \, ln \sum_{j \in n} exp(x_{nj}\beta))}{\sum_{j \in m} exp(\alpha Z_n + \lambda_j \, ln \sum_{j \in n} exp(x_{nj}\beta))}$	
CNL	$P_n = \sum_{m=1}^{M} \frac{\sum_{i \in S_M} (V_{jm})^{\lambda_m} V_{im})}{\sum_{l=1}^{M} (\sum_{j \in S_l} (V_{jl}))^{\lambda_l} \sum_{j=1}^{J} V_{jm}}$ with V_{jm} as $\alpha_{jm} exp(U_{ij})^{(1/\lambda_m)}$	α_{im} describing the allocation of alternative j: FSP, PSP or PUP to nests Area: On-street or Underground and Money: Free or Paid.λ_m: λ_{Area}, and λ_{Money}. Estimations of α_{jm}: α_{Area} and α_{Money}.

Table 7: Summary of the presented models.

Appendix B

Normal distribution:

$$\beta_k, i_r = \beta_k + \sigma_k w_k, i_r$$
$$w_k, i_r \sim N(0, 1)$$

where β_k and σ_k are estimated. Then, $\beta_{k,i} \sim N(\beta_k, \sigma_k^2)$. Since the domain of the normal distribution is $(-\infty, +\infty)$, assuming a given coefficient to follow a normal distribution is equivalent to making an a priori assumption that there is a proportion of individuals with a positive coefficient and another proportion with negative ones. For example, the proportion of positive coefficients can be computed as $\theta(b\beta_k/\sigma_{bk})$. The main disadvantage of the normal distribution is that it has infinite tails, which may result in some individuals having implausible extreme coefficients. If this is the case, the triangular or uniform distribution may be more appropriate. [Sarrias. 2016]