Multimodal and Nested Preference Structures in Choice-Based Conjoint Analysis:

A Comparison of Bayesian Choice Models with Discrete and Continuous Representations of Heterogeneity

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Vorwort

> „So eine Arbeit wird eigentlich nie fertig, man muß sie für fertig erklären, wenn man nach Zeit und Umständen das Möglichste getan hat.“ (Johann Wolfgang von Goethe)

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AIC	Akaike’s information criterion
ANOVA	analysis of variance
BIC	Bayesian information criterion
BS	Brier score
CAIC	consistent Akaike’s information criterion
CBC	choice-based conjoint
cf.	confer
DPM	Dirichlet Process Mixture
DPP	Dirichlet Process Prior
e.g.	exempli gratia (Latin) = for instance
etc.	et cetera (Latin) = and so forth
et al.	et alia (Latin) = and others
GEV	generalized extreme value
HB	hierarchical Bayes
i.e.	id est (Latin) = that is
IHR	in-sample hit rate
IIA	Independence of Irrelevant Alternatives
iid	independent and identically distributed
IIN	Independence of Irrelevant Nests
LC	latent class
LL	log-likelihood
LML	log marginal likelihood
MAE	mean absolute error
MCMC	Markov Chain Monte Carlo
ML	marginal likelihood
MNL	multinomial logit
MNP	multinomial probit
MoN	mixture-of-normals
MXL	mixed logit
NMNL	nested multinomial logit
OHR	out-of-sample hit rate
OLS	ordinary least squares
PC	percent certainty

RLH	root likelihood
RMSE	root mean square error
RMSE(V)	root mean square error between “true” and predicted deterministic utilities
RUM	random utility model
SpS	Spherical score
vs.	versus
w.r.t.	with respect to
%TrueBetas	percentage of “true” part-worth utilities that lie in the corresponding 95 % credible intervals of the draws

1 Introduction

In 1971 Green and Rao introduced conjoint analysis in the marketing literature. Since then, conjoint analysis has become a widely applied marketing tool for measuring and analyzing consumer preferences. The commercial use of choice-based conjoint (CBC) analysis, the most widely used variant of conjoint analysis, goes back to Louviere and Woodworth [1983] and became increasingly popular in the 1990s. The main advantage of CBC in contrast to traditional conjoint analysis is that preferences for attributes and attribute levels are collected through choice decisions rather than by ranking or rating competing alternatives. The primary reason for the increasing dominance of the CBC approach over time has been that simulating choice decisions closely mimics the real choice behavior of consumers. Precisely, in CBC studies respondents are asked repeatedly to choose their preferred alternative from sets of several offered alternatives (choice sets). The CBC approach is widely used in practice for pricing and product design decisions, for product positioning objectives as well as for market segmentation.

The simplest choice modeling approach to analyze CBC data would be to estimate an aggregate (simple) multinomial logit (MNL) model. However, the aggregate MNL model does not account for any consumer heterogeneity. It assumes homogeneous preferences across consumers and carries the danger to model an average consumer who actually does not exist in the real market. Because of that researchers pushed the development of advanced modeling approach to address heterogeneous consumer preferences, leading to conjoint choice models with different representations of consumer heterogeneity. The marketing literature distinguishes between continuous and discrete representations of consumer heterogeneity [Wedel et al. 1999; Wedel and Kamakura 2000; Wedel and Kamakura 2002]. On the one hand, the finite mixture MNL approach, firstly proposed by Kamakura and Russell [1989] for the analysis of panel data, was applied to CBC data [Kamakura et al. 1994; DeSarbo et al. 1995; Moore et al. 1998]. The finite mixture MNL model, also known as latent class (LC) MNL model, divides the market into a manageable number of homogeneous segments with different preference and elasticity structures. On the other hand, Allenby et al. [1995], Allenby and Ginter [1995] and Lenk et al. [1996] published milestone articles for the application of models with continuous representations of heterogeneity to CBC data using hierarchical Bayesian (HB) estimation techniques. Using a normal distribution became the standard procedure to represent preference heterogeneity, referred to as HB-MNL model in the following [e.g., Chiang et al. 1998; Wedel et al. 2000; Andrews et al. 2008; Gilbride and Lenk 2010; Kurz and Binner 2016; Aribarg et al. 2017; Voleti et al. 2017; Akinc and Vandebroek 2018; Hein et al. 2019a, 2019b].

The HB-MNL model allows the estimation of part-worth utilities at the individual respondent level, even when there are insufficient degrees of freedom [Lenk et al. 1996]. Although the “true” distribution of consumer heterogeneity is often continuous, the concept of the existence of a discrete number of market segments is more attractive and easier to understand especially from a managerial point of view [e.g., Tuma and Decker 2013]. Whereas discrete approaches often over-simplify the concept of heterogeneity distributions, continuous approaches especially in form of an assumed single normal distribution may not be flexible enough to reproduce consumer heterogeneity (distribution of response coefficients) appropriately [Allenby and Rossi 1998; Rossi et al. 2005; Rossi 2014]. Further, the thin tails of a normal distribution tend to shrink unit-level estimates toward the center of the data. This shrinkage, especially in multimodal data settings, could mask important information (e.g., new or different market structures) [Rossi et al. 2005].

As a generalization of the finite mixture model, the mixture-of-normals (MoN) approach avoids the drawbacks of both the finite mixture model and the HB model, respectively [Lenk and DeSarbo 2000]. In a discrete choice situation, a mixture of several multivariate normal distributions representing consumer heterogeneity is applied to a choice model (e.g., the MNL model) here [Allenby et al. 1998]. Using a sufficient number of components, any desired heterogeneity distribution can be approximated using a MoN (e.g., heavy-tailed, multimodal and skewed distributions) [Rossi et al. 2005; Train 2009]. In an empirical application, Allenby et al. [1998] found strong support for the MoN-MNL approach regarding model fit and predictive performance in comparison to LC-MNL and HB-MNL models.

The Dirichlet Process Mixture (DPM) MNL model allows for a countable infinite mixture of normal components by supplementing the component parameters with additional priors [e.g., Gilbride and Lenk 2010]. The DPM-MNL model also draws the part-worth utilities from continuous distributions (in this thesis from a mixture of multivariate normal distributions), where population means and covariances follow a Dirichlet Process. In other words, the continuous distributions are centered around the discrete part-worth utilities of the Dirichlet Process Prior (DPP) [e.g., Voleti et al. 2017]. With a DPP the researcher is able to model heterogeneity of an unknown form [Rossi 2014]. The application of DPPs and the usage of DPM-MNL models in in the context of CBC data has been proposed only recently [Voleti et al. 2017]. An advantage of the DPM-MNL model is that the number and composition of components are determined as a result a posteriori. Post hoc procedures [e.g., Andrews and Currim 2003] to find the optimal number of segments − like in LC-MNL or MoN-MNL models − are no longer required [Kim et al. 2004; Voleti et al. 2017].

However, statistical findings on the comparison of these models are ambiguous. Moore et al. [1998], Allenby et al. [1998], Pinnell [2000], Natter and Feurstein [2002] and Moore [2004] for example showed that HB models outperformed aggregate models or LC models applied to CBC data. Other studies showed that HB models did not lead to any substantial improvement [Pinnell and Fridley 2001; Andrews et al. 2002a]. In an empirical comparison on the basis of eleven CBC data sets Voleti et al. [2017] found out that DPM-MNL models had a better predictive validity than common choice models with either a discrete or a continuous representation of consumer heterogeneity. Importantly, on average, the HB-MNL model provided the second-best predictive performance in the study of Voleti et al. [2017] whereas the empirical findings of Allenby et al. [1998] speak in favor of the MoN-MNL model, as mentioned above (compared to LC-MNL and HB-MNL models).

While the previously cited articles mainly focused on the comparison of different extensions of the standard MNL model to capture preference heterogeneity, the marketing literature also addresses further limitations of the (simple) MNL model. One of the major limitations of the MNL model is its Independence of Irrelevant Alternatives (IIA) property. The IIA property states that the ratio of choice probabilities of two alternatives remains constant independent of other available alternatives and hence implies proportional substitution patterns as well as constant cross-elasticities across alternatives. Because in real choice situations the ratio of choice probabilities of two alternatives should be dependent of the appearance of other alternatives (e.g., if competing brands belong to different price-quality tiers), these constant cross-elasticities can lead to biased predictions. The most famous example illustrating this anomaly is the "red-bus/blue-bus paradox" [Debreu 1960; Hausman and Wise 1978; Ben-Akiva and Lerman 1985]. It is well-known that accounting for random taste variation in extensions of the standard MNL model can strongly soften the IIA property [Brownstone and Train 1998; Train 2009; Elshiewy et al. 2017]. A different approach to soften the IIA property is the nested multinomial logit (NMNL) model. The NMNL assumes that consumers follow a sequential or hierarchical decision making process, that way enabling a partial relaxation of the IIA property. Here, the ratio of choice probabilities between two alternatives within a predefined nest (subset with similar alternatives) is independent of the availability of other alternatives so that the IIA property holds within nests. Accordingly, the ratio of choice probabilities of two alternatives in different nests can depend on other alternatives, which belong to either nest containing these alternatives. While the simple MNL model is fully prone to the IIA property over all alternatives, the standard NMML model only suffers from the IIA property over alternatives within each nest [Ben-Akiva and Lerman 1985]. Ailawadi et al. [2007] combined both approaches to relax the IIA, i.e. they accounted for random taste variation and considered nested structures. A heterogeneous NMNL model (i.e., accounting for random taste variation) was proposed to analyze promotion-induced consumer stockpiling in an integrated brand choice / purchase incidence / purchase quantity model. In particular, the purchase incidence and brand choice parts were treated in the nested logit framework, assuming that a household chooses a specific brand on her/his shopping trip given that the household decided to make a purchase in the product category considered. Model estimation was performed in a frequentist setting using simulated maximum likelihood [Train 2009]. Nevertheless, the number of studies exploring or applying a heterogeneous NMNL model is limited in the marketing literature, especially in the context of CBC analysis.

In the present thesis, we focus on the comparison of Bayesian choice models with different representations of heterogeneity (discrete vs. continuous) and with different substitution patterns. Using both synthetic data and empirical data, we compare simple MNL, LC-MNL, HB-MNL, HB-NMNL, MoN-MNL and DPM-MNL models with respect to parameter recovery, goodness-of-fit and predictive accuracy. In particular, we focus on multimodal preference structures as well as on nested preference structures and want to investigate how robust the HB-MNL model works under these conditions. Therefore, the statistical performance of the HB-MNL is of special interest (as compared to the other choice models).

Related studies in the context of CBC analysis and model comparisons are summarized in table 1. The HB-MNL as well as the LC-MNL model represent the state-of-the-art approaches for analyzing CBC analysis. Both models are implemented in Sawtooth Software [Sawtooth Software 2016, 2017]. In particular, the estimation of part-worth utilities at the individual respondent level using HB-MNL models enjoys great popularity in marketing theory and practice. The most recent publications here dealt with the prior settings of HB-MNL models [Akinc and Vandebroek 2018; Hein et al. 2019b]. It turned out that the prior settings of the HB-MNL model are very robust as a rule but can have a big impact on the estimates under special conditions. Further, Voleti et al. [2017] compared advanced choice models and reported that DPM-MNL models outperform the more established choice models in predictive validity. However, the authors only examined the predictive capabilities of these models. This raises the question whether the empirical findings of Voleti et al. [2017] can be generalized in terms of predictive accuracy, and how the DPM-MNL models perform with regard to goodness-of-fit and especially parameter recovery. On the contrary, in marketing contexts NMNL models have been mainly applied to investigate sequential or hierarchical decision making processes (e.g., purchase incidence-brand choice models) [Elshiewy et al. 2017]. Empirical studies by e.g. Bhat

[1997] or Hoffman and Duncan [1988] showed that an appropriate nested structure can lead to a better model performance and to a more sensible model interpretation. This raises the further question whether an additional relaxation of the IIA property by accommodating heterogeneity in the NMNL model has further advantages over the HB-MNL model.

To the best of our knowledge, there are no previous Monte Carlo studies related to conjoint choice data that have systematically explored and compared the performance of the simple MNL, LC-MNL, HB-MNL, MoN-MNL and DPM-MNL models for multimodal preference structures, or the performance of the HB-MNL and HB-NMNL models for nested preference structures.

Table 1: Selected studies concerning models of heterogeneity related to this work

Paper	***Field of research***	***Data Basis***	***Models***	***Main findings***
Akinc and Vandebroek [2018]	Logit choice models	Synthetic data	• HB-MNL models	• The default prior settings for the covariance matrix in many software packages can lead to implausible results • Prior distributions other than the inverse Wishart are more flexible
Allenby et al. [1998]	Logit choice models	Empirical data	• Aggregate MNL models • LC-MNL models • HB-MNL models • MoN-MNL models	• Consideration of within- and between-component heterogeneity is substantial • LC-MNL models do not appear to approximate the market accurately
Andrews et al. [2002a]	Logit choice models	Synthetic data	• Aggregate MNL models • LC-MNL models • HB-MNL models	• No differences between HB-MNL and LC-MNL models in terms of parameter recovery and predictive accuracy • In an extreme scenario with few observations, the LC-MNL model performs better • HB models fit the data better • Models are quite robust to violations of the respective model assumptions
Andrews et al. [2002b]	Metric conjoint analysis models	Synthetic data	• Aggregate models • Finite mixture models • HB models • Individual-level conjoint models (ordinary least squares (OLS) regression)	• No differences between HB models and finite mixture models in terms of parameter recovery and predictive accuracy • HB models fit the data better • Individual-level conjoint models overfit the data • Models are quite robust to violations of the respective model assumptions

Paper	***Field of research***	***Data Basis***	***Models***	***Main findings***
Andrews and Currim [2003]	Finite mixture logit models	Synthetic data	• Finite mixture logit models	• Akaike's information criterion with a penalty factor of three works best in determining the number of latent segments
Bhat [1997]	Logit choice models	Empirical data	• Aggregate MNL models • NMNL models (with and without individual log-sum parameters)	• Not accounting for covariance heterogeneity (individual log-sum parameters) leads to an inferior model fit and also to biased estimates • Both NMNL models show a better fit than the aggregate MNL model
Burda et al. [2008]	Logit choice models	Synthetic data/Empirical data	• DPM models • HB-MNL models	• DPM models are more appropriate to uncover skewed and multimodal preference structures
Conley et al. [2008]	Instrumental variables models	Synthetic data/Empirical data	• Bayesian semi-parametric approach with a Dirichlet Process Prior • Classical (Bayesian) methods (e.g., OLS or two stage least squares methods, Bayesian procedure assuming normal errors)	• The use of a Dirichlet Process Prior outperforms classical methods or standard Bayesian procedures
DeSarbo et al. [1995]	Choice-based conjoint analysis models	Empirical data	• Aggregate MNL models • LC-MNL models • Aggregate MNL models applied to priori determined segments	• LC-MNL model is preferable in terms of fit • Aggregate MNL models applied to a priori determined segments and aggregate MNL models have a similar fit • Congruence between LC classification of respondents and a priori segmentation is only small

Paper	*Field of research*	*Data Basis*	*Models*	*Main findings*
Elshiewy et al. [2017]	Logit choice models	Empirical data	• Aggregate MNL models • NMNL models • LC-MNL models • HB-MNL models • MoN-MNL models	• NMNL and aggregate MNL parameter estimates are very similar • NMNL model fits the data marginal better compared to an aggregate MNL model • Difficulties in determining a reasonable substitution pattern (NMNL model) • LC-MNL model fits the data better than an aggregate MNL or a NMNL model • MoN-MNL model clearly identifies a multimodal distribution
Hein et al. [2019a]	Choice-based conjoint analysis models	Synthetic data	• HB-MNL models	• For “simple” CBC settings HB estimation is quite robust • For “complex” CBC settings (little information on an individual level and a high number of part-worth utilities) parameter recovery and predictive capabilities strongly suffer under certain conditions • More attributes can be used in CBC studies than previously thought • Number of choice tasks and sample size can be kept rather small
Hein et al. [2019b]	Choice-based conjoint analysis models	Synthetic data	• HB-MNL models	• The prior degrees of freedom only have a little effect on the model performance • Overfitting problems occur with an increase of the prior variance • Predictive accuracy is not markedly affected when increasing the prior variance

Paper	*Field of research*	*Data Basis*	*Models*	*Main findings*
Hoffman and Duncan [1988]	Logit choice models	Empirical data	• Aggregate MNL models • NMNL models	• Both models differ substantially in the estimated part-worth utility structure • High degree of substitutability between alternatives belonging to the same nest
Kamakura et al. [1994]	Logit choice models	Synthetic data/Empirical data	• Aggregate MNL models • LC-MNL models with and without consumer background variables	• LC-MNL models with consumer background variables are able to recover "true" segment membership structures • LC-MNL models lead to a better fit and predictive accuracy compared to aggregate MNL models • Differences between LC-MNL models with and without consumer background variables are marginal
Keane and Wasi [2013]	Logit choice models	Empirical data	• Mixed MNL models (normal mixing distribution) • LC-MNL models • MoN-MNL models • Generalized MNL models • Scale heterogeneity MNL models • Mixed MNL models with theoretical sign constraints	• MoN-MNL models, mixed MNL models with theoretical sign constraints and generalized MNL models outperform mixed MNL and LC-MNL models in terms of fit
Kim et al. [2004]	Logit choice models	Synthetic data/Empirical data	• DPP-MNL models	• A large number of components must be used to represent the distribution of heterogeneity • "Real" number of components is far smaller than the estimated number of components

Paper	*Field of research*	*Data Basis*	*Models*	*Main findings*
Krueger et al. [2018]	Logit choice models	Synthetic data/Empirical data	• DPP-MNL models • Aggregate MNL models • Two mixed MNL models (different mixing distributions) • LC-MNL models	• DPP-MNL models outperform LC-MNL and mixed MNL models in terms of fit and predictive accuracy • Aggregate MNL models perform worst • DPP-MNL models can capture differently shaped distributions
Li and Ansari [2014]	Logit/Probit choice models	Synthetic data/Empirical data	• DPM models • Multinomial probit models with multivariate normal prior assumptions	• DPM models outperform models with multivariate normal prior assumptions
Moore [2004]	Metric conjoint analysis models/choice-based conjoint analysis models	Empirical data	• OLS metric conjoint models • HB metric conjoint models • LC metric conjoint models • HB-MNL models • LC-MNL models • Aggregate models (metric and discrete models)	• HB models have a better predictive accuracy than LC or aggregate models • Metric conjoint analysis (HB and OLS) has the best predictive accuracy
Moore et al. [1998]	Metric conjoint analysis models/choice-based conjoint analysis models	Empirical data	• OLS metric conjoint models • HB metric conjoint models • LC metric conjoint models • HB-MNL models • LC-MNL models • Hybrid choice models • Aggregate models (metric and discrete models) • Models estimated for a priori determined segments (metric and discrete models)	• HB models (metric and discrete models) have the highest out-of-sample hit rates
Natter and Feurstein [2002]	Choice-based conjoint analysis models	Empirical data	• Aggregate MNL models • LC-MNL models • HB-MNL models	• HB-MNL models have a better out-of-sample hit rate (internal validity) than MNL and LC-MNL models • Models are similar in terms of external validity

Paper	***Field of research***	***Data Basis***	***Models***	***Main findings***
Otter et al. [2004]	Metric conjoint analysis models	Synthetic data/Empirical data	• HB models • LC models • MoN models (Empirical data sets)	• Continuous preference distribution: 1) HB models dominate LC models, 2) Number of segments depends on the sample size • Discrete preference distribution: LC models dominate HB models • MoN model with two components performs best in an empirical data set • Differences between MoN model and HB model are marginal
Pinnell [2000]	Choice-based conjoint analysis models	Empirical data	• Aggregate MNL models • HB-MNL models	• HB-MNL models have the highest out-of-sample hit rates
Pinnell and Fridley [2001]	Choice-based conjoint analysis models	Synthetic data/Empirical data	• Aggregate MNL models • HB-MNL models	• In partial-profile experiments aggregate MNL models outperform HB-MNL in some data sets (predictive accuarcy)
Voleti et al. [2017]	Choice-based conjoint analysis models	Empirical data	• Aggregate MNL models • LC-MNL models • HB-MNL models • MoN-MNL models • DPP-MNL models • DPM-MNL models	• DPM-MNL models are superior to common choice models (predictive accuracy) • HB-MNL models show a good performance
Vriens et al. [1996]	Metric conjoint analysis models	Synthetic data	• Four two-stage conjoint segmentation methods • Five integrated conjoint segmentation methods	• Integrated segmentation models outperform two-stage segmentation models • LC models perform best
Wirth [2010]	Choice-based conjoint analysis models	Synthetic data/Empirical data	• Best-Worst-CBC models • HB-MNL models • Non-Bayesian approach by Louviere et al. [2008b]	• HB-MNL models perform well • Best-Worst-CBC models outperform the HB-MNL models in terms of parameter recovery and predictive validity • Louviere et al. [2008b] approach works well when considering share predictions

The present thesis will show that the HB-MNL model appears to be highly robust against violations in its assumption of a single normal distribution of consumer preferences. HB-MNL models are able to uncover multimodal preference structures and to handle different similarities between alternatives within nests similarly well or better compared to other (advanced) choice models. Incorporating of both more flexible prior distributions to represent consumer heterogeneity and more parameters to capture some amount of correlation between alternatives is not always beneficial.

Objectives and outline

In chapter 2, the main focus lies on the comparative performance of the HB-MNL versus the HB-NMNL for nested preference structures. Although accounting for random taste variation in choice models can strongly soften the IIA property [e.g., Brownstone and Train 1998; Elshiewy et al. 2017], we investigate whether an additional relaxation of the IIA property by accommodating heterogeneity in the NMNL model (leading to the HB-NMNL model) has further advantages over the HB-MNL model. We conduct a Monte Carlo study in order to analyze the capabilities of the HB-MNL model and the HB-NMNL model under varying data conditions. Using statistical criteria for parameter recovery, goodness-of-fit and predictive accuracy we evaluate the comparative performance of the HB-MNL versus the HB-NMNL model under varying nest sizes, different nested structures, different levels of preference heterogeneity, varying numbers of alternatives within choice sets and different numbers of parameters to be estimated at the individual respondent level (model complexity).

In chapter 3, we deal with multimodal and segment-specific preference structures. More precisely, to carve out differences between the classes of models with different representations of heterogeneity, we specifically vary the degrees of within-segment and between-segment heterogeneity. We compare the simple MNL, LC-MNL, HB-MNL, MoN-MNL and DPM-MNL models under varying experimental conditions with respect to parameter recovery, goodness-of-fit and predictive accuracy. We manipulate the number of segments (including symmetric versus asymmetric masses), the levels of between-segment heterogeneity (i.e., separation of segments) and within-segment heterogeneity, the number of attributes and attribute levels (model complexity) and the number of choice sets per respondent. The number of choice sets per respondent addresses the implementation of CBC studies in market research practice and the related problem that clients want to incorporate more and more attributes while the choice task should be kept manageable for respondents [e.g., Hauser and Rao 2004; Hein et al. 2019a]. By varying the length of the choice task we are able to analyze the statistical effects of shorter-than-optimal designs (regarding the criterion of orthogonality on the individual respondent level) on the model performance.

In chapter 4, we apply the previously presented choice models to a real-life CBC data set sourced from a known market research institute. In particular, we assess the comparative performance of simple MNL, HB-MNL, LC-MNL, MoN-MNL, DPM-MNL and HB-NMNL models in terms of goodness-of-fit and predictive accuracy. Hence, all the choice models with continuous and discrete representations of heterogeneity employed and analyzed in the two Monte Carlo studies before (chapter 2 and chapter 3) are now compared in an empirical study. That way, it can be assessed whether our findings for synthetic CBC data also hold for (our) empirical data.

The experimental designs of the Monte Carlo studies (chapter 2 and chapter 3) lean on the designs of Vriens et al. [1996], Andrews et al. [2002a], Andrews et al. [2002b] and Wirth [2010]. The advantage of using synthetic data is that experimental factors that are assumed to affect the model performance can be varied systematically, and undesirable confounding factors can be held constant. A synopsis of the findings from our Monte Carlo studies and from the empirical analysis in chapter 4 should enable us to answer the research questions (1) which representation of heterogeneity is favorable for analyzing CBC data, (2) if there is a clear recommendation toward one model for discovering multimodal heterogeneous preference structures, and (3) whether an additional relaxation of the IIA property by accommodating heterogeneity in the NMNL model has important advantages over the HB-MNL model or other state-of-the-art (LC-MNL) or advanced (MoN-MNL, DPM-MNL) choice models for nested preference structures. Moreover, we can use our Monte Carlo designs to check (4) whether the findings on the research questions depend on specific experimental factors that are believed to affect model performance. Finally, we are particularly interested in (5) how robust the HB-MNL model performs especially in terms of parameter recovery and predictive accuracy compared to the other heterogeneous models.

Last, the findings of the Monte Carlo studies in chapters 2 and 3 and the results of the empirical study in chapter 4 will be summarized and discussed in chapter 5. We used the R software [R Core Team 2017] for data generation, model estimation and model evaluation. The choice designs were constructed using SAS software[1].

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5 Concluding discussion

5.1 Summary of results

In marketing research, choice models are widely used for measuring consumer preferences. The simple MNL model, the most frequently used discrete choice model (especially for CBC data), suffers from two main limitations: 1) It implies proportional substitution patterns across alternatives, also known as IIA property, and 2) it does not account for unobserved consumer heterogeneity. In the present thesis, we focused on the comparison of CBC choice models, which solve (at least partially) these limitations. We studied the statistical performance of choice models with different representations of heterogeneity (discrete vs. continuous) and models with different substitution patterns across alternatives to relax the IIA property. In particular, we investigated how robust the HB-MNL model works to violations in its assumption of a single multivariate normal distribution of consumer preferences.

In chapter 2, the focus was on the comparison of the performance of HB-MNL and HB-NMNL models under experimental varying conditions (especially under experimental varying nested preference structures). We investigated whether an additional relaxation of the IIA property by accommodating heterogeneity in the NMNL model has further advantages over the HB-MNL model. We conducted a Monte Carlo study in order to analyze the capabilities of the HB-MNL model (as compared to the HB-NMNL) under varying data conditions. Using statistical criteria for parameter recovery, goodness-of-fit and predictive accuracy we evaluated the comparative performance of the HB-MNL versus the HB-NMNL under (a) varying nest sizes, (b) different degrees of similarity between alternatives, (c) different levels of preference heterogeneity, (d) varying number of alternatives offered per nest, and (e) different numbers of parameters to be estimated at the individual respondent level (model complexity). Our results showed that there seems to be no major differences between both types of models with regard to goodness-of-fit measures and in particular their ability to predict respondents' choice behavior, despite the underlying bimodal distribution of preference structures and the varying scenarios with respect to the correlations assumed for the unobserved portions of utilities between alternatives. It could therefore be concluded that the HB-MNL model is also able to uncover bimodal preference structures and to handle different similarities between alternatives within nests similarly well compared to the HB-NMNL model. The second major finding was that the similarity between alternatives in the nests plays a key role for the performance of the choice models with regard to all performance dimensions (parameter recovery, model fit, and predictive validity).

Regarding parameter recovery measured in absolute errors (RMSE, MAE) the HB-MNL model performed increasingly worse when correlation in at least one nest was higher, while the HB-NMNL model was only marginally affected by the size of the log-sum parameters (degree of similarity) and adapted to the degree of similarity between alternatives, as expected. Consequently, we concluded that the HB-NMNL model has advantages as far as parameter recovery is concerned. Furthermore, a high similarity between alternatives improved the fit and the prediction accuracy of both models positively. Further drivers for the performances of both models were the model complexity (parameter recovery measures), the level of heterogeneity (parameter recovery and predictive accuracy measures) and the number of alternatives offered per nest (fit and predictive accuracy measures). Overall, we summarized that the HB-MNL model fits and predicts equally well for the considered nested structures compared to the HB-NMNL model, but that the HB-NMNL model shows the expected advantages for parameter recovery.

In chapter 3, we studied the statistical performance of choice models with different representations of heterogeneity (discrete vs. continuous) in a further Monte Carlo study. In particular, we compared the simple MNL, LC-MNL, HB-MNL, MoN-MNL and DPM-MNL models under varying experimental conditions with respect to parameter recovery, goodness-of-fit and predictive accuracy. To carve out differences in the statistical performance between the classes of models with different representations of heterogeneity, we varied (a) the number of segments (including (b) symmetric versus asymmetric masses), (c) the level of between-segment heterogeneity (i.e., separation of segments), (d) the level of within-segment heterogeneity, (e) the number of attributes and attribute levels (model complexity), and (f) the number of choice sets per respondent (optimal for estimating main effects vs. manageable for respondents). Again, we wanted to investigate how robust the HB-MNL model works to violations in its assumption of a single multivariate normal distribution of consumer preferences. Further, we wanted to find out whether the findings of Voleti et al. [2017] who analyzed the predictive performance of the different models for several empirical CBC data sets hold for simulated data, too. The core finding from our Monte Carlo study was that the HB-MNL model appeared to be highly robust in multimodal preference settings. The MoN-MNL model and the DPM-MNL model on the other hand overestimated the “true” number of components in many cases, which led to a kind of overfitting and as a result of that to large absolute errors regarding parameter recovery and prediction accuracy. The latter was particularly distinctive for less complex treatments and for data sets with low inner-segment heterogeneity. In addition, the LC-MNL model proved to be the definitely best approach to recover the “true” number of segments (especially for symmetric treatments concerning segment sizes), while the MoN-MNL and DPM-MNL models clearly failed with regard to this criterion. This is especially noteworthy since beyond parameter recovery and prediction accuracy the identification of “true” segment structures is of particular importance for managers. Surprisingly, the HB-MNL model performed significantly better or at least as good as all other models as far as parameter recovery (the identification of “true” utility structures) and prediction accuracy is concerned. Primary drivers for the model performance were the model complexity (parameter recovery, predictive accuracy), the separation between segments (parameter recovery), the number of choice sets per respondent (predictive accuracy), and not least the type of model itself which substantially affected all three performance dimensions (parameter recovery, fit, predictive accuracy). The other factors (number of segments, inner-segment heterogeneity, segment masses) only had a marginal impact on the three performance dimensions.

In chapter 4, we applied the aggregate MNL, LC-MNL, HB-MNL MoN-MNL, DPM-MNL and HB-NMNL models to an empirical data set and assessed their comparative performance in terms of goodness-of-fit and predictive accuracy. The results indicated that models with a continuous representation of heterogeneity performed better than models with a discrete representation of heterogeneity. In terms of predictive accuracy, the HB-MNL model provided either a (considerably) higher or at least a comparable cross-validated hit rate compared to all other models and, importantly, markedly outperformed the DPM-MNL model on this measure. Again, the MoN-MNL models (with five and six components) as well as the DPM-MNL model tended to overfit the data and the LC-MNL model proved to be the best approach to identify specific market segments. However, the predictive performance (measured by the out-of-sample hit rate) of the LC-MNL model was about 10 % lower compared to the HB-MNL model. Considering different nested structures, we obtained for the HB-NMNL model every time log-sum coefficients larger than one. Therefore, the “true” hierarchical decision process of respondents (if one existed) could not be approximated satisfactorily.

Summing up, the core finding of the present thesis is that the HB-MNL appeared to be highly robust against violations in its assumption of a single normal distribution of consumer preferences in the considered multimodal and nested preference structures. More flexible advanced choice models (MoN-MNL and DPM-MNL models) were prone to overfitting problems. Furthermore, it turned out that the LC-MNL model was the best approach to recover the underlying “true” number of segments.

5.2 Managerial implications, limitations and outlook

Addressing consumer heterogeneity in choice models is an issue in the marketing literature since the mid-1990s [e.g., Allenby and Ginter 1995; Rossi et al. 1996; Allenby and Rossi 1998]. State-of-the-art methods to represent heterogeneity in discrete choice experiments are LC-MNL models [Kamakura and Russell 1989] which address between-segment heterogeneity by discrete support points, and HB-MNL models [Allenby et al. 1995] which address within-segment heterogeneity using a normal distribution. Currently, the marketing literature discusses models representing both between-segment and within-segment consumer heterogeneity [e.g., Voleti et al. 2017]. By additional prior assumptions MoN-MNL models and DPM-MNL models can estimate part-worth utilities based on a mixture of multivariate normal distributions in a more flexible way than previous choice models. In contrast to LC-MNL models or HB-MNL models, mixture of multivariate normal distributions accommodate multimodal and skewed distributions as well as distributions with thick tails.

From a managerial point of view parameter recovery, predictive accuracy as well as the identification of “true” segment structures are important criteria. Therefore, we can conclude that the LC-MNL model proved to be the definitely best approach to recover the “true” number of segments (especially for treatments with equal segment sizes). Because companies often use third-degree price discrimination [e.g., Tuma and Decker 2013], LC-MNL models show clear benefits compared to other choice models when the identification of segment structures is the main objective. However, our analyses showed that HB-MNL models performed significantly better or at least as good compared to all other choice models as far as parameter recovery (the identification of “true” utility structures) and prediction accuracy is concerned. Some previous empirical studies already indicated a better predictive performance of the HB-MNL model over the LC-MNL model [Moore et al. 1998; Natter and Feurstein 1999; Moore 2004]. However, Allenby et al. [1998] and more recently Voleti et al. [2017] analyzed the performance of the more advanced choice models based on empirical data and in turn reported a superior predictive performance of the DPM-MNL [Voleti et al. 2017] or the MoN-MNL [Allenby et al. 1998] model compared to the HB-MNL model, respectively. To explore the causes for those discrepancies there is a need for further research. Of course, different real-life data sets can provide different results. Voleti et al. [2017] stated that it would be interesting to study the performance of the competing models under a reasonable distribution of heterogeneity. We expect that results will depend on the assumption about the underlying heterogeneity distribution. Because in chapter 3 we generated normal distributed part-worth utilities and data sets which were partly highly informative on an individual respondent level, the data generation process favors a good performance of LC-MNL, MoN-MNL, DPM-MNL and HB-MNL models. This probably explains the similar performance with regard to parameter recovery (mean correlations) and out-of-sample hit rate of the LC-MNL, MoN-MNL, DPM-MNL and HB-MNL models in chapter 3. In chapter 2, the data generation process suggested by Garrow et al. [2010] clearly favors the HB-NMNL model. However, except for parameter recovery, the HB-MNL model and the HB-NMNL model performed similarly here. On the one hand, this result provides strong support in favor of the HB-MNL model and strong evidence for an adequate relaxation of the IIA assumption already when consumer heterogeneity is taken into account in the simple MNL model. One the other hand, parameter recovery is an important criterion for product design decisions as parameters (part-worth utilities in CBC studies) relate to values of product attribute levels and managers are interested to find the best attribute levels for their products. Therefore, future research can begin exactly at this point. Future work should verify if our findings hold for different distributions of heterogeneity or different assumptions regarding the "true" nested structure. For example, if the distribution of inner-segment heterogeneity is rather skewed, one would expect a superior performance of MoN-MNL or DPM-MNL models compared to HB-MNL, LC-MNL and aggregate MNL models. It should be noted that Andrews et al. [2002b] found no differences in measures of performances between different choice models when comparing normally distributed preferences to gamma distributed preferences. However, they only compared a LC model, a HB model and an aggregate model and did not consider the MoN and the DPM models. Moreover, Kim et al. [2004] concluded that the recovery performance of models with a DPP was getting worse for data sets with a mixture of skewed distributions compared to data sets with a mixture of normal distributions. Unfortunately, they did not compare the recovery performance to a HB-MNL model with a univariate distribution of heterogeneity or to LC models.

These points of discussion highlight the pros and cons of simulation studies. The advantage of using synthetic data is that experimental factors that are assumed to affect the model performance can be varied systematically, and undesirable confounding factors can be held constant. A Monte Carlo study does not necessarily reflect the real behavior of respondents. A certain number of parameters are varied, whereby some parameters cannot be varied in practical CBC applications. In particular, the part-worth utility structures, the segmentation of respondents (into nests or segments), the similarity between alternatives (the log-sum coefficients) and the amount of inner-segment heterogeneity cannot be influenced by the analyst in empirical studies.

Irrespective of the data generation process, the application of all models to a real-life data set showed that HB-MNL models worked extremely well for predictive purposes and provided at least as good if not considerably better predictions compared to the other models, which is an important aspect for managers. Moreover, the LC-MNL model seemed to be best suited to identify specific market segments. However, as mentioned above, the predictive performance (measured by the out-of-sample hit rate) of the LC-MNL was about 10 % lower compared to the HB-MNL model. Managers thus need to solve the trade-off between (a) a better predictive validity of choice models with a continuous representation of consumer heterogeneity (in particular the HB-MNL model) and (b) a probably more intuitive, well-interpretable segment approach (LC-MNL model). In this context, the decision of how many segments to select based on LC models and MoN models is a discussed issue [Andrews and Currim 2003]. Frühwirth-Schnatter [2006] pointed out that the LML estimator introduced by Newton and Raftery [1994] is a convenient estimator on the one hand but that the estimator tends to be unstable on the other hand. Nevertheless, in chapter 3, we could recover the "true" number of components in 82 % of all scenarios (and with a 100 % hit ratio for treatments where segment masses were equal) using the LC-MNL model and the LML criterion for model selection, which was a higher rate of success than reported in previous simulation studies [Andrews et al. 2002b; Andrews and Currim 2003]. Furthermore, this finding is comparable to Andrews et al. [2008], who developed a heuristic for identifying the correct model[37] (strict application of model selection criteria resulted in a lower rate of success). For treatments with unequal segment masses, we observed a similar hit ratio as in Andrews et al. [2002b] or Andrews and Currim [2003]. It should be once more mentioned that the masses of segments are outside of the analyst's control.

Considering these results, it can be concluded that the HB-MNL model performs well even if part-worth utilities stem from a multimodal distribution or groups (nests) of alternatives share certain characteristics. MoN-MNL and DPM-MNL models tend to overfit the data under certain conditions. Furthermore, it is difficult to determine an adequate substitution pattern reflecting the complex choice behavior of respondents ex ante, which is necessary for the estimation of NMNL models. In our empirical study, the log-sum coefficients of the HB-NMNL model turned out slightly larger than one, thus, indicating a less advantageous predefined nest structure. Regarding the log-sum coefficients, similar results can be found in Train et al. [1987], Train et al. [1989], Lee [1999] and Elshiewy et al. [2017]. Consequently, the superior parameter

[37] Andrews et al. [2008] did not consider the LC model. They applied logit models with varying specifications of (a) parameter heterogeneity (no parameter heterogeneity vs. multivariate normal assumption for the distribution of heterogeneity), (b) state dependence effects, and (c) choice set heterogeneity.

recovery of the HB-NMNL model in the presence of highly correlated nested structures contrasts with the more difficult model specification and estimation process, which is not as straightforward as that for the HB-MNL model. In particular, the HB-NMNL model is not yet implemented in commercial software packages for CBC studies (e.g., Sawtooth Software).

In addition, the log-sum coefficients were assumed to be fixed parameters over all respondents. Empirical studies showed that respondents might differ in the perception of similarity of alternatives. Bhat [1997] allowed for varying log-sum parameters across respondents by defining a continuous, monotonically increasing function that maps to the interval [0,1]. The function transforms socio-demographic characteristics of respondents to individual log-sum coefficients. Empirical results showed that accounting for log-sum heterogeneity leads to a better fit and a better parameter recovery.

Further, future research should analyze the performance of the competing models when taking into account simplification strategies of respondents which are known to occur in empirical studies. Simplification strategies can, for example, be the result of (a) straightlining behavior of respondents who pay attention to only one or two key attributes when choosing brands, (b) some kind of cheating behavior of professional respondents as can be more and more observed in online panels, or (c) simply boringness of respondents [Hein et al. 2019a]. Simplification strategies reduce the quality of the data compared to artificial studies and thus may affect the relative performance of the different models studied in this work. Hein et al. [2019a] who thoroughly investigated the capabilities of the HB-MNL model for choice-based conjoint analysis, found that mean Pearson correlations decline by about 10-20% if 30% of the respondents apply simplification strategies but that out-of-sample hit rates were much less affected. To the best of our knowledge, no simulation study has yet compared the performance of the aggregate MNL, LC-MNL, HB-MNL, HB-NMNL, MoN-MNL and DPM-MNL models in the presence of simplification strategies of at least parts of respondents.

Overall, we have highlighted that HB-MNL estimation proves to be quite robust against violations of the underlying assumptions, especially in multimodal data structures and in the presence of nested structures in data. In particular, different to previous Monte Carlo studies that compared the performance of choice models with different representations of heterogeneity, we showed how robust the HB-MNL model works. Other studies mainly suggested the application of more flexible advanced choice models to account for consumer heterogeneity [Allenby et al. 1998; Otter et al. 2004; Voleti et al. 2017; Krueger et al. 2018]. In addition to the findings of Hein et al. [2019a], who analyzed the statistical capabilities of the

HB-MNL model with regard to extreme settings of design parameters such as the number of attributes, number of choice sets, and sample size, we can conclude that the HB-MNL model proves to be extremely robust for multimodal and nested preference structures, too.

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