Chapter 1
Introduction

In marketing, one is interested in how consumers react to products in the marketplace. The marketeer wants to know what makes a product attractive and what price consumers are willing to pay for a product, or for a specific feature of a product. Conjoint analysis is a technique to measure preferences or utilities of consumers for certain characteristics of products or services. Based on the results of a conjoint experiment, a wide range of marketing questions can be solved. A conjoint study, for instance, may answer the question what features of a product are preferred by consumers and what price they are willing to pay for these features. Furthermore, the introduction of a new, or modified, product will have consequences for the market shares of brands in the market. With conjoint analysis a prediction can be made how these market shares will change as a result of that introduction.

In conjoint analysis respondents are asked to indicate their preference for a certain product. For that purpose, products are defined on a limited number of key attributes, each with a limited number of levels. Based on these attributes and levels a set of (often hypothetical) products (called profiles) are constructed. The traditional way to measure the preferences of respondents for these profiles is to let them rank the total set of profiles or to let them rate each of them, for instance on a 0-100 scale. However, ranking and rating of products is not how respondents normally act in the real marketplace. In the conjoint choice approach respondents do not have to give a score to all profiles, including the non-preferred ones, but they have to choose their most preferred product from a small set of profiles. In this case, the total set of profiles is divided into several smaller choice sets from which respondents have to choose one product. Since this way of selecting a preferred product is much closer to the way people select products in the real marketplace, conjoint choice experiments have become
very popular. Chapter 2 discusses the general elements in conjoint analysis, as well as the “classic” approach and the choice approach in conjoint analysis to measure preferences.

Once choice data are collected, they need to be analyzed. The models used for that purpose, conjoint choice models, fall within the class of random utility choice models, in which each alternative is selected with a certain probability. Most often the Multinomial Logit model is used to analyze conjoint choice data. The major advantage of this model is its simple form for the choice probabilities. However, the Logit model has some serious limitations that may make it less suitable for the conjoint choice approach. One of these limitations is the so-called IIA property that states that the probability to select an alternative over a second alternative must be independent of the presence of whatever other alternatives in the choice set. Furthermore, the Logit model assumes that choice observations are independent of each other. This implies that several choices made by one respondent are treated as independent observations. This assumption and the IIA property probably do not hold in practice. Choice alternatives that are closely related to each other may influence each others choice probability in a way not captured by the choice design. Furthermore, when respondents make a choice from a specific choice set, they remember what profiles, attributes and levels they saw in earlier choice sets, which may clearly influence their choice in the current choice set. They may also have some specific opinions about certain attributes or levels, which may carry over from choice set to choice set and therefore makes choices from various choice sets dependent on each other.

A model that is not based on such restrictive assumptions as the Logit model is the Multinomial Probit model. However, the use of this model has been hampered by its structure, which was too complicated to be applicable in practice. Since the 90s, the practical limitations of the Probit model have been solved by the introduction of simulation techniques to obtain the choice probabilities, which were impossible to calculate previously in many instances. Chapter 3 describes the random utility model as well as the
Logit and Probit model with their (dis)advantages in a general context. Furthermore, the simulation techniques to obtain the choice probabilities in the Probit model and some studies in the marketing literature that have used the Probit model will be discussed.

One advantage of the choice approach in conjoint analysis with respect to the “classic” approach is that in choice sets the option not to choose can be introduced, which makes the task even more realistic to respondents. In many conjoint choice applications such a no-choice option is included. However, implementing this alternative in a conjoint choice design is not straightforward. Chapter 4 discusses several ways to model the “no-choice” alternative. In this chapter only the Logit model for conjoint choice experiments is considered, despite its restrictive assumptions, since for the purpose of this chapter this simple model suffices to make our point. An application shows that a no-choice constant has to be added in the design matrix to set the level of utility for the no-choice option.

In chapter 5 a Probit model is developed for the conjoint choice approach. This model no longer assumes that choice observations for the same respondent are independent. In order to make the Probit model suitable for the conjoint choice approach a specific parsimonious and identified structure is imposed on the covariance matrix. Several versions of this conjoint Probit model are developed. Two applications show that relaxing the independence assumption within and between choice sets improves model and predictive fit substantially. Furthermore, it is shown that market simulations also differ substantially depending on whether independence between choice sets or within and between choice sets is no longer assumed.

In a choice experiment the time a respondent needs to make his choice may give essential information about the certainty of that choice. However, the effect of the response time can go in two directions. A quick choice could indicate an easy choice and hence a certain choice. On the other hand, it may indicate a not well thought-out choice, and hence an uncertain choice. Similarly, a choice taking much time may indicate a well thought-
out and hence certain choice. On the other hand, it may indicate the situation that a respondent does not know what to choose and selects just anything eventually and hence makes an uncertain choice. In chapter 6, the Probit model of chapter 5 is extended to account for both of these situations. In effect, the covariance matrix of the Probit model is scaled using the response times. A certain choice is related with an extreme choice probability (i.e., close to 1) and low (co)variances, while an uncertain choice is related with a choice probability close to guessing and therefore with high (co)variances in the covariance matrix of the Probit model. In two applications it is shown that it depends on the strength of the brands and the types of attributes in the experiment whether a fast or slow response indicates a certain or uncertain choice. Most important, however, chapter 6 shows that the inclusion of response times in the Probit model improves in-sample fit and holdout predictive fit. Furthermore, this chapter shows that the observed “crude” response times need to be adjusted to account for order effects over choice sets. A “filtered” response time is constructed that is used to scale the covariance matrix of the Probit model.

Finally, chapter 7 gives the conclusions and directions for further research and the appendix to this thesis gives a description of the CONPRO program that is used to obtain most estimation results in the applications.