CONSUMER CHOICE OF MODULARIZED PRODUCTS:

A CONJOINT CHOICE EXPERIMENT APPROACH

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Abstract
Recent increases in flexibility and automation in the production of goods and services allow a growing number of suppliers to offer their products in flexible sets of modules from which consumers can create their own individualized packages. This paper addresses the question how consumer choices of such modularized products can be modeled and measured by applying conjoint choice experiments. We analyze conceptually the structure of individual consumers' choices of modularized products and the role of the error component in random utility models of these choices. We propose a simple experimental conjoint choice design strategy that can support estimation of this type of models. An empirical illustration in the area of travel package choice is discussed.

Key words: Marketing, Consumer choice models, Conjoint experiments, Heteroscedastic logit, Mass-customization.

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1. Introduction

Recent increases in flexibility and automation in the production of goods and services allow a growing number of manufacturers and retailers to 'mass-customize' their products and offer flexible sets of modules from which consumers can create their own individualized packages (e.g., Anderson 1997). This paper takes a closer look at some individual-level aspects of consumer demand involved in the marketing of such new developments. In particular, we develop a conceptual framework to analyze consumer choices of modularized products and discuss how these choices can be modeled using multi-attribute choice experiments (e.g., Lazari and Anderson 1994, Louviere and Woodworth 1983).

Multiattribute choice experiments can assist researchers and managers who want to explore possible impacts of product modularization on consumer choice. Because the approach is based on statistically designed experiments in which consumers make trade-offs between competing product offerings, it can be used to gain insight into complex consumer responses to marketing actions before the actions are implemented in real markets. Thus, the approach we propose provides a way to address marketing management questions that arise when existing products are unbundled into several different modules and/or bundled by adding new modules. For example, such issues arise when brands are extended to new product categories, marketing actions of competitors demand changes in key product features or an industry shifts towards stronger vertical or horizontal integration leading to product bundling or unbundling.

Our paper makes three specific contributions:

(i) A conceptual framework based on random utility theory, from which we derive a model of the structural and random error components in individual consumers' choices of modularized products,

(ii) a simple way to design multiattribute choice experiments for modularized choices based on the conceptual framework, and

(iii) an application/illustration of the proposed model and experimental design strategy in a study of travel package choice.

2. Conceptual Framework

To facilitate the discussion that follows, we introduce some definitions and assumptions that will serve to formalize our approach to the analysis and modelling of modularized product choices. Let each product p be described by a set of functionalities, N_p, that the product provides consumers. We define modularization as a market situation in which all N_p functionalities of a product can be produced and sold separately. For example, automobile functionalities that can be unbundled and sold separately include engines, air-conditioners; radios, etc.; clothing functionalities might include designs, fabrics, and sizes; and travel package functionalities include destination, transportation and sight-seeing tours.

We assume that consumers select the 'package' of modules that constitutes their most preferred combination when they choose to buy a modularized product. Consumers can choose an available option to obtain a functionality or can choose not to purchase that functionality at all. We assume that the combinations consumers can create to obtain mixes of different functionalities aren't restricted (e.g., each make of car is available with all types of air-conditioners, or each style of jeans in all colors). We also assume that consumers will choose no more than one option per functionality (e.g., consumers can't buy several types of air-conditioners for one car or more than one color per pair of jeans).

Random utility theory acknowledges the fact that researchers cannot perfectly measure and model consumer preferences because of unobserved variables, which is captured by a stochastic or random (error) component in the theory. In the case of modularized choices, we extend the basic framework used to conceptualize consumer preferences for single alternatives to preferences for *packages* of functionalities. This then leads us to discuss how random error in package choices may be effected by package composition.

We develop the formal model as follows (omitting individual and product specific subscripts for notational simplicity). Let U_{jn} be the utility of option j for functionality n, with $jn \in J_n$, the set of all options that provide functionality n, and $n \in N$, the set of all functionalities. Let V_{jn} be the structural component of utility U_{jn}, with $V_{jn} = \beta_{jn}'\mathbf{x}_{\mathrm{jn}}$, where β_{jn} and $\mathbf{x}_{\mathrm{jn}}$ are vectors of utility parameters and explanatory variables, respectively. Let $\varepsilon_{\{j1,\ldots,jN\}}$ be the error component for the utility of a package of functionalities *{j1,...,jN}*. Then, a consumer choice model of packages of functionalities can be expressed in the following utility and purchase probability functions for a package *{j1,...,jN}*:

$$U_{\{j1,\ldots,jN\}} = \sum_{N} V_{jn} + \varepsilon_{\{j1,\ldots jN\}} \tag{1}$$

And

$$P(\{j1,\ldots,jN\}) = P(U_{\{j1,\ldots,jN\}} \geq U_{\{j'1,\ldots,j'N\}};\ \forall j'n \in J_n;\ j'n \neq jn) \tag{2}$$

If the random error components are IID Gumbel (independently and identically distributed) across all choice situations, the following closed form model for the choice probabilities arises, which is widely known as the multinomial logit (MNL) model:

$$P(\{j1,\ldots,jN\}) = \frac{\exp\left(\sum_{N} \lambda \boldsymbol{\beta}_{\mathbf{jn}}'\mathbf{x}_{\mathbf{jn}}\right)}{\sum_{J1}\sum_{J2}\cdots\sum_{JN}\exp\left(\sum_{N}\lambda\boldsymbol{\beta}_{\mathbf{j'n}}'\mathbf{x}_{\mathbf{j'n}})\right)} \tag{3}$$

where λ is a scale parameter inversely related to the standard deviation of the Gumbel error distribution underlying the model (Ben-Akiva and Lerman 1985, p.105), and all other components are as previously defined. Formally the relationship between λ and the standard deviation of the Gumbel distribution is defined as follows:

$$\lambda = \tfrac{1}{6}\sqrt{6}\,\frac{\pi}{s.d.(\varepsilon_{\{j1,\ldots,jN\}})} \tag{4}$$

In most applications λ cannot be identified uniquely, instead only the combined effect of λ and $\boldsymbol{\beta}$ can be estimated (Swait and Louviere 1993). Therefore, λ typically is set (arbitrarily) by the analyst to a value of one (e.g., Ben-Akiva and Lerman 1985, p. 71). However, in the modularized choice case, we believe that the role of λ requires special attention.

In particular, we hypothesize that choices between packages that share identical modules should have lower error variances than choices between packages that differ in all modules. This expectation is based on previous research involving choices among single (non-modularized) alternatives, which suggests that levels of random error in consumer choices decline if the alternatives share certain attributes (e.g., Ben-Akiva and Lerman 1985 p. 285, Meyer and Johnson 1995, Shugan 1980). This result obtains because the more similar alternatives are, the more they share unobserved components (Ben-Akiva and Lerman 1985) and/or are easier to compare (Shugan 1980). We expect a similar effect to obtain for choices between product packages that share identical modules.

To amplify the latter point, consider the following example of a two-component day trip package that offers choices of morning and afternoon activities, hence consumers can customize a package. Let A be the set of possible activities for morning, and B the set of activities for afternoon. Then, we can express the utility of this combination as:

$$U_{ab} = \beta_a'\mathbf{x}_\mathrm{a} + \beta_b'\mathbf{x}_\mathrm{b} + \varepsilon_{\{a,b\}} \tag{5}$$

where $a \in A$, and $b \in B$ and all other elements are defined as before. Equation (5) suggests that when consumers choose between packages that contain a common morning or afternoon activity their choices should have less random error variance than when they are asked to choose between packages with different activities.

Differences in random error components can be captured by allowing the model scale (λ) to depend on the number and type of modules that differ between packages, which is consistent with a relatively new choice model called the heteroscedastic logit model (cf., Allenby and Ginter 1995). The latter specification relaxes the IID error assumptions of the MNL model by allowing each alternative to have a different error variance (ie, independent, but not identically distributed). In particular, we specify λ as a function of a parameter vector that captures the effect of the number and type of different modules that exist between all packages in the choice set on the random error in the consumer choice. That is, we specify the following:

$$\lambda = \sum_{N} \gamma_{jn} \Delta jn \tag{6}$$

where and $\gamma_1 \ldots \gamma_N$ are scale function parameters that capture the effects of per module differences, Δjn, on unexplained variance in the model. Δjn is an indicator variable that takes on a value of 1 if module n differs between packages and 0 otherwise. One parameter Δjn is set arbitrarily to a fixed value because only N-1 parameters can be identified in expression (6).

This leads to the following formal definition of the probability model:

$$P(\{j1, \cdots, jN\}) = \frac{\exp\left[\left(\sum_{N} \gamma_{jn} \Delta jn\right) \; \boldsymbol{\beta}_{\mathbf{jn}} \mathbf{x}_{\mathbf{jn}}\right]}{\sum_{J1} \sum_{J2} \cdots \sum_{JN} \exp\left[\left(\sum_{N} \gamma_{j'n} \Delta j'n\right) \; \boldsymbol{\beta}_{\mathbf{j'n}} \mathbf{x}_{\mathbf{j'n}}\right]} \tag{7}$$

The model in equation (7) can be estimated using the method of full information maximum likelihood (FIML) by maximizing the log-likelihood of the model simultaneously with respect to the structural parameters β_{jn} and the parameters γ_{jn} in the scale function λ. Alternatively, a method proposed by Swait and Louviere (1993) can be used if consumer choices can be observed under each random error condition. We use the latter estimation approach in conjunction with our proposed experimental design framework in the empirical illustration in section 4.

3 Multiattribute choice experiments for modularized choices

Despite growing interest in choices models that relax the IID error assumptions of simple MNL (e.g., Chintagunta and Honoré 1996 discuss non-IID probit, and Allenby and Ginter 1995 introduce heteroscedastic logit), few researchers seem to have recognized that the types of experimental designs traditionally used in multiattribute choice experiments may not be appropriate to estimate the newer, more complex models. Although there are exceptions, many traditional designs for choice experiments rely on the IID error assumption, and, in turn, are consistent with models such as MNL and IID probit (e.g., Louviere and Woodworth 1983). An exception is the class of designs that capture so-called "cross-effects" (e.g., Lazari and Anderson 1994), but these designs permit one to estimate only certain non-IID model forms, which may include heteroscedastic logit, but not in the case of the component model proposed above. That is, orthogonal (or nearly orthogonal) fractional factorial designs typically are used to create choice alternatives and choice sets simultaneously (Dey 1985, Louviere and Woodworth 1983). However. unless specifically designed to estimate specific non-IID forms such as nested logit, it may not be possible to estimate variance-covariance structures because error term differences are confounded with choice situations and structural parameter effects.

For example, a simple 2^2 factorial design + its fold-over can be used to design pairs of packages described by two modules with two functionalities. But there are not enough degrees of freedom to estimate all the structural effects (intercept, module option per functionality and their interactions), *as well as* possible variance differences between choice sets. Indeed, the model is fully saturated even if only the structural parameters are estimated, hence such a traditional design must be extended in other ways to estimate non-IID variance-covariance parameters.

Recently some researchers have proposed designs for such non-IID models, particularly in biostatistics (see, eg, Mentré, Mallet and Baccar 1997; Kushner 1997; Uddin and Morgan 1997). However, non-IID designs proposed thusfar deal with applications in agriculture, medicine and the physical sciences, and cannot be adapted easily to multiattribute choice experiments in marketing for a number of reasons:

(i) Typically, they focus on continuous rather than discrete measurement outcomes,

(ii) They address issues of designing alternatives but not choice set construction, and

(iii) The numbers of variables and/or attribute levels accommodated are much less than in many choice experiments, limiting their applicability.

Thus, we propose a modest step in the direction of an experimental design strategy that can estimate models of modularized consumer choices involving heteroscedastic errors. The proposed strategy is simple, flexible and generally applicable, but does not offer optimal solutions to specific experimental design problems. However, optimal designs for choice experiments in the area of consumer decision making often are elusive anyway because design efficiency depends on the particular characteristics of each research problem, such as (possible) differences among respondents, and a priori knowledge of parameter values (e.g., Kuhfeld, Tobias and Garret 1994).

Our proposed approach is to design and combine *interrelated sub-designs* representing choices in different variance scenarios like those described in the model discussion. That is, we make the sub-designs in such a way that we allow identical modules to share the same unobserved (not manipulated) attributes, which allows us to test whether there are lower error variances in choices between packages that contain identical modules. For example, choices among packages that differ only in a single module (e.g., design, size, color) should produce different levels of random error than choices among packages that differ in all modules. Moreover, even in the case of choices among packages that differ only in a single module (e.g., design), levels of random error may differ from module to module (e.g., error variances for color may differ from those for design).

An example may be useful to clarify the proposed approach. Recall the case we considered earlier in which there were two module packages for day trips. If one anticipated that the levels of random error for choices involving the first module (eg, morning programs) would differ from choices involving the second module (eg, afternoon programs), one would need to design three sub-experiments:

(i) Joint module choices in which both 'morning' and 'afternoon' options differ between packages,

(ii) Within-module 'morning' choices only, and

(iii) Within-module 'afternoon' choices only.

This design strategy explicitly allows estimation of structural utility parameters within and between sub-designs. If variance differences exist in the three choice conditions, they can be captured by estimating variance corrections between sub-designs.

More generally, the strategy is as follows: If variance differences are expected between random utility (error) components of packages with one or more identical modules, designs are required to estimate the variance differences. These error variance estimates are additional to the traditional estimates of structural variable effects.

Thus, our previous discussion of the specific structure of modularized choices suggests:

(i) The error of a package of functionalities can be expressed as a single overall error term $\varepsilon_{\{j1,\ldots,jN\}}$, and

(ii) Error variances of alternatives may differ as a function of the number of modules that packages in choice sets have in common.

This design approach provides an opportunity to estimate the sizes of different error components in the model separately. Specifically, if the overall error term $\varepsilon_{\{j1,\ldots,jN\}}$, is set to an arbitrary value in order to scale the model, our objective is to estimate the effect of different levels of package similarity on the variance of $\varepsilon_{\{j1,\ldots,jN\}}$.

These additional estimates of variance differences between sub-designs can be obtained if respondents are asked to make choices in N sub-designs containing choice sets (scenarios) in which packages share one common module (one sub-design for each of N different functionalities). This approach is summarized in table 1, and can be described as follows:

(i) Construct one ‘reference’ sub-design to describe choices between packages that differ on all modules. These choices should exhibit a maximum level of random error because all module-based random components are involved.

(ii) Construct sub-designs to describe choices between packages that share one specific module, which requires N additional sub-designs. In each sub-design the error components can differ, depending on which module is constant between packages. Thus, differences between estimates in the reference sub-design and other sub-designs should be due to differences in levels of random error, which allows one to estimate the error variance contribution γ_n of each module.

- INSERT TABLE 1 ABOUT HERE -

Our estimation approach follows that of Swait and Louviere (1993), who discussed noted that error components in utility functions have a fixed relationship to parameter estimates in choice models. That is, if two or more choice situations share a common set of underlying utility parameters but differ in their levels of random error, the absolute magnitudes of the estimated parameters will differ in each situations. Importantly, however, the parameters will differ by a constant scale factor, which is inversely proportional to the magnitude of the error variance in each situation. Hence, scale corrections (or more properly, variance-scale ratios) can be estimated for S-1 of S total scenarios to capture differences in error variances between choice scenarios.

More specifically, one can estimate the ratios $r_{1\text{-}n}$ of the scales λ^1 and λ^n of the parameter estimates for a reference sub-design relative to the other, conditional choice scenario sub-designs. Swait and Louviere (1993) show how these scale ratios can be expressed in terms of the standard deviations of the error components of each choice situation (σ_1 and σ_n).

$$r_{1,n} = \frac{\lambda^1}{\lambda^n} = \frac{\sigma_n}{\sigma_1} \tag{8}$$

If the scale of the variance in the reference choice scenario is arbitrarily set to 1 (i.e., $\lambda^1 = 1$), the difference in variance between choice scenarios provides information about the effects of package similarities on the variance of the random errors. This is expressed as follows:

$$\gamma_n = \lambda_n - \lambda_1 = \lambda_n - 1 = \frac{1}{r_{1,n}} - 1 \tag{9}$$

The variance in a choice scenario *n* can be expressed as:

$$var(\varepsilon_n) = \frac{\pi^2}{6} r_{1,n}^2 \tag{10}$$

because the variance of the Gumbel distribution for the error component in the reference scenarios equals $\frac{\pi^2}{6}$ if the scale of the distribution is set to 1 (Ben-Akiva and Lerman 1985).

An attractive feature of the proposed design strategy is that each sub-design of the proposed structure can be constructed using the basic strategies described by Louviere and Woodworth (1983), and extended by subsequent authors (e.g., Bunch, Louviere and Anderson 1996, and Huber and Zwerina 1996). Essentially, each sub-experiment relies on traditional experimental design theory because sub-designs are defined in such a way that traditional IID assumptions should hold within each sub-experiment.

The adequacy of the proposed model as an approximation to the underlying choice process tests can be tested by comparing fits of the estimated model with variance corrections to fits of models with fewer variance corrections or to a model without variance corrections. A log-likelihood ratio test statistic can be used for such comparisons (e.g., Theil 1971). That is, the quantity $2[L^*(\beta_1) - L^*(\beta_2)]$ is asymptotically Chi-square distributed, where $L^*(\beta_1)$ and $L^*(\beta_2)$ are the adjusted log-likelihoods of models with and without variance corrections, respectively.

It should be noted that the proposed approach is conservative in the sense that one can also test if variance differences are the only underlying differences between the choice situations. More generally, however, the proposed design strategy allows one to test if the composition of choice sets not only affects error variances of package choices, but also explains different structural preferences. This can be important because it has been shown that in some cases, shifts in structural preferences occur when alternatives are added to choice sets (e.g., Huber, Payne and Puto 1982, and Simonson and Tversky 1992).

It also is worth noting that much recent research in marketing has focused on modeling differences in unobserved variance between respondents (e.g., Chintagunta and Honore 1996; Gönül and Srinivasan 1993), which is not the focus of our research. Instead, we adopt the so-called "average individual" approach and estimate models from the aggregate responses of all respondents. In our modelling approach, error terms capture also the unobserved differences between respondents and structural parameters represent average respondent utilities. Thus, our approach may be inadequate for situations in which there are clearly defined market segments who express different and opposite preferences for certain modules. That is, our approach would incorrectly suggest that these modules do not influence respondent choice because the estimated structural parameters would not differ significantly from zero, and/or would be weighted in the direction of the segment with the largest sample representation. For example, in the case of holiday choice, if there is one segment of beach-lovers and another of beach-haters, preferences of these segments could average out.

Nevertheless, in choice experiments it usually is the case that respondents are randomly assigned to choice situations and the occurrence of different module options is balanced by design. Hence, respondents are equally likely to be confronted with all choice options. This implies that if the model is correctly specified except for possible heterogeneity, heterogeneity effects will bias estimates downwards, but this bias will be systematic and equal in all choice situations (i.e., both for high and low variance scenarios). That is, the heterogeneity effect is orthogonal to the estimates of variance differences in modularized choice processes, and hence should not affect tests of module-based heteroscedasticity. Moreover, if one knows or suspects that unobserved heterogeneity is a problem, one can apply alternative methods to capture these effects (e.g., Kamakura, Kim and Lee 1996, Swait 1994). Because the purpose of this paper is to propose and illustrate a design approach to study modularized choice, and not to compare complex model forms per se, we eschew further discussion of previous research accounting for unobserved herteogeneity.

4. Illustration for travel package choice

Our proposed design and modelling approach is illustrated using consumer choices of short-break city vacation packages consisting of combinations of transportation and destination components. Formally this choice problem can be expressed as:

$$\begin{aligned} P(T_j D_k) &= P(U_{TjDk} \geq U_{Tj'Dk'}; \forall j' \varepsilon\ J, \forall k' \varepsilon\ K) \\ &= P(V_{Tj} + V_{Dk} + \varepsilon_{\{Tj,Dk\}} > V_{Tj'} + V_{Dk'} + \varepsilon_{\{Tj',Dk'\}}) \end{aligned} \tag{11}$$

where V_{Tj}, $V_{Tj'}$, are the structural utility components of transportation options T_j , and $T_{j'}$ ε J , the set of all transportation options, V_{Dk} and $V_{Dk'}$ are the structural utility components of destination options D_k, and $D_{k'}$ ε K , the set of all destinations options, and $\varepsilon_{\{Tj,Dk\}}$ and $\varepsilon_{\{Tj',Dk'\}}$ are the error components related to the respective utilities.

Three different variance structure situations are distinguished:

(i) Choices in which both transportation mode and destination differ, and hence the error component should be largest,

(ii) Choices in which only transportation modes differ, with smaller expected error component, and

(iii) Choices in which only destinations differ, also with a smaller expected error component, but one that may differ in size from the error component in situation (ii).

To construct the actual choice experiment, influential attributes for city trip choices were identified on the basis of consumer and expert interviews, as well as previous research on city trip choice (e.g., Jansen-Verbeke 1988). Eight attributes were used to describe generic city destinations, and the two transportation modes (bus and train) were described by two attributes. The respondent's own car was used as a base option for transportation choice in each choice set. An unattractive combination of attributes defined the base destination. The experimental design was constructed as follows:

(i) One sub-design (*A*) was used to estimate parameters in choices between completely different vacation packages. Each row in this sub-design represented a choice between a bus-destination package and a train-destination package and the base alternative. A 3^{10} fractional factorial design was used to generate 81 alternatives (or profiles) per transportation mode. Two of the 10 three-level attributes were transportation attributes and eight were destination attributes; all main effects were independent of interaction effects. Alternatives were randomly combined into choice sets.

(ii) A second sub-design described destination choices conditional on transportation mode. There were two parts to this design (B_1, B_2), such that destinations were varied: a) within a bus transportation mode (B_1), and b) within a train transportation mode (B_2). A 3^{10} fractional factorial design in 32 profiles (i.e., the attributes in a 4^{10} design in 32 were reduced to 3 levels) was used for each of these two parts. The profiles in this design described transportation-destination packages. In each choice set, alternatives were combined in such a way that transportation attributes did not vary within choice sets.

(iii) A third sub-design (C) was used to describe transportation alternatives conditional on destination. In this case, destinations were constant in each choice set and were combined with one bus and one train alternative. A 3^{12} design in 64 profiles was used (i.e., the attributes in a 4^{12} in 64 were reduced to 3 levels). The eight destination attributes were varied systematically across choice sets, but not within choice sets.

Thus, the total design consisted of 209 (i.e., 81 + 2*32 + 64) two-alternative choice sets. A base alternative was added to each choice set, which was not a profile in the design. For the conditional choices in the design (sub-designs *B* and *C*), destination and transportation attributes in the base alternative were changed to the same condition as the fixed component in the travel packages (e.g., if trips were conditional on a certain bus option, the base also was changed to this option). Separate intercepts were estimated for each sub-design. This experimental design is summarized schematically in Table 2.

- INSERT TABLE 2 ABOUT HERE-

Data were collected in June and July 1993 in a medium-sized European city. Questionnaires were delivered to 2040 randomly selected households and later collected at the door. These data were combined with a sample of 480 respondents who were contacted through travel organizations and received the questionnaire with their travel tickets. Respondents were selected on the basis of having made a short, city break trip in the past three years. Response rates were 30.5% and 10.9% respectively.

Respondents were asked to imagine that they were planning to take a short city break in the near future. They were asked to allocate one hundred points to the three options in every choice set to indicate their preferences. These hundred points were rescaled later to one (the unit interval) for estimation. Each respondent received 12 choice sets from the total design on the basis of random draws with equal expected response for each choice set, which yielded an average of 27.9 observations per choice set (min. 16, max. 36). Responses were aggregated across respondents in the analysis.

Estimation was conducted in two stages. First, separate MNL models were estimated from the choices in each of the three different choice scenarios (i.e., each experimental sub-design). As earlier stated, we expect errors within each sub-design to be approximately IID; consequently, even if heteroscedasticity exists, module-based parameters should be estimated consistently within each sub-design. Second, the heteroscedastic logit model was estimated by pooling the data across all three sub-designs, and allowing different error components in the three choice scenarios. Because separate designs were used to create the experimental choice sets for each of the three scenarios, differences in error components between scenarios could be estimated independently. This procedure guarantees a global maximum in the log-likelihood of the heteroscedastic logit but does not provide estimates of the standard errors of the variance corrections themselves (Swait and Louviere 1993; Allenby and Ginter 1995 apply a more advanced Bayesian estimation procedure). In testing our approach this was not a major drawback as likelihood ratio tests could be used to compare the fit of competing models rather than tests of separate parameter estimates.

4.1 Results

Table 3 contains the parameter estimates of the heteroscedastic logit model and the estimates of between-module variance differences. Only linear effects are reported because quadratic effects were not significant. In the interest of brevity and clarity of exposition, we avoid substantial interpretation of the attribute parameter estimates; however, we do note that the fit of the estimated model was quite satisfactory by traditional standards (i.e., McFadden's rho–squared = 0.40), and that all parameters had the expected signs.

-INSERT TABLE 3 ABOUT HERE-

We tested the appropriateness of the heteroscedastic model by comparing it with several simpler models with fewer corrections for unobserved variance differences between the three choice situations. These other models were: (i) a heteroscedastic logit model involving a variance correction for transportation choices only, (ii) a heteroscedastic logit model involving a variance correction for destination choices only, and (iii) a joint logit model in which no variance corrections were made.

The results of this exercise revealed that although the differences in model fits were relatively small, there were some significant differences in model structures. The log-likelihood

(LL) differences for each model are in Table 4. In particular, the LL of the overall heteroscedastic logit model was -757.28, whereas the LL's for the simpler heteroscedastic logit models were -759.29 (if only destination choices had variance corrections) and -757.83 (if only transportation choices had variance corrections). A one degree of freedom Chi-square test (for one omitted scale parameter) revealed a significant difference in variance between the choice scenarios in which packages differed in both transportation and destination components (sub-design *A*) and the scenarios in which packages differed only in transportation (sub-design *C*). However, there was not a significant difference in the error variance between choices in which the alternatives differed in both transportation and destination components (sub-design *A*) and choices in which alternatives differed only in destinations (sub-designs B_1 and B_2). Thus, the joint logit model was rejected in favor of the heteroscedastic logit, due to the observation that omitting the variance correction for transportation choice led to a significant reduction in model fit. The variance correction for destination choice was not significant.

We also tested the within-experiment predictive validity of the model with variance corrections for transportation module choices, against the joint logit model without variance corrections. For this purpose, responses in a holdout choice set were used in which respondents were asked to choose between the following alternatives: a) two shared the same destination, b) and two shared the same transportation option. The results of this test are in Table 5, which indicates that the heteroscedastic logit again outperformed the joint logit. A chi-square test revealed that the difference between observed and predicted choices was not significant at the 95 percent confidence level for the heteroscedastic logit model (χ^2 = 1.51), but was significant and large for the joint logit model (χ^2 = 54.46).

- INSERT TABLES 4 AND 5 ABOUT HERE -

5. Conclusion and discussion

The objective of this paper was to develop a conceptual framework for the analysis of consumer choices of modularized products and to use that framework to propose a strategy to design choice experiments that allow estimation of models of modularized choices. The proposed approach offers new possibilities to develop conjoint choice experiments that satisfy the estimation requirements of consumer choices involving several functionalities within products. An empirical case study illustrated the proposed model and design strategy.

The proposed approach should assist marketing researchers wanting to apply designed choice experiments to study modularized choice by allowing them to investigate a much wider and richer array of possible consumer choice processes using experimental market situations. For marketing managers, our approach provides the opportunity to gain insights into complex consumer responses to marketing actions before they are implemented in the market. Experiments that support estimation modularized choice models are especially relevant for addressing marketing management questions in areas such as branding, product innovation, bundling and packaging decisions and competitive analysis. The reason is that modularized model structures can be expected to manifest themselves in areas that are characterized by the fact that consumers compare multiple functionalities between packages and/or within brands.

More generally, our conceptual analysis and proposed experimental design strategy provides a first step towards exploring the potential impact of highly flexible and individualized marketing and production methods on consumer choice, and their consequences for marketing managers. We expect that in future research it will be especially fruitful to explore the impact on consumer choices of different levels of module bundling (e.g., the impact of limited availability of certain functionalities for certain brands or models). Also, the conditions under which different levels of modularization would be most efficient from a welfare point of view (i.e. the joint benefits to producer and consumer) are worth investigating.

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TABLE 1 SUMMARY OF PROPOSED EXPERIMENTAL DESIGN STRATEGY

Strategy	Measurement objective	Number of sub-designs
use one sub-design with choices between packages that differ on all modules	estimate structural parameters	1 (across all modules)
use *N* sub-designs to capture choices between packages that differ on all but one module	estimate error variance contribution for each module	*N* (one for each module)

TABLE 2 EXPERIMENTAL DESIGN STRUCTURE OF EMPIRICAL ILLUSTRATION

CHOICE SETS

$$
\begin{array}{c}
\text{Sub-design} \\ A \\ B_1 \\ B_2 \\ C
\end{array}
\quad
\begin{array}{cccccc}
\multicolumn{2}{c}{\textit{Alt. 1}} & \multicolumn{2}{c}{\textit{Alt. 2}} & \multicolumn{2}{c}{\textit{Base}} \\
\textit{Dest.1} & \textit{Bus} & \textit{Dest.2} & \textit{Train} & \textit{Base Dest.} & \textit{Car}
\end{array}
$$

$$
\begin{array}{c}
A \\ B_1 \\ B_2 \\ C
\end{array}
\quad
\begin{bmatrix}
3^{8} & 3^{2} & 3^{8} & 3^{2} & base & car \\
3^{8} & 3^{2} & 3^{8} & 0 & base & 0 \\
3^{8} & 0 & 3^{8} & 3^{2} & base & 0 \\
3^{8} & 3^{2} & 0 & 3^{2} & 0 & car
\end{bmatrix}
$$

TABLE 3 PARAMETER ESTIMATES HETEROSCEDASTIC LOGIT MODEL

Attribute	Parameter estimate	*t*-value
Constant fully different packages	**0.78**	13.6
Constant package fixed train option	**0.68**	7.7
Constant package fixed bus option	**0.79**	8.9
Constant package fixed destination option	**-0.27**	-15.9
Country 1 (Holland vs. Belgium)	-0.01	- 0.2
Country 2 (Germany vs. Belgium)	-0.03	- 1.9
Distance (km)	-0.01	- 0.5
Restaurants and bars (few - very many)	**0.09**	3.3
Shopping facilities (few - very many)	**0.14**	5.3
Special sights (few - very many)	**0.25**	9.2
Hotel price per night (NLG 50 - 100)	**-0.10**	- 3.7
Hotel quality rating (2 star - 4 star)	**0.10**	3.5
Hotel location (city center - city border)	**0.07**	2.7
Constant difference between bus and train	-0.02	- 0.9
Price (bus) (NLG 30-60)	**-0.05**	- 2.1
Travel time (bus) (1.5-2.5 hrs)	-0.04	- 1.8
Price (train) (NLG 45-75)	-0.04	- 1.9
Travel time (train) (1.5-2.5 hrs)	-0.03	- 1.5
error variance different packages**	1.64	
error variance package fixed transportation	1.39	
error variance package fixed destination	0.53	

* **McFadden's RhoSq:** 0.400

** This value derives from setting the scale of the model for choices of fully different packages to 1, as is commonly done in estimating logit type models (Ben-Akiva and Lerman 1985). The other two error variances are estimated relative to this value.

TABLE 4 LOG-LIKELIHOOD IMPROVEMENTS FOR THE VARIOUS MODELS

	No of parameters	Transportation variance only	Destination variance only	No variance correction
Heteroscedastic logit: variance correction for both modules	31	1.10	4.02 *	5.12 *
Heteroscedastic logit: variance correction for transportation only	30		2.92 *	4.02 *
Heteroscedastic logit: variance correction for destination only	30			1.10
Joint logit: no variance correction	29			-

* significant at the 0.05 level

TABLE 5 OBSERVED AND PREDICTED FREQUENCIES ON HOLD OUT CHOICE TASK

	Observed	Heteroscedastic logit (transportation variance correction)	Joint logit*
alt D_1T_1	139	145	183
alt D_2T_2	333	318	242
alt D_1T_2	141	150	188

* Significantly different in Chi-square test at 95% confidence interval.