Distinguishing taste variation from error structure in discrete choice data

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Abstract

We propose as a practice that researchers investigate other sources of heterogeneity besides taste variation in the search for parsimonious recommendations about new product development and marketing program design. Some evidence exists that regularities in choice processes may be more common than previously thought (Louviere and Swait, 1996, Louviere et al., 1999; see also Stigler and Becker, 1977). In fact, it may be that taste homogeneity is more prevalent than expected, if we recognize other sources of heterogeneity properly. In this paper we show how discrete choice models confound taste heterogeneity and differences in error structure. We then illustrate the use of the Tree Extreme Value (TEV) model to investigate taste homogeneity in three trans-oceanic air travel markets, while controlling for error structure heterogeneity. We conclude that partial taste homogeneity exists across the markets, despite accentuated cultural differences; in addition, two of the routes exhibit a much higher degree of taste homogeneity, despite a significant difference in trip length. © 1999 Elsevier Science Ltd. All rights reserved.

Keywords: Choice modeling; Taste heterogeneity; Heteroscedasticity

1. Introduction

The study of consumer behavior using discrete choice models has long allowed for the existence of taste variation, as can be seen through the extensive use of a priori market segmentation in transport demand models (see, e.g., Ben-Akiva and Lerman, 1985). More recently, methodological advances in econometrics and computation have permitted the estimation of sophisticated model specifications in which taste variations are given particular parametric forms (e.g.
Gopinath and Ben-Akiva, 1995; Bhat, 1997a, b; Brownstone and Train, 1999). Such latent class and random parameter specifications have a relatively long history in certain other disciplines (see review in Longford, 1993), but are relative newcomers to transportation (though see Cardell and Reddy, 1977) and marketing (see Cardell et al., 1978; Kamakura and Russell, 1989; Dillon and Kumar, 1994; Swait, 1994; Kamakura et al., 1996).

This interest in the existence of taste segments is natural for those who must plan and manage products and services for a population. The marketing implication of taste variation is that multiple products in the same category are required to meet differing attribute sensitivities (price, speed, comfort, etc.). For firms, of course, it may be profit maximizing to identify these taste variations and cater to them. There are many examples of this in transportation: business and first class service differentials in airlines, second-day versus next-day courier delivery services. Associated with each of these examples we find significant price differentials, which are not always justified from the cost perspective but certainly are from a higher willingness-to-pay for improved levels of service on the part of segments of consumers.

Such taste variations are the basis for a proliferation of products and services in the market, justifiable from the perspective of meeting differentiated customer needs. While our empirical modeling experience in a large number of different product and service areas has led us to find that taste variations do indeed exist, we have been led to wonder whether the conceptual appeal of the notion of taste variation has not obscured the alternative explanation that consumers’ tastes might exhibit a higher degree of homogeneity than we normally seek to find, but that differences might exist along other dimensions. At a philosophical and theoretical level, this challenge was taken up by Stigler and Becker (1977) (see also Becker, 1996, chapter 2), who extended the traditional utility maximizing framework to explain certain thorny issues (e.g. addiction, advertising effectiveness, fashion and fads) assuming that “… one may usefully treat tastes as stable over time and similar among people …” (Becker, 1996, p. 25). At a more empirical level, Louviere and Swait (1996) (see also Louviere et al., 1999) have found that a significant number of choice processes across space, time, even product categories, exhibit a surprising degree of regularity. 2

While we believe that the existence of taste heterogeneity is an empirical issue to be established on a case-by-case basis, we believe that choice analysts should also direct their quest for differences to other dimensions (to be discussed subsequently). It may prove fruitful, from both practitioners and researchers points of view, to have differences attributed to their correct sources as opposed to have them create (potentially) spurious differences attributed to taste variation. Nevertheless, we also find it unrealistic to expect full taste homogeneity in most real-world situations. Thus, the development of model specifications can start with the assumption of full taste homogeneity (while accounting for other sources of differences), which yields ground to statistical evidence of taste heterogeneity. In this way we will develop parsimonious representations of consumer behavior that yield correspondingly parsimonious recommendations about new product development and marketing program design.

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2 To transport planners and modelers, this discussion may be reminiscent of the intense interest in spatial and temporal demand model transferability that occurred in the 1970s and early 1980s (see Koppelman and Wilmot, 1981; Kozel, 1985 and references therein).
We suggest as a practice that researchers investigate other sources of heterogeneity besides taste variation in the search for these parsimonious representations. It is well known that taste variation is not the only source of differences between consumers. In fact, the random utility framework identifies a large number of them. Let each alternative $i$ in a set $C_n$ be characterized by an attractiveness measure $U_{in} = V_{in}(X_{in}; \beta_n) + \varepsilon_{in}(\theta_n)$, with $X_{in}$ a vector of alternative attributes and decision-maker characteristics, $V_{in}$ a known function, $\varepsilon_{in}$ an error term, $\beta_n$ an individual-specific taste parameter vector and $\theta_n$ a deep vector of parameters characterizing the distribution of the error terms of all $i \in C_n$. Upon these attractiveness measures the consumer operates with decision rule $D_n$, which may or may not select the most attractive alternative. Looking across an aggregate of consumers, myriad sources of differences between consumers can be identified even within the confines of this framework. From a modeling perspective, variability among consumers can arise if they have different

- (a) functional forms for the deterministic utility ($V_{in}$),
- (b) tastes ($\beta_n$),
- (c) decision rules ($D_n$),
- (d) choice sets ($C_n$), or
- (e) error structures ($\varepsilon_{in}$).

As we shall see, in discrete choice models there is a confound among several of these sources, which may lead researchers to attribute heterogeneity to improper sources (e.g. confounding taste variation with error structure heterogeneity, or taste variation with choice set formation). In this paper we shall confine ourselves to studying the effect of confounding taste variation (item 2) with differences in error structure (item 5) in discrete choice models of the Multinomial Logit (MNL) family. The impact of this misattribution is not trivial: as we have pointed out above, it makes the difference between gearing a marketing program to develop multiple products to cover the entire market (or conversely, developing products for niche markets) versus developing a single product and addressing competitive strategy and informational needs about the product within segments. The cost implications of this difference in outcome can be substantial.

The objective of this paper, then, is to explore the distinction between taste variation and error structure heterogeneity in discrete choice models. To accomplish this we show in Section 2 how these two effects can be confounded in MNL and Tree Extreme Value (TEV) models, and particularly how we can use the TEV model as a testing vehicle for hypotheses of interest. In Section 3 we proceed to an empirical example using Stated Preference data from a survey about trans-oceanic air travel on three different routes. In Section 4 we discuss our empirical findings, and in Section 5 we present our conclusions and directions for future research.

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3 Some of these issues have previously been reported upon in the literature. As mentioned earlier in the text, taste variations have been of great interest to several fields including transportation (e.g. Gopinath and Ben-Akiva, 1995; Bhat, 1997a, b; Brownstone and Train, 1999) and marketing (e.g. Kamakura and Russell, 1989). Swait (1984) and Swait and Ben-Akiva (1987a, b) have examined the impact of choice set formation on discrete choice models. Kamakura et al. (1996) report on the use of a latent class Nested MNL model to uncover segments based on market structure in scanner panel data. See Steckel and Vanhonacker (1988) for an example of models that assume homogeneity in the deterministic component and heterogeneity in the random term.
2. Using the TEV model to separate taste from error structure differences

In all discrete choice models there is a confound between scale and taste (Ben-Akiva and Lerman, 1985; Ben-Akiva and Morikawa, 1991; Swait and Louviere, 1993; Hensher, 1994; Bhat, 1995; Hensher et al., 1999). In the MNL model, in which all alternatives have scale factor $\mu > 0$ (note that the variance of the error term is $\sigma^2 = \pi^2/6\mu^2$, see Ben-Akiva and Lerman, 1985), the choice probability is given by

$$P_{in} = \exp(\mu \beta X_{in}) / \sum_{j \in \mathcal{C}_n} \exp(\mu \beta X_{jn}),$$

where we have assumed that the non-stochastic utility is given by $V_{in} = \beta X_{in}$, $\beta$ a row-vector of taste weights. In actuality, one estimates the product $(\mu \beta)$; that is to say, the magnitude of the coefficients printed out by an MNL estimation routine are not the taste weights themselves, but this product of a vector of tastes and a scalar related to the degree of variability of the error term. Since the variance of the error terms is inversely related to the scale, the smaller (larger) the variance of the error term, the larger (smaller) the scale, hence the larger (smaller) the estimated coefficients.

A similar confound exists in the TEV model. As presented in McFadden (1981), pp. 230–238, the TEV model is a utility maximization consistent generalization of the MNL model that allows the representation of alternative patterns of inter-alternative substitution through preference tree structures. As we shall see below, the TEV model can be written as a nested sequence of MNL models. Adopting and adapting Daly’s (Daly, 1987) notation, let $T$ be a preference tree characterizing the relationships between elemental and construct alternatives by indicating the predecessor (or parent) node of each alternative, equal to $\mathcal{C} \cup \mathcal{E}$; $\mathcal{E}$ be the set of elemental nodes (i.e. real alternatives); $\mathcal{C}$ be the set of construct alternatives, composed of $\forall a \in T - \mathcal{E}$ plus the root node (designated node 0); $P(a)$ be the parent node of $a \in T$; and $S(a)$ be the alternatives in the subnest of node $a \in T$, including $a$.

Let the conditional choice probability $\ell(a, S(a))$ of any node $a$ among its siblings $S(a)$ be given by an MNL model, like so:

$$\ell(a, S(a)) = \exp(\tilde{V}_a / \theta_{P(a)}) / \sum_{j \in S(a)} \exp(\tilde{V}_j / \theta_{P(j)}),$$

where $\tilde{V}_a$ is an average attractiveness measure defined as

$$\tilde{V}_a = \begin{cases} V_a(X_a; \beta_n) & \text{if } a \in \mathcal{E}, \\ \theta_a \ln \left( \sum_{j \in S(a)} \exp(\tilde{V}_j / \theta_{P(j)}) \right) & \text{if } a \in \mathcal{C}. \end{cases}$$

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4 There has been some confusion in the literature concerning the naming of the TEV and Daly’s (Daly, 1987) similar model. Koppelman and Wen (1998a, b) have suggested calling the former McFadden’s Nested Logit model and the latter the Non-Normalized Nested Logit model. We have preferred to return to the somewhat less familiar, but original name for McFadden’s (McFadden, 1981) model: Tree Extreme Value model.

5 Note that for clarity of exposition we have omitted the possibility of independent variables in the composite utility of construct alternatives, but that is a straightforward generalization of expression (3) that in no way compromises the essence of this development.
In the expressions above the parameters \( \theta \) are called inclusive value coefficients, for which there is one associated with each construct node. Thus, \( \theta_{P(a)} \) refers to the inclusive value associated with the subset of alternatives whose parent is the same as the parent of node \( a \). Given these two definitions, the unconditional choice probability of the elemental alternatives \( i \in E \) is given by

\[
P_i = \prod_{a \in K(i)} \ell(a, S(a)),
\]

where \( K(i) \) is the path of nodes from \( i \) to the root of \( T \), that is, \( K(i) = \{i \rightarrow P(i) \rightarrow P(P(i)) \rightarrow \cdots \rightarrow r_0\} \), where \( r_0 \) is a node that has the root (0) as its parent, i.e. \( P(r_0) = 0 \).

Note that when \( T \) contains only elemental nodes and all these have the root as parent, Eq. (4) reduces to an expression identical in structure to the standard MNL model shown in Eq. (1), after defining \( \mu = 1/\theta_{\text{root}} \). For more general trees, since the utilities in a particular sub-nest of alternatives are divided by the inclusive value of the parent node, there exists this same confound of taste and scale (see particularly expression (2), where the utilities are in the form \( V_a = \theta P_a \)).

Although not identifiable in any one data set, the inclusive value \( \theta_{\text{root}} \) of the root node of a preference tree is related to the overall scale (i.e. variance) of the latent utility variable. Hence, two TEV models with identical preference trees calibrated on data generated from the same taste parameters but different scales will yield what look like two different taste parameter vectors, solely because of different scales. This results also holds in the MNL model (see, e.g., Ben-Akiva and Lerman, 1985 and Swait and Louviere, 1993) and was mentioned above. Thus, when comparing two or more TEV model results it is necessary to control for both heteroscedasticity (scale) and different correlational structures among alternatives.

Therefore, if we are considering a situation in which multiple a priori market segments potentially have different tastes and different structures for their error terms (i.e. different variances and/or covariances), we must take certain precautions in testing whether the market segments actually have different tastes. Suppose there are \( S \) market segments, each characterized by its own tastes \( \beta_s \) and preference tree structure \( T_s \). The hypothesis of interest is whether taste homogeneity and error structure heterogeneity exist, versus the alternative of simultaneous taste and error structure heterogeneity. Thus, the formal statement of this hypothesis is

\[
H_0: \beta_1 = \cdots = \beta_S = \beta, \text{ given error structure heterogeneity.}
\]

In order to test this hypothesis we first need to define each market structure separately, then test for taste variation across market segments given the structure of each particular market. We illustrate this test procedure in the following section.

3. Separating taste variation from error structure heterogeneity: An empirical illustration

In our empirical application, we will consider an airline choice problem for three different transoceanic routes. These three market segments have different countries of origin but a common (fourth) country of destination, hence it is reasonable to assume that there may be both taste and preference tree heterogeneity. The data we utilize were collected through a Stated...
Preference (SP) choice task inserted in a survey instrument examining a number of other research items of interest (see, e.g., Louviere and Woodworth, 1983, Hensher, 1994 and Swait et al., 1994 for illustrations of SP choice tasks). The task was administered in a paper and pencil modality to respondents recruited from among actual travelers on the three routes, each of whom did eight SP choice scenarios involving multiple airlines. On each route the airlines involved are largely different, though certain ones are common: Route 1 has airlines \{G, K, R, X, Z, All Others\}, Route 2 has \{A, B, X\} and Route 3 \{A, B, R, X, All Others\}. (The “All Others” alternative represents all other airlines that operate on the route but are not explicitly named in the SP task.) In any particular SP scenario, travel options for the trip in question were described in terms of price, in-flight characteristics (seat characteristics, crew attitude, food choice, in-flight entertainment and number of crew members speaking passenger’s native language), frequent flier program characteristics, and pre- and post-flight service quality (check-in waiting time, baggage waiting time). Because of the differing number of airlines per route and the fact that Route 1 had an attribute specific to itself, there are actually 22 taste parameters that are common across routes. Hence, the taste vector in hypothesis (5) is composed of 22 elements.

For each route we developed TEV models for the SP choice data. After extensive testing it was found that each route was characterized by a different preference tree structure, which we present graphically in Table 1 along with certain estimation results. It is clear from these results that on each route the hypothesis that the choice process is characterized by the IIA property (i.e. the MNL model holds) is strongly rejected. From models that are not reported in the table, it is also clear that each route is distinctly characterized by the reported preference tree structure: the optimal preference trees reported in Table 1 dominate the others. This implies, from the traditional interpretation of TEV models, that distinct correlational structures are at work on each route, a result that seems eminently plausible given different sets of competitors and different customer bases.

As they stand, the three models in Table 1 assume that both tastes and error structures differ across the three routes. Now let us impose hypothesis (5) upon the three routes and test whether the tastes are homogenous across them. Table 2 presents a joint model for the three routes, in which we have forced the 22 common taste parameters to be equal across routes, but allow each route to maintain its unique error structure (we also keep route-specific the alternative-specific, or brand, constants). Note that this joint model requires the specification of an additional level in the “preference tree” structure, so as to “join” the three routes. In fact, we should not interpret the top tier of the tree in Table 2 from a covariational point of view; as Bradley and Daly (1994) show, we interpret the inclusive value coefficients at the top level of this tree as estimates of the inverse of the scale of each route, relative to the route which has fixed scale of unity (in this case, Route 1). Under the hypothesis of homogenous tastes across the three routes, and based on the scale and inclusive value coefficients presented in Table 2, we can state that Routes 2 and 3 have larger scale (smaller variance) than Route 1. While there is no theoretical justification for this observation, it is noteworthy that the destinations for Routes 2 and 3 have similar cultures that are significantly different from that of the destination country of Route 1. In other contexts, there may be plausible and/or theoretical reasons to expect certain relative scale orderings.

Comparing the joint model in Table 2 to the route-specific models of Table 1, we find a $\chi^2$ statistic of 149.0 with 42 degrees of freedom. Thus, the hypothesis of full taste homogeneity across the routes, while controlling for route-specific error structure, is rejected at the 95% confidence...
<table>
<thead>
<tr>
<th>Route 1</th>
<th>Route 2</th>
<th>Route 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Optimal Preference Tree</strong></td>
<td><img src="image.png" alt="Diagram" /></td>
<td><img src="image.png" alt="Diagram" /></td>
</tr>
<tr>
<td>LL (TEV Model)</td>
<td>-2729.7</td>
<td>-3387.7</td>
</tr>
<tr>
<td>McFadden's $\rho^2$</td>
<td>0.198</td>
<td>0.207</td>
</tr>
<tr>
<td># Parameters (TEV)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Taste (Brand Constants)</td>
<td>5</td>
<td>2</td>
</tr>
<tr>
<td>Taste (Route-Specific Attributes)</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>Taste (Common Attributes)</td>
<td>22</td>
<td>22</td>
</tr>
<tr>
<td>Inclusive Value</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>$\chi^2$ for MNL Model (df)</td>
<td>14.6 (3)</td>
<td>19.0 (1)</td>
</tr>
<tr>
<td>Inclusive Value Coefficient Estimates (t-stats)*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Route 1: Domestic</td>
<td>0.566 (4.7)</td>
<td></td>
</tr>
<tr>
<td>International</td>
<td>0.827 (2.0)</td>
<td></td>
</tr>
<tr>
<td>Not Airline X</td>
<td>0.759 (2.1)</td>
<td></td>
</tr>
<tr>
<td>Route 2: Not Airline X</td>
<td></td>
<td>0.655 (5.4)</td>
</tr>
<tr>
<td>Route 3: Major Airlines</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Minor Airlines</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* t-statistics are calculated for the hypothesis that the inclusive value coefficient equals one.
### Table 2

Joint three-route TEV model

<table>
<thead>
<tr>
<th></th>
<th>All Routes</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Joint Preference Tree</strong></td>
<td>![Diagram of preference tree]</td>
</tr>
<tr>
<td><strong>LL (Joint Model, Fully Taste Homogenous)</strong></td>
<td>-9113.5</td>
</tr>
<tr>
<td><strong>McFadden’s $\rho^2$</strong></td>
<td>0.224</td>
</tr>
<tr>
<td><strong># Parameters (TEV)</strong></td>
<td></td>
</tr>
<tr>
<td>Taste (Brand Constants)</td>
<td>11</td>
</tr>
<tr>
<td>Taste (Route-Specific)</td>
<td>2</td>
</tr>
<tr>
<td>Taste (Common Attributes)</td>
<td>22</td>
</tr>
<tr>
<td>Scale Factors &amp; Inclusive Value</td>
<td>8</td>
</tr>
<tr>
<td><strong>Inclusive Value Coefficient Estimates (t-stats)</strong></td>
<td></td>
</tr>
<tr>
<td>Route 1</td>
<td>1.0 (base)</td>
</tr>
<tr>
<td>1/Scale</td>
<td></td>
</tr>
<tr>
<td>Domestic</td>
<td>0.427 (7.8)</td>
</tr>
<tr>
<td>International</td>
<td>0.607 (6.5)</td>
</tr>
<tr>
<td>Not Airline X</td>
<td>0.652 (3.9)</td>
</tr>
<tr>
<td>Route 2</td>
<td>0.778 (2.9)</td>
</tr>
<tr>
<td>1/Scale</td>
<td></td>
</tr>
<tr>
<td>Not Airline X</td>
<td>0.569 (7.2)</td>
</tr>
<tr>
<td>Route 3</td>
<td>0.674 (4.8)</td>
</tr>
<tr>
<td>1/Scale</td>
<td></td>
</tr>
<tr>
<td>Major Airlines</td>
<td>0.626 (5.7)</td>
</tr>
<tr>
<td>Minor Airlines</td>
<td>0.461 (9.7)</td>
</tr>
</tbody>
</table>

* t-statistics are calculated for the hypothesis that the inclusive value coefficient equals one.
level. At this point, most analysts might conclude that the possibility of taste homogeneity has
been eliminated and proceed with route-specific models, thus allowing for full taste and error
structure heterogeneity.

However, we believe that there are other (intermediate) hypotheses of interest. What of the
possibility that many, though not all, taste parameters are equal? This would allow for consumers
on the three routes to be taste homogenous to some degree, with specific exceptions at the at-
tribute level. The question then becomes how to select the (hopefully small) subset of taste pa-
rameters that are to be allowed to be segment specific.

Swait and Louviere (1993) and Louviere and Swait (1996) show that for the MNL model, under
the hypothesis of taste homogeneity and scale (i.e. variance) differences between two data sources,
plotting the taste parameter pairs from both sources on an $X$–$Y$ plot will result in a positively sloped distribution of points; the slope of the cloud of points is related to the ratio of the scale factors of the two choice data sources. Louviere and Swait (1996) show that this holds for other discrete choice and ordinal response models; it holds also for the TEV models used in this paper.

Hence, we plotted the 22 element taste parameter vectors for each of the three route pairs (see
Fig. 1). The overall impression given by the three plots is that the taste parameters are consistent
with the idea of taste homogeneity across the three routes, up to scale differences. However, we
have already seen that the formal hypothesis of full taste homogeneity is rejected across the three
routes. By looking at Fig. 1, we begin to discern the underlying reasons for rejection of this fully
restrictive form of the taste homogeneity hypothesis. A detailed study of the plots suggested that
we should test a hybrid model which would allow some heterogeneity to exist across the routes.
We indicate by dashed polygons in Fig. 1 a number of possible candidates for taste parameters
that may have led to the rejection of the full taste homogeneity hypothesis. These are basically
parameters that have different signs on different routes, or are relatively stronger/weaker on one
route versus another.

Our final hybrid joint model has 8 taste parameters homogenous across all routes, 10 taste
parameters homogenous across Routes 2 and 3, and the remaining 22 parameters heterogeneous
(specific to each route). Table 3 presents a comparison of the fully taste heterogeneous model, the
fully taste homogeneous model and this hybrid joint model. The log likelihood is $-9056.0$ with 61
parameters for this third model, compared to $-9039.0$ with 85 parameters for the fully hetero-
geneous model. This means that the $\chi^2$ statistic of 34.0 with 24 degrees of freedom is smaller than
the critical value of 36.4 at the 95% confidence level. We cannot, therefore, reject the hypothesis
that the hybrid joint model is statistically equivalent to the fully heterogeneous model.

Interestingly (and comfortingly!), the taste parameters that remain homogeneous across the
three routes relate to price, crew quality of service, and seat comfort attributes. It seems to us
reasonable that these should be uniform across the three routes, for they are dimensions of
product evaluation that are plausibly cross-cultural. On the other hand, those parameters that are
route-specific are items that can reasonably be assumed to have relative weights that are culture-
specific (e.g. availability of ethnic food, waiting times at check-in and baggage pick-up, frequent
flyer programs and types of in-flight entertainment).

7 Please note that the plotting of estimated parameters is done only for hypothesis generation. The final model is
chosen based on rigorous statistical tests.
Fig. 1. TEV coefficient plots by route pairs.
4. Discussion

As pointed out in Section 1, the sources for differences between consumers are many: choice set structures, evaluation functions, tastes and decision rules. We have proposed that, with due rigor, choice modelers should seek regularities in choice processes whenever possible. While total taste homogeneity may be something of a chimera, we believe it realistic to quest for partial taste heterogeneity.

The three-route airline choice example in Section 3 recognized that there are certain taste similarities and differences between the three routes, after controlling for preference tree differences. If these tree differences were not accounted for, it is likely that further taste differences would occur. Such a misattribution would result in added service differentiation across the various routes, likely leading to increased costs. Based on the model results, service design and optimization (as well as marketing activities in general) can proceed to build upon the similarities and use the differences to build competitive advantage for the carrier. Specifically, we have found the following:

(a) market structures differ significantly across the routes. This is likely to impact mostly the advertising and market positioning activities taken by the carriers in each route;

(b) pricing and crew-training policies can be the same across the three routes, which greatly simplifies tariff structures for the carrier and increases labor mobility across the routes to accommodate carrier needs;

(c) the impact of seat comfort is also the same across routes, allowing for homogeneity in the interior design and décor of the fleet;

(d) in this particular case, it was found that two of the routes have further common characteristics, such as food and entertainment requirements and responsiveness to frequent flier programs, which can be exploited by carriers. These two routes are, however, significantly different from the third route in terms of certain culture-specific issues;

(e) finally, certain sensitivities are culturally based or may be related to route length, so marketing activities must be tailored appropriately to enable carriers to meet specific consumer needs.

Contrast this targeted differentiation with the original situation in which we would have recommended that each route be treated as a separate market. Not only would this have been an invalid conclusion, it would have misled the carrier into making (potentially) wasteful expenditures by unnecessarily tailoring marketing activities to each route. Goodwin and Verhage (1989) compare

<table>
<thead>
<tr>
<th>Model</th>
<th>Tastes</th>
<th>Log likelihood (# parameters)</th>
<th>$\chi^2$ statistic with respect to model 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Models by route</td>
<td>66 Heterogenous</td>
<td>$-9039.0$ (85)</td>
<td></td>
</tr>
<tr>
<td>2. Joint model</td>
<td>22 Homogenous</td>
<td>$-9113.5$ (43)</td>
<td>$149.0$ (42)</td>
</tr>
<tr>
<td>3. Joint model (hybrid)</td>
<td>8 Homogenous (all routes)</td>
<td>$-9056.0$ (61)</td>
<td>$34.0$ (24)</td>
</tr>
<tr>
<td></td>
<td>10 Homogenous (Routes 2 and 3)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>22 Heterogenous</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

$^a$ Numbers of parameters do not include brand constants, which are route-specific in all models. In addition, two parameters are specific to Route 1 throughout.
perceptions of customer/provider interactions in a number of different service categories for US and Dutch respondents. While their work does not involve choice models, as does our research, it is nonetheless supportive of the concept of taste homogeneity across cultures, as is our empirical example.

In our analysis we have assumed intra-segment homogeneity of tastes and error structure. Allowing for taste heterogeneity within segment (say, through a random parameter version of the TEV model, or by using an MNP random parameters specification), while a more difficult and complicated analysis than we have performed here, could affect inferences about the respective tree structure; this could, ultimately, change the overall conclusions reached in this example. However, we note that in using more sophisticated specifications incorporating taste heterogeneity, we have nonetheless come upon situations in which we have found segments to be partly, if not wholly, ascribable to average preferences (i.e. ASCs) and scale differences, not taste differences with respect to attributes.

5. Conclusion and further research

Economists, transport planners and marketers have generally sought to explain consumer behavior in markets using models that recognize systematic variations in tastes between individuals that might arise due to personal or decision-context characteristics, as well as stochastic variations that may nonetheless persist after systematic differences have been accounted for. We believe that this approach is often adopted because of a widely held belief that consumers’ tastes are innately unique, and that this uniqueness plays an important role in their market behavior. We suggest, however, that a more fruitful goal for these disciplines might be to seek quite the opposite, taste homogeneity, and allow heterogeneity when statistical evidence supports it. If nothing else, if this quest pays off in a particular instance, it shall make marketing managers live far less complex than they are today with the marked proliferation of look-alike products and hair-splitting service differentiation.

In this paper, we have highlighted that in the case of discrete choice models taste heterogeneity is potentially confounded with heterogeneity in error structure (see, e.g., Ben-Akiva and Morikawa, 1991; Swait and Louviere, 1993). We illustrated how the TEV model can be used to separate these two effects with an application involving airline choice in three separate markets (three origin countries to a common fourth destination country). We found some taste homogeneity across all three routes, as well as more extensive taste homogeneity across a subset of two of the routes. Taste heterogeneity was found to hold across a number of attributes for which culture has high face validity as a determinant of taste differences (see also Goodwin and Verhage, 1989). This example points to a type of outcome we find eminently reasonable: while total taste homogeneity is unlikely to hold generally, it is quite possible that partial taste homogeneity holds widely in choice processes (see also Louviere and Swait, 1996).

Because of the latent nature of the variable of interest (i.e. utility) in choice models, certain issues that are treated rather straightforwardly in other model forms can become quite complicated. Determining taste homogeneity is one such issue. In choice model specification the effect of scale (i.e. heteroscedasticity) is itself confounded with the effect of market structures (i.e. preference trees). Thus, identification of taste homo(hetero)geneity requires that we control for
heteroscedasticity and preference tree structure. We have demonstrated in this paper a rigorous approach which controls for these while testing for a priori segment effects, within the framework of the TEV model.

Conceptually, the same general approach can be applied to more sophisticated models, such as the Multinomial Probit, Random Parameters MNL, etc. The approach can also be applied to latent class models of choice, where the issue then becomes whether the identified classes are actually based on taste heterogeneity, scale differences or both (see Swait, 1994). There are indications that, just as in the case of a priori segments, latent class and random coefficient models can actually attribute effects that are due to heteroscedasticity and/or inter-alternative substitutability to taste heterogeneity (see Swait, 1994; Kamakura et al., 1996; Hensher et al., 1999). While at the level of forecasting or estimating elasticities this misattribution is largely irrelevant, it is very relevant for product design and marketing program design.

Our recommendation for researchers and practitioners specifying segment-based choice models is that they carefully consider the interaction between choice set structure, taste variation, decision rule heterogeneity, preference tree structure and heteroscedasticity. The random utility approach explicitly lays out a playing field on which all these factors can be used to capture consumer preferences. The question for the analyst then becomes one of attribution of effects to specific theoretical constructs. For example, segment-specific choice set formation differences will lead to different sets of ASCs; a pooled model should not restrict the ASCs to be the same across segments because (1) choice set formation is a likely source of heterogeneity across segments, and (2) inclusion of the ASCs in the “taste” parameters might lead to obfuscation of the main substantive question, which relates to homogeneity of tastes for product attributes. While this may seem an obvious point, the example is sufficiently rich to illustrate the need for careful consideration of the multiple components of random utility choice theory during model specification.

Our future research program in this area will strive to incorporate other sources of heterogeneity in modeling consumer behavior. We feel that priority should be given to distinguishing between heteroscedasticity and covariational effects. We also recognize the need to incorporate choice set and decision rule heterogeneity into choice models in the process of searching for choice regularities. However, we recognize that both of these are difficult problems to tackle (with respect to the difficulties of modeling choice set formation, see the discussion in Swait and Ben-Akiva, 1987a, b).

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