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# PARKING CHOICE AND SOCIAL INFLUENCE

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## Parking choice and the role of social influence

### 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 advices 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, sociodemographic 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 estimate 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.