Modifying Conjoint Methods to Model Managers’ Reactions to Business Environmental Trends: An Application to Modeling Retailer Reactions to Sales Trends

Harmen Oppewal
UNIVERSITY OF SURREY
Jordan J. Louviere
UNIVERSITY OF SYDNEY
HARRY J. P. TIMMERMANS
EINDHOVEN UNIVERSITY OF TECHNOLOGY

This article proposes and demonstrates how conjoint methods can be adapted to allow the modeling of managerial reactions to various changes in economic and competitive environments and their effects on observed sales levels. Because in general micro-level data on strategic decision making over time are difficult and expensive to obtain, this approach can be of much value to the further study of managerial strategic behavior and market dynamics. In our application we model retailer reactions to changes in their sales, focusing in particular on the actions that affect the demand for retail space and possibilities to improve retail sites. Choice responses to hypothetical sales and environmental trend scenarios are collected from 183 retailers and used to estimate a logit regression model that predicts retailers’ probabilities of choosing actions. The model results confirm that retailers are more likely to take action when sales go down than when they go up, and also that they react more quickly if sales go down. It is also found that retailers are more reluctant to change the positioning of their store when confronted with a sales increase than when confronted with a sales decrease. The model is compared with a non-experimental model that is based on retailers’ reactions to the trends they report to have observed for their own stores. The article concludes with a discussion of the implications of this research for the further development of conjoint-like approaches to studying entrepreneurial behavior.

The purpose of this article is to demonstrate that conjoint analysis methods, which traditionally have been used to model multi-attribute model consumer decisions (for reviews, see Green and Srinivasan, 1978, 1990; Louviere, 1988, 1994), also can be applied to model how managers are likely to react to various changes in economic and competitive environments. Rather than using conjoint techniques to develop multi-attribute product descriptions (profiles), we use them to create profiles of past and current levels of economic conditions and trends in such conditions. Rather than expressing preferences for, or intentions to, purchase product profiles, the managers in our sample tell us which one or more of several strategic actions they would be most likely to take now or in the near future in response to the profile information. Our results demonstrate that managers can and will provide reasonable responses to this type of survey, and the resulting models provide useful insights into their strategic thinking.

Our approach represents an extension of the choice-based conjoint paradigm, which was pioneered by Louviere and Woodworth (1983); for a recent review, see Carson et al. (1994). That is, using random utility theory (McFadden, 1974), we seek to model the choice of one or more strategic actions that managers say they are likely to take in response to information about economic conditions and trends. Our approach is motivated by the relative lack of, and difficulty in, obtaining the panel observations of managerial strategic decisions that could enhance our understanding of how strategic actions change over time in response to changing economic conditions.
conditions. Instead, much past research has relied on case studies, cross-sectional data, and retrospective observation. While valuable in their own right, the field could benefit from access to micro-level data on strategic decision making over time. Such data are typically expensive and difficult to obtain; hence, it is relevant to develop an alternative approach.

We believe that additional progress can be made by using various types of conjoint analysis and experimental choice methods to study managerial decisions in contexts in which temporal aspects of economic variables can be manipulated. Conjoint and experimental choice analysis refers to a family of methods for studying and modeling decisions that use empirical experiments to manipulate combinations of key decision factors in a systematic and (usually) independent manner to create hypothetical alternatives which are evaluated by the experimental subjects. The use of statistical control permits one to infer effects of changes in key decision factors, and status and trend factors can be manipulated over ranges that encompass both past and likely future levels (e.g., Green and Srinivasan, 1978; 1990; Louviere, 1988; Carson et al., 1994). Although there have been some attempts to apply conjoint techniques to model managerial decisions (cf. Montgomery, 1985), we are unaware of any attempt to manipulate status and trend variables to observe temporal changes in decisions.

Our interest focuses in particular on retailer strategic behavior. There is a growing empirical literature on general managerial decision-making processes (e.g., de Chernatony et al., 1993; Day and Nedungadi, 1994) and frameworks for describing retailer strategic behavior (e.g., Bennison, Clark, and Pal, 1995). However, there is little empirical research on how retailers actually manage stores, make decisions, and respond to changes in retail environments (cf. Specht, 1987; Corstjens and Doyle, 1989; Perkins and Rao, 1990). The following observations are typical of the present state of our knowledge about retailer strategic behavior. Retailers are typically reactive and focus primarily on the short term. Burt (1989) concludes “retail management appears to be more reactive and dedicated to crisis firefighting than long-term analysis and planning;” while Arnold, Capella, and Smith (1983, p. 107) reported changes in macro-retail management environments to be typically monitored and reviewed irregularly and in ad hoc ways. They also conclude that reviews often are crisis-initiated and retrospective, and focus on current or near future only. As a final example, Krider and Weinberg (1997) described retailers as “scrambling astutely.” Support for these insights comes from a small number of empirical studies of retail managers. These studies found that retailers tend to neglect long-range planning, instead relying on sales trends as key indicators of store performance (Robinson, Logan, and Salem, 1986; Gable and Topol, 1987).

Hence, to further our understanding of retailer strategic behavior it is particularly relevant to model the relation between sales trends that retailers observe and the strategic decisions they take. Improved insight in this relation may help to gain a better understanding of the processes that underlie the dynamics in retail markets (cf. Erdem and Keane, 1996; Krider and Weinberg, 1997; Messinger and Narasimhan, 1995). We specifically wish to know the effects of sales trend changes on retailers’ probabilities of taking actions that affect the demand for retail space and/or the possibilities to improve retail sites. In this study we therefore focus on the following possible actions: open new branch stores, close the current store, relocate the store, renovate the store, change the store’s image, alter the size of floor space, or invest in the immediate store environment. Note however that the random utility-based methodology that we develop can be used to study very different types of actions.

Our interest focuses on building a quantitative model to assess and predict the strategic reactions to sales changes that resulted from trends in the retailers’ business environment. We control trends in the retail environment by specifying them as explicit variables (factors) in the experiment discussed in the next section.

We are only aware of one previous application of random utility theory to estimate discrete choice models from the strategic choices made by retailers. Miller and Lerman (1979, 1981) developed a model of store owners’ choice of “location, scale and intensity” and tested this model in Boston on the location pattern of 161 clothing stores, their sizes, and numbers of employees. Miller and Lerman (1979, 1981) thus demonstrated that models can be developed to predict the probability that particular retailers choose particular actions or combinations of actions. They however also demonstrated some of the problems that occur when only data from real markets are available. In the real market it is likely that many factors of research interest are correlated, both cross-sectionally and latitudinally—this forced Miller and Lerman to limit their estimation to a much simpler model than was developed earlier. Also, actual store/chain performance measures such as sales revenues, profits, ROI, or costs may be difficult or even impossible to obtain because many retailers will not provide them. Similarly, response rates to surveys among retailers are often low (e.g., Robinson et al., 1986).

We are unaware of any other researchers who have tried to develop conjoint-like experiments to study managers’ strategic decisions. Trying to design and execute meaningful strategic decision experiments to study retailers is not an easy task, as is demonstrated in this article. For example, strategic decisions are by definition “longer-term” choices that are made infrequently, hence the temporal unit of measurement may not be obvious.

Thus, the empirical portion of the study should be viewed as an exploratory research project, and like most attempts to modify an existing method to apply it in another area, it will require further refinement and iterative updating to perfect. Nevertheless, the results reported in the empirical research section are sufficiently encouraging to warrant further work.

Consistent with the literature above, we hypothesize, first, that retailer choice of action depends on the sales trends they observe. Second, we hypothesize that retailers are mostly
defensive, that is, they are more likely to take action if sales decrease than if sales increase. Third, we hypothesize that sales decreases result in an increase in the probability of choosing actions that represent more strategic changes, such as altering store image, whereas positive sales trend changes will result in higher probabilities of actions that foster or exploit the observed trend without changing the store’s positioning. Typical examples of this latter type of action are store renovations and floor space alterations. Fourth, we hypothesize that retailers react more quickly when sales go down than when sales go up.

The remainder of this article discusses the proposed conjoint approach, using as an example our application to modeling retailer choice of strategic action. We next present the results of our application, report tests of the hypotheses, and present a small example of how the estimated model can be applied. We finally discuss our results and suggest some potentially fruitful future research possibilities.

Research Approval

Experimental Design of Decision Scenarios

Recall that our primary research interest lies in understanding and modeling how changes in sales volumes and broad business and economic environment factors influence retailer strategic choices. Literature reviews and exploratory research interviews with retailers suggested a number of factors that play key roles in such decisions. As previously mentioned, unlike traditional applications of conjoint analysis, these factors are contextual factors insofar as they describe environments in which retailers operate (cf. Oppewal and Timmermans, 1991). Thus, our conjoint experimental objective is to create different hypothetical business environments, with desirable properties from a modeling standpoint, and in each scenario observe the action(s) retailers would be likely to initiate in response. By manipulating the levels of the environmental factors according to an experimental design we can infer the effects of each on the action(s) taken by retailers.

The final decision factors and scenario profiles used in the empirical research reported later were based on pilot tests involving 30 retailers sampled from a wide range of stores/locations. To maximize cooperation and response validity, we tried to describe the experimental factors in a way that would be easy for retailers to understand. We also tried to closely simulate business decision environments that retailers actually face in the ways in which we developed the scenarios. Figure 1 contains an example of a scenario used in our research.

The experimental scenarios represent hypothetical shifts in sales trends observed for each retailer’s own store over the past three years. That is, a retailer first reported his/her own actual sales trend by comparing last year’s sales volume with the volume obtained three years before. Next, they had to imagine another trend, which involved an additional increase (or decrease). In addition, the scenarios had to inform the retailer if the hypothetical sales trend shift appeared (1) suddenly three years before; (2) suddenly last year; or (3) steadily developed over the previous three years.

As Figure 1 shows, the final part of each scenario described shifts in environmental trend factors such as competition, atmosphere, and spending power. We framed these trend changes as if they co-occurred with the hypothetical sales trend shift in order to control inferences that retailers might make about underlying causes of scenario sales trends. We used trends defined on past developments because our pilot work suggested that some retailers questioned the credibility of forecasts of “future” trends and/or some became suspicious that we were working for a large firm or local planning authority. Neither of the foregoing happened when trends were presented as past developments.

Seven experimental factors described changes in environmental trend during the past three years (see Figure 2). These factors were expressed as physical quantities to the extent possible to minimize interpretational variances between retailers (e.g., area atmosphere was expressed as the proportion of visitors who were satisfied with the atmosphere, and competition as total competing floor space).

An orthogonal fraction of a $2^3$ factorial and its foldover were used to create 108 scenarios. The resulting design permits estimation of all main effects plus all two-way interactions with the framing factor (positive or negative relative sales trend shift). The aforementioned effects are independent of one another and of all the other linear-by-linear two-way interactions. This design should protect well against bias from unobserved interactions (Louviere, 1988).

The experimental task was administered in subsets of two scenarios per retailer to reduce the task demands because we anticipated that many retailers would not be willing to participate in our research, and we wanted to give them as little reason not to cooperate as possible. Of the two scenarios each retailer received, one always represented a positive sales trend and the other a negative trend. Half of the retailers received a positive scenario first and the other half received a negative sales trend scenario. Retailers were randomly assigned to scenario conditions and whether they received a positive scenario first.

Subjective Probability Choice Task and Model

Seven retailer actions were selected to represent and operationalize strategic initiatives that retailers can choose from their stores. These seven actions are (1) close or sell store; (2) relocate; (3) open an (additional) branch outlet; (4) alter floor space; (5) renovate interior and/or exterior; (6) change image (i.e., reposition on retail mix variables; and/or (7) invest in improving immediate (micro-) environment. Other actions such as buying and merchandise mix decisions are more tactical and short-term and therefore were not included. As previously noted, we are interested primarily in longer-term, more consequential decisions that eventuate after sufficient time passes.
We developed a choice task to measure how likely the retailers would be to take each of the actions in respect to their store in the near future. All possible sets of actions that could be taken are given by a $2^7$ factorial in which each action is taken or not. From this factorial we selected eight choice action combinations using a $2^{7-4}$ fractional factorial design. We asked retailers to evaluate these eight sets of action combinations and from each choose the one action that they thought they would be most likely to take for their store in the next three years. This approach allowed us to obtain subjective probability estimates indirectly, and in a way that minimizes task load and requires few measurement assumptions (cf. Wise, 1970; Wallsten and Budescu, 1983). An eighth choice option “no action” was added to all eight sets, as shown in Figure 3. To minimize presentation order effects we used six random orders of combinations and listings of actions within combinations.

We asked retailers to complete this choice task three separate times. Before the scenario task we asked them how likely they would be to take each action given their current retail conditions. Second, after they had read the first experimental scenario, we asked them how likely they would have been to take each action if the scenario had come to pass. Finally, we asked them a similar question after they had read the second experimental scenario.

We had to frame the decision task as a subjective probability task instead of a management decision task to avoid issues that might distract or confuse retailers or make them reluctant to respond. For example, such issues include (1) who does or who should make decisions within retail organizations, and/or (2) how to take into account the likely success of implementing actions chosen. The need for framing surfaced in pretests when we found that on the one hand managers were anxious about making decisions beyond their responsibility, but on the other hand were much less reluctant to provide information if approached as the “best available expert on their stores” instead of the decision maker.

The design of our experiment is consistent with the family of choice experiments based on random utility theory (e.g., Louviere and Woodworth, 1983; Louviere, 1994). In random utility theory one posits a true but unknown level of utility $U_i$ that the decision maker associates with actions $i$ in choice set $C$. This utility is composed of a measurable, systematic component $V_i$ and a random component $e_i$ (e.g., Ben-Akiva and Lerman, 1985). In the present case we assume that the retailer will choose the one action that gives him/her the highest utility for the particular scenario. We can calculate the probability of choosing action $i$ by making assumptions about the distribution of the $e_i$. By assuming that $e_i$ is IID Gumbel distributed, the closed form multinomial logit (MNL) model can be derived (McFadden, 1974), but note that other possibilities like the normal would lead to different model
forms (Ben-Akiva and Lerman, 1985). In the usual estimation of the MNL model, which can be written as follows:

$$P(i|C) = \frac{\exp(V_i)}{\sum \exp(V_j)},$$

one imposes further assumptions to derive a tractable model, such as the $V_i$ are a linear-in-the-parameters function of a design matrix which describes the characteristics of the choice options and the choosers. In the present case the choice options consist of single actions; hence, the “design matrix” consists of seven columns of dummy variables that uniquely identify each action. The “no action” option is set to zero for convenience.

Because the retailers choose only a single action in each of the eight choice sets for each scenario, our model is equivalent to a series of alternative-specific parameter vectors estimated from the data (Ben-Akiva and Lerman, 1985). Our focus is on reactions to sales trends; hence, we limit analyses in this present article to the nine sales trend components and eight stratification components (see below) to illustrate the proposed approach. This still results in a non-trivial modeling exercise requiring us to estimate a total of $7 \times (9 + 8)$, or 119 parameters.

The logic behind the choice task is as follows. Let the probability of choosing action $A$ instead of choosing not any action be an approximation to the subjective probability that $A$ is chosen at all. If the IID assumption of the MNL model is satisfied (hence, IIA is satisfied), multinomial logistic regression can be used to estimate this probability from choices observed for the designed eight sets of actions. In particular, the subjective probability of choosing action $A$ is derived as:

$$P(A \mid \{A, None\}) = \frac{\exp(V_A)}{\exp(V_A) + \exp(V_{\text{None}})},$$

where $V_A$ represents the “utility” of alternative $A$ and $V_{\text{None}}$ the utility of taking none of the defined actions.

In each of the eight sets of actions, retailers picked the action that they would be most likely to initiate. They made these eight choices in response to each of the two scenarios they received. There were a total of 108 such scenarios, thus, for each scenario we have a vector of choice responses associated with each of the eight choice sets of actions. We can estimate the effect of each of the scenario factors on the eight action choice options because we have sufficient data on both choices and scenario factors to do so.

### Sample Design and Procedure

The respondents in our empirical study were obtained from a stratified random sample of 344 retail outlets drawn from a database of all stores in a medium-sized European city. Each stratum was in a 3 x 3 factorial design involving the following factors (and levels): (1) types of merchandise (food and packaged goods; clothing, textiles, and shoes; other less frequently purchased goods); and (2) relative store location vis-à-vis the CBD (in the most expensive area of the city center; in the city center but not the most expensive area; in a suburban neighborhood). This particular stratification was of interest because we wanted to demonstrate that our results could be generalized across types of retailers and because several strategic actions might be expected to vary by relative urban location (e.g., opening/closing branches). It also is worth noting that the data used in this illustration of the proposed conjoint approach were collected as part of a much larger research project targeted at a broad selection of retailer types from one geographical region.

Retailers were randomly sampled until each of the 108
scenario treatments had been observed at least once within each stratum. This was accomplished by adding the two stratification factors to the scenario design, which resulted in three to four replications of each scenario treatment, and 18 to 20 retailers in each stratum. Sampled retailers were mailed an introductory letter and then contacted by interviewers to schedule a personal interview; 203 retailers agreed to be interviewed and 183 completed all parts of the survey. This is a usable response rate of about 53%. The sample represented a broad cross-section of retailers in the urban area studied. Most retailers in our sample were small independents (68.7% independent); rented or leased their stores (63.7%); and had small shops (74.4% < 100 m² floor space).

Before receiving and evaluating the two experimental scenarios (they received the second only after completing the first), retailers answered questions about trends in their store’s retail environment and sales in the past three years. That is, for sales as a whole and each environmental factor, they reported if each had increased, been stable, or decreased over the past three years. They estimated how much the level of each had changed in this period relative to a base index of 100 defined to be the level of each in a particular month three years past. They also completed the choice task described in the previous section regarding possible strategic actions that might be taken in the next three years. Next they evaluated and responded to the two experimental scenarios. As a manipulation check, we asked retailers to rate how favorable each scenario would be for their business in relation to each of the environmental factors manipulated in each scenario. Finally, retailers rated the scenarios and survey on several dimensions related to how realistic the scenarios were, how well they understood the task, etc.

**Analysis and Results**

Because the purpose of this article is to propose and illustrate a new way to use conjoint analysis techniques to study and model strategic managerial decisions, we restrict attention to the analysis of the choice data only. To obtain base-line probabilities for each action, we estimated logistic regression models from the choices made in response to the sets of actions most likely to be taken in the next three years. These results suggest that (across all stores in the sample) subjective probabilities were smallest for closing/selling (0.80), investing in immediate environments (0.12), and choosing to open or relocate branches (0.13 and 0.14, respectively). Choice probabilities for other strategic actions were substantially higher (e.g., floor space alterations = 0.25; storage image
changes = 0.23; store renovations = 0.45; and “no change” = 0.32). We also found some stratification differences. Retailers who operate neighborhood stores were more likely to close stores or open branch stores, alter floor space, and invest in immediate store environments than other store location types. Retailers who operate clothing, textile, and shoe stores were less likely to close stores. Retailers in food and packaged good were more likely to choose to relocate.

We next estimated a logistic regression model with a sales trend effect for each of the seven actions to represent effects of reported sales trends on these action choices. The addition of the sales trend parameters significantly improved the model fit (the likelihood ratio statistic for the increase was 1627.58, which is $\chi^2$ distributed, df = 35; the Akaike or ‘adjusted’ $R^2$ value increased from 0.18 to 0.20). The effect of sales trends on choice probabilities is graphed in Figure 4. It appears that the more positive a sales trend, the more likely retailers are to choose to take an action relative to no action. Only the probability of the strategic action “close or sell store” decreases with increasing sales.

These results for the base-line probabilities confirm a relation between sales trends and the probability of choosing each of the strategic actions but do not appear to support the hypothesis that retailers are “fire-fighters.” It is important to note, however, that the base-line probabilities are based on cross-sectional data, hence, one or more uncontrolled variables may account for this result. That is, these data do not allow us to determine if sales trends cause retailers to take actions or if the actions are influenced by some underlying external variables. Fortunately, and a key advantage of our proposed approach is the fact that the experimental controls implemented in the scenarios allow us better insight into these issues. In particular, factors such as sales trend were systematically manipulated across all scenarios, and the scenarios, in turn, were randomly allocated to retailers. Hence, the choices of strategic actions made by the retailers in response to the scenarios allow us to infer causal relations between sales trends and strategic action choice probabilities.

**Experimental Scenario Results**

Before developing choice models, we analyzed the manipulation check data for evidence that our scenario manipulations were effective. That is, we regressed retailer favorableness ratings for each scenario against the scenario design matrix. This revealed that favorableness ratings were significantly related to changes in all environmental factors, and the changes

---

**Figure 4.** Subjective probabilities of actions as a function of the reported sales trend.
were in the expected directions. This suggests that most retailers attended to the manipulations and understood their consequences. Inspection of the ratings for how much they could identify with the scenarios, their experience with actions and trends like those presented in the scenarios, and how much they would recommend the study to other retailers, further confirmed that the retailers were involved and understood the tasks.

We estimated MNL regression models from the choice responses to the scenarios to explain the effects of sales trend conditions on the retailer choices, the final results are displayed in Table 1. The dependent variable in the model analyses consisted of the total number of times each action was chosen over all eight action choice sets in response to each scenario, after correcting for the fact that the base alternative occurred twice as often in the sets than each of the other alternatives. Some of the respondents failed to complete both scenarios; hence, the total number of completed choice designs was 363 rather than 366. The model therefore was estimated from 2904 observations in each of 363 scenarios. The action “close or sell store” produced many zero choice outcomes in positive sales trend conditions; hence, we could not estimate the effect of positive scenario factors on this action.

The fit of this model to the data is satisfactory by choice modeling standards ($\rho^2 = 0.29$; see Ben-Akiva and Lerman, 1985). Its explanatory power was assessed by comparing it to a model with only action-specific constants, showing a significant improvement ($LR = 11714.4$, which is $\chi^2$ distributed with 45 degrees of freedom; Akaike or adjusted $\rho^2$ values increased from 0.24 to 0.29). Thus, we can conclude safely that sales trend factors explain significant proportions of retailers’ choices of strategic action.

As mentioned above, the sample of retailers can be expected to be heterogeneous in their choices. Because the purpose of this article is illustrative rather than substantive, we do not pursue this issue extensively, but we do report on two additional models. The first model included stratification factors as additional parameters, that is each action can have different stratification effects. This model fit significantly better than the model with action-specific constants and sales scenario effects (difference in LL was 2195.2 with 56 degrees of freedom). The second model used dummy variables to represent the actions chosen by retailers as most likely in the next three years, given their reported current conditions. These dummies capture the “loyalty” or “inertia” associated with retailers’ current expectations (cf. Guadagni and Little, 1983; Morikawa, Ben Akiva, and McFadden, 1990). Table 1 demonstrates that these inertia components were highly significant, and the fit increased considerably (Akaike’s $\rho^2$ reaching 0.44). This last result suggests that retailers tended to choose similar actions as their most likely strategic choices in both scenario and current conditions. Importantly, however, the scenario effects not only were significant but also did not differ substantially from the model without inertia effects. Thus, scenario effects were relatively robust across different types of retailers.

**Hypothesis Tests**

We now summarize and interpret the model results for the effect of the experimental factors in the scenarios, in particular the ones that are relevant to our hypotheses.

**SALES TREND SIZE AND DIRECTION (POSITIVE OR NEGATIVE).** First, as hypothesized, there is a relation between observed sales trends and the choice of action. Second, Figure 5 shows that as hypothetical sales trends increase, the probability that retailers choose to take action decreases, thereby confirming our second hypothesis. Note that this result is in contrast with the relation that we found between the reported sales trends and the probability of taking action. Third, increasing sales raise the probabilities that retailers will alter their floor space or open new branch stores, but they decrease the probabilities that they will relocate, alter their store image, or close their store. With respect to renovations however we only observe a relative decrease in probability if the sales levels show a moderate decrease. We thus find only partial confirmation for the third hypothesis we formulated. We find no difference between positive and negative sales trend scenarios on the probability of investing in the immediate store environment is minimal. Within the negative sales scenario however the probability of this action is highest if sales conditions are lowest.

**SALES TREND RECENCY AND SUDDENNESS.** Figure 6 shows that the longer the period over which a sales decrease or increase was observed, the higher the probability that retailers will take action. Figure 6 furthermore shows that in the negative sales frames the probabilities of actions with respect to store image, renovations, floor space, and store closure, are higher if the sales change was more recent. This confirms that retailers tend to react quickly when sales go down. The effects of sales trend recency and suddenness in the positive sales frames also show quick reactions with respect to renovations and floor space alterations but a reverse pattern for store image. If a sales increase appeared suddenly three years ago retailers are more likely to adjust their store image than if the sales increase appeared only last year. A similar effect is observed for investments in the immediate store environment, the investments being more likely if a longer-term sales increase was observed.

**SAMPLE STRATIFICATION FACTORS.** There were several significant effects, such as city core retailers being less likely than other locations to close stores if sales trends are negative, but store closure probabilities being relatively high for clothing and shoe stores regardless of location. We eschew the description and interpretation of additional stratification differences in the interest of space, and because they are not germane to the primary focus of the article. It is sufficient to note that the findings suggest that effects of sales trend shifts probably
### Table 1. Retailer Action Choice Model Estimated from Responses to Hypothetical Sales Scenarios

<table>
<thead>
<tr>
<th>Variable name</th>
<th>Close/sell</th>
<th>Relocate</th>
<th>Open Branch</th>
<th>Floor space</th>
<th>Renovate</th>
<th>Store Image</th>
<th>Environment</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Param</td>
<td>t-stat</td>
<td>Param</td>
<td>t-stat</td>
<td>Param</td>
<td>t-stat</td>
<td>Param</td>
</tr>
<tr>
<td>Inertia²</td>
<td>0.05</td>
<td>41.75</td>
<td>0.07</td>
<td>51.11</td>
<td>0.05</td>
<td>40.30</td>
<td>0.05</td>
</tr>
<tr>
<td>Sales trend</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trend direction³</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>L,P</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trend size</td>
<td>L,P</td>
<td>0.00</td>
<td>-0.69</td>
<td>-12.74</td>
<td>0.69</td>
<td>11.90</td>
<td>0.34</td>
</tr>
<tr>
<td></td>
<td>L,N</td>
<td>0.53</td>
<td>13.51</td>
<td>0.18</td>
<td>3.62</td>
<td>0.05</td>
<td>0.60</td>
</tr>
<tr>
<td></td>
<td>Q,P</td>
<td>0.00</td>
<td>-0.45</td>
<td>-15.37</td>
<td>-0.50</td>
<td>-19.15</td>
<td>-0.01</td>
</tr>
<tr>
<td></td>
<td>Q,N</td>
<td>-0.06</td>
<td>-3.17</td>
<td>-0.03</td>
<td>1.25</td>
<td>-0.23</td>
<td>0.50</td>
</tr>
<tr>
<td>Trend suddenness</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>L,P</td>
<td>0.00</td>
<td>-0.27</td>
<td>-5.60</td>
<td>-0.04</td>
<td>0.95</td>
<td>0.51</td>
</tr>
<tr>
<td></td>
<td>L,N</td>
<td>0.33</td>
<td>9.28</td>
<td>0.21</td>
<td>4.02</td>
<td>0.42</td>
<td>5.60</td>
</tr>
<tr>
<td></td>
<td>Q,P</td>
<td>0.00</td>
<td>-0.27</td>
<td>7.37</td>
<td>0.06</td>
<td>-2.69</td>
<td>0.16</td>
</tr>
<tr>
<td></td>
<td>Q,N</td>
<td>0.12</td>
<td>5.73</td>
<td>-0.13</td>
<td>-5.04</td>
<td>0.00</td>
<td>0.22</td>
</tr>
<tr>
<td>Location</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>City core vs. city fringe</td>
<td></td>
<td>-1.94</td>
<td>-13.55</td>
<td>0.02</td>
<td>0.46</td>
<td>0.29</td>
</tr>
<tr>
<td></td>
<td>City vs. neighborhoods</td>
<td></td>
<td>-0.52</td>
<td>-10.04</td>
<td>0.65</td>
<td>7.52</td>
<td>0.05</td>
</tr>
<tr>
<td>Merchandise</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Clothing and shoes vs. other non-food</td>
<td></td>
<td>-0.80</td>
<td>-15.50</td>
<td>0.00</td>
<td>0.04</td>
<td>-0.20</td>
</tr>
<tr>
<td></td>
<td>Food vs. non-food</td>
<td></td>
<td>0.02</td>
<td>8.10</td>
<td>0.13</td>
<td>4.70</td>
<td>0.59</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Statistics:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of choice sets</td>
<td>363</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of cases</td>
<td>2904</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RhoSq = 445</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RhoSq(Akaike) = 443</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

¹ For each action a parameter is estimated for each predictor variable.
² Inertia is the initial probability (0–100) of choosing this action.
³ Positive trend is coded +1, negative trend is -1.
⁴ Suffix L indicates a linear contrast (factor coded as -1,0, +1), Q indicates quadratic contrast terms (coded +1, -2, +1).
⁵ Suffixes P and N indicate nesting within positive or negative sales trend conditions.
differ for different types of retailers, even after differences in individual “inertias to choose actions” across scenario conditions have been taken into account.

ENVIRONMENTAL TRENDS FACTORS. The major purpose of the environmental trend factors was to help control inferences that retailers might make about potential causes of presented shifts in sales trends. In the interests of space, and because they are not the primary focus of the article, we do not report them further. Instead, we mention in passing that many of the environmental trend parameters were significant. This result suggests that retailers not only react to sales trend shifts but that their reactions are conditional on changes in environmental factors which may be attributed by them to be different causes of sales trend changes. As well, different changes in environmental and sales trends seem to call for different types of actions.

**Model Application**

We now briefly demonstrate how the model can be used to predict strategic action probabilities for different types of retailers in our study area. Suppose we wish to derive the probability that a food retailer located in a neighborhood center chooses to close or sell when this retailer observes a sudden 25% sales decrease. Suppose we know that this retailer’s initial probability of store closure was 10%. The predicted utility of action “close/sell” for this retailer is (see Table 1, note that terms have been coded as outlined in the table footnotes):

\[
V_{\text{close/sell}} = -3.10 + .05 \times (10) - 1.21 \times (-1) + .53 \times (1) \\
- .06 \times (1) + .33 \times (1) + .12 \times (1) \\
- .13 \times (0) + .06 \times (1) + .42 \times (0) - .18 \times (-2),
\]

which is -.050. Because the utility of “no change” was scaled to zero in all cases, the probability that action “close/sell” is chosen over “no change” is derived as:

\[
p(\text{Close/sell}) = \exp(-.050)/\exp(-.050 + \exp(0)),
\]

which is .487. If, instead of an initial probability of 10%, this retailer’s initial probability of store closure were 50%, then the calculations would lead to a predicted probability of 0.875.

**Conclusions and Discussion**

The purpose of this article was to propose a new way to use conjoint analysis techniques to study and model strategic managerial decisions. We used a retail management example to illustrate how this can be done. The effects of sales and environmental changes on retailers’ choices of likely near-term
future actions were modeled by estimating logistic regression models from choice responses to strategic scenarios that describe hypothetical sales trends. Each scenario involved either a positive or negative sales trend relative to trends reported by retailers for their own store during the past three years. To control inferences that retailers may have made about the causes of the hypothetical sales trends in the designed scenarios, the sales trend information was varied together with selected environmental trends, which were negative, unchanged, or positive relative to trends reported by retailers as representing their current situation.

The presented sales trends had significant impacts on strategic choices, which confirmed the hypothesis that choice of action depends on sales trends. Choice of action was further found to depend on the environmental conditions in which the sales trends are realized. The importance of this result is not just that a naïve null hypothesis has been rejected. It demonstrates that with the presented method the relation between sales trends and action probabilities can be modeled. Models as developed here allow one to make predictions of strategic action probabilities, as was demonstrated with a small example for our application. Hence, empirical models now can be developed to complement theory-based models in simulations of competitive strategy and market dynamics (cf. Erdem and Keane, 1996; Krider and Weinberg, 1997; Messinger and Narasimhan, 1995). By extending the model to include environmental conditions as an additional set of predictors, the model can become an increasingly fine-tuned instrument for studying managerial reactions.

As far as the strategic actions were concerned, we found that the higher the sales, the more retailers tended to choose no action. More specifically, we found that the higher the sales, the lower the probability of altering store images or representing their current situation.

The above conclusions were derived from a sample across
different types of retail category and retail location. Because retailer samples are typically heterogeneous, we showed how one could include additional parameters in models to capture inertia or loyalty of individual retailers to their choices in current conditions. It appeared that retailers tend to pick similar actions as most likely regardless of which scenario is presented. Inclusion of the loyalty factors however did not substantially change the scenario-based parameters.

Another important finding emerged from an analysis of the strategic choices made by retailers in their current circumstances. Retailers provided choice data about the actions that they would be most likely to take in the context of their present business and economic conditions, and reported their current sales trend. Results from a discrete choice analysis of the strategic choices regressed against the sales trends suggested a different result than the scenario experiment: retailers seemed to use sales increases as opportunities to act (e.g., invest in their store), but reacted to sales decreases by taking no action. This result may be spurious, however, because it is based on cross-sectional data that can be confounded with underlying unobserved other variables. In contrast, the proposed and illustrated scenario approach allows experimental control; hence, it allows one to draw causal and not merely associative conclusions, and also controls for many sources of association lurking in cross-sectional data.

Limitations and Future Research

There are many issues and trade-offs involved in adapting conjoint methods to study managerial strategic behavior. First, we had to use somewhat restrictive ranges of percent changes in sales and environmental factors to ensure that the scenarios would be feasible to all types of retailers within our study area. Individual stores may however easily observe sales and environmental trends double the sizes we varied, and we would be cautious of extrapolating our results to such situations. Future research might investigate adapting the experiments to individual retailers’ personal circumstances and/or at least using preliminary data to classify retailers into groups in which scenario factor levels may differ in ranges.

Second, we could have broadened the scope of this research by including a control condition for sales (e.g., a set of scenarios with neither sales increases nor decreases). If environmental factors have effects in control conditions, this would reveal pro-active behavior because there are no effects on sales. We did not add a control group to our study because it would have further increased the size of the design and duplicated data collected for retailers’ current conditions. Future research should examine this issue, because it is germane to the empirical question of passive or active involvement in strategic decisions.

Third, the present application included only seven actions because we wanted no more than eight choice sets per task. In other applications however, one might wish to include more actions or include actions that vary on particular attributes. Future research could benefit from “pick-any” choice formats, which allow managers to choose as many actions as they believe they would realistically undertake.

Finally, our results should be viewed as tentative insofar as we made rather restrictive assumptions about the nature of heterogeneity. In particular, we assumed that a simple three-by-three classification of retailer type and location and/or inclusion of a set of simple “inertia” parameters would capture much of the heterogeneity. Although this significantly improved the fit of our models, such a classification is likely to be much too simplistic to capture all sources of heterogeneity. Further segmentation is limited by the fact that choice data cannot be analyzed for each individual separately, although this latter problem is common to most experimental choice applications. Future research may wish to consider the use of latent segmentation to segment the respondents on the choice responses (e.g., Desarbo et al., 1992), although we caution that insufficient attention has been given in this approach to the possibility that latent segments can differ by mean (model parameters) as well as by error variances or both.

Thus, this article represents a first step toward developing an experimental approach to understanding how managers respond to changes in their marketing environment. Despite the aforementioned limitations, the present study demonstrated several benefits of the scenario-based choice experiment approach. In contrast to many previous studies, we obtained high response rates and multiple observations per respondent. We obtained sufficient variation in the responses to estimate meaningful models and test hypotheses, which is a key benefit of the experimental controls. We also found that retailers were less reluctant to answer questions about their stores if they were framed as hypothetical conditions. Manipulation checks showed that they had little trouble understanding or completing the evaluation and choice tasks. Most important however is the increased control over unobserved underlying factors that may covary with the factors under study. The use of experimental design methods allows one to disentangle effects that otherwise would be impossible to separate. Moreover, it allows one to establish causality between market factors and managerial response.

Thus, our results suggest that the proposed modification and application of conjoint analysis methods to the study of retailer strategic decisions probably can be improved and extended to the study of a wide variety of other managerial decisions. The latter finding is consistent Timmerman’s (1986) results on modeling retailer locational preferences and recent work by Collins-Dodd and Louviere (1999), who used conjoint analysis techniques to model retailers’ new product listing decisions. Both the latter articles demonstrate that retailers will respond to well-designed surveys, especially if accompanied by cover letters from senior executives in their trade organizations. Thus, we conclude that it now seems possible to undertake research into a wide variety of retail management...
and strategy decisions not previously examined, and we hope that this article will be seen as a first step in that direction as well as call for more research in this vein.

This research was supported by the Social and Environmental Research Foundation, which is part of the Netherlands Organization for Scientific Research (N.W.O./O.S.R.). The authors thank the editor and two reviewers of the Journal of Business Research for their helpful comments.

References


