Chapter 7
Conclusions and Discussion

In a conjoint choice experiment, respondents have to select their most preferred alternative from each of several choice sets. In a Multinomial Logit (MNL) context, all choices made by a single respondent are treated as independent observations, where it is assumed that a respondent starts each new choice set with a “clear” mind and does not remember which profiles or attribute levels he saw in earlier choice sets. So, it is assumed that there are no correlations between choice sets. Furthermore, most MNL-type models assume that choice alternatives within a choice set are uncorrelated. This means that an alternative cannot influence the utility of another alternative in the same choice set. However, these restrictions on the choice process of respondents are too restrictive in most cases.

The most important conclusion of this thesis follows from chapter 5, where a Multinomial Probit (MNP) model was specified that allows for correlations within and between choice sets. A parsimonious, identified, covariance structure was developed that, in addition, allows for predictions of new profiles not considered in the conjoint choice task, which is not possible with a general covariance structure in the MNP model. The resulting model was called the Random Coefficients (RC) Probit model. Several alternative models were developed to allow for different correlation structures, where for example one model accommodated correlations only within choice sets and not between. Both applications (on car data and coffee-makers data) in this chapter showed that only accounting for covariances within choice sets improves model fit. However, accounting also for correlations between choice sets (i.e., the RC specification) gives a further substantial improvement in model fit for both applications. Furthermore, holdout predictive fit improved with the RC model for the application where holdout choice results were collected. In addition, it was shown that for this latter application the RC specification leads to more realistic predictions in three market simulations; a product line extension, a product modification and the introduction of a me-too brand.

In chapter 6 similar results with respect to the RC model were found as in chapter 5. Since the RC model turned out to be the superior model in chapter 5, only this covariance MNP model was used in chapter 6. When the response time models of chapter 6 are ignored for the moment, the RC model also showed in this chapter substantial better model fit in two other applications compared to the results of a model (the Independent Probit model) that does not allow for correlations within and between choice sets. In one of these applications, the RC model in addition provided much better holdout predictive fit, and similar holdout predictive fit results as the IP model in the other application. However, in this latter case, the holdout task was substantially different from the main conjoint choice task, which may very well have influenced the predictive performances of the models in this application.

In chapter 5, the results of the RC model were hypothesized to be caused by context effect. Respondents do remember what profiles and attribute levels they saw in earlier choice sets and this influences their choices in later choice sets. Furthermore, within a choice set, profiles can indeed influence the attractiveness of other profiles, especially when these profiles are close substitutes. The estimated covariance parameters in the RC model give an indication which attributes or levels are responsible for these context effects. Chapter 5 also showed that it is important to allow each attribute to contribute to the covariances. Although only specifying covariance parameters for brand attributes improves the estimation and predictive results, allowing covariance parameters for all attributes gives substantially better results.

Finally, chapter 5 showed that the size of the choice set seems to play a role in the performance of the RC model. When more alternatives are present in a choice set, the respondent has better sight on the range of attribute levels in the experiment and ignoring context effects between choice sets is (relatively) less severe compared to the situation that there are only a few choice alternatives present in a choice set and respondents cannot see the full range of all attribute levels in the complete experiment from only one choice set. The size of the choice sets in the holdout task also seems to be important in that respect. However, further research should be conducted to investigate what the optimal size of (holdout) choice sets should be, to minimize possible context effects.

A practical limitation of using MNP models is the necessity to use simulation techniques to obtain the choice probabilities, since the MNP model is too complicated to calculate these probabilities analytically. Because these simulation techniques are rather time consuming, estimation of the RC model on a personal computer may in fact take several days for conjoint choice experiments in witch many respondents, choice sets, attributes or levels are used. However, because of the rapid improvement in computer speed, this disadvantage of conjoint MNP models probably will disappear in the near future.

Chapter 4 showed that, when a no-choice alternative is present in the design, care must be taken in specifying the design matrix of the conjoint choice experiment. When attributes are coded with effects-type or linear coding, the presence of a no-choice alternative can influence the estimates of the part-worths of these attributes. This is caused by the fact that a no-choice alternative is most often coded as a series of zeros in the design matrix. However, these zeros act as real levels of attributes in a design with effects-type or linear coding and lead to misleading estimates of the attributes' part-worths. Therefore, a constant has to be added in the design matrix to set the level of utility of the no-choice alternative. It was shown that adding such a constant may be preferable to using a Nested Logit formulation, and this constant was specified throughout the remainder of the thesis.

Chapter 6 showed that the time needed by respondents to make a choice contains information about the certainty of that choice. Two situations are possible. A fast choice could indicate an easy choice and a slow choice a difficult choice, but alternatively, a fast choice could indicate a not well though-out choice and a slow choice a well though-out choice. The RC model developed in chapter 5 was extended to account for both these situations. The results in chapter 6 show, first of all, that including response times in estimation further improves estimation fit and holdout predictive fit. Furthermore, it seems to depend on the product category, and respondents' involvement with that product category, whether a quick choice is a "good" or a "bad" choice. When respondents are involved with the product category, and therefore probably have strong initial preferences about brands in the experiments, they can quickly retrieve information about these brand from memory and make a certain choice without using much time. In case brand names give no clear initial preference for a profile, respondents have to use more time to select their preferred alternative from the choice set, and in this situation a long response time indicates a certain choice.

To model these possible effects of response time on choice, in the applications of chapter 6 only one additional parameter was estimated, which sign indicates whether fast or slow choices lead to certain choices. In further research, one may allow for respondents differing in the effect of their response time on the certainty of their choice. Within one conjoint choice experiment, there may be respondents that have clear pre-specified opinions on brands (or on other attributes) in the experiment and, hence, are able to make fast and certain choices, while others may need more time to evaluate the profiles, in case they do not have initial preferences for brands (or other attributes) and make slow and certain choices. This would imply that for each individual respondent a time-parameter needs to be estimated which may lead to a too complicated model. Further research should indicate whether this can be done. Alternatively, several segments of respondents may be constructed that show similar response time and choice behavior. One segment may produce fast certain choices and another segment may produce slow certain choices. Additionally, there may be another segment showing a more random behavior with respect to the relation between response time and certainty of a choice. Again, further research should indicate whether these kind of segments can be found in a conjoint choice experiment.

Several other issues need to be investigated also. The findings of chapter 5 that local and background contrast effects play a role in respondents' choices should be studied more closely. The importance of these effects in relation to the number of attributes, choice sets, levels of attributes and alternatives could be given additional attention. The attribute level effect found in the literature could be related to these context effects. Furthermore, the involvement of respondents and their knowledge on the product category, as well as the product category itself, could also influence the importance of these context effects. These issues could of course also be related to the response time effect of chapter 6 and to the importance of the presence of a no-choice alternative in the choice set of chapter 4. The influence of all these factors on the choice, and hence ultimately on the parameters of interest, should be minimized or at least be accounted for. Research should be done on the optimal design for conjoint choice experiments analyzed with Probit models, since optimal designs are not yet available. The results obtained from such an optimal conjoint experiments should lead to managerial more insightful information on the product in question. In addition, one needs much research on many product categories, designs, etcetera to investigate how generalizable findings from context effects, response time effects and the no-choice option are with different product categories. Finally, the SML method explored in this thesis as optimization methods should be compared with Bayesian estimation using the Gibbs sampler.

In short, the main conclusion from this thesis is that the assumptions underlying MNL-type of models are too restrictive for conjoint choice experiments and do not represent the way how consumers choose products in real-life. Especially assuming that choices from one respondent are independent over choice sets is too restrictive. MNP-type models therefore should be used to account for correlations between choice sets.

Furthermore, in most conjoint choice experiments only the observed choices are used in estimating the part-worths, but this thesis showed that in addition using information from the observed response times in model estimation leads to better model and predictive fit.