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An Integrated Model of Alternative Mechanisms of In-Store Display and Feature Advertising on Brand Choice

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ABSTRACT

Although many studies have documented that in-store displays and feature advertising can significantly increase brand choice probabilities, the *mechanism* through which they affect the choice decision process is not well understood. The marketing literature has suggested two prominent decision mechanisms through which their effects may take place, which I call: *the price cut proxy effect* and *the consideration set formation effect*. The primary objective of this study is to *jointly* examine these two decision mechanisms suggested in the literature using scanner panel data of actual purchase behavior. I construct a brand choice model based on the behavioral premises of both effects. The proposed model allows consumers to use a combination of various decision processes with different probabilities, and accommodates the correlation in utilizing different decision mechanisms of display and feature ad. Results of the empirical analysis reveal distinct consumer segments with regard to their tendencies to use displays and/or feature ads as price cut proxies or for forming consideration sets, and the pattern is consistent with consumer characteristics in each segment, such as degree of state dependence and price sensitivity. Findings from this study shed light on some mixed patterns of promotion interaction effects documented in the literature, and also have interesting implications for promotion decisions.

Key words: promotion decisions, brand choice models, decision mechanism, consideration set formation, econometric models

1. Introduction

Although many studies have documented that in-store displays and feature advertising can significantly increase brand choice even when the price discount effect is controlled for (e.g., Gupta 1988; Grover and Srinivasan 1992; Chintagunta 1992; Papatla 1996), the *mechanism* through which they affect the choice decision process is not well understood. Most brand choice models simply assume that feature ads and displays increase a brand's utility and thus its probability of being chosen. It is not clear, however, why being on display or feature ad itself would increase a brand's perceived utility.

The marketing literature has suggested two prominent decision mechanisms through which their effects may take place. One explanation for the observed effects of promotion signs is offered by Inman, McAlister, and Hoyer (1990). They propose that consumers on the peripheral route to persuasion do not engage in detailed information processing and simply interpret a promotion marker as a proxy for a price cut, and therefore the mere presence of a promotion signal would lead these consumers to believe that the brand has been offered a price discount. We refer to this mechanism as the *price cut proxy effect*. Inman et al. (1990) find that this effect only occurred in consumers who exhibited low need for cognition, and a promotion sign without a price cut did not increase the choice probability for high need-for-cognition individuals.

At the mean time, the growing literature on consideration sets provides an alternative explanation for why display and feature ad affect brand choices. Behavioral research has observed that, for low-involvement product categories, consumers often rely on certain heuristics to form a consideration set first and then engage in more elaborate evaluation of the remaining alternatives (e.g., Payne 1976; Lussier and Olshavsky 1979; Hauser and Wernerfelt 1990; Roberts and Lattin 1991). Various studies in this stream of research have shown that in-store displays and feature ads can be utilized to form consideration sets (e.g., Fader and McAlister 1990; Allenby and Ginter

1995; Andrews and Srinivasan 1995; Bronnenberg and Vanhonacker 1996; Mehta, Rajiv, and Srinivasan 2003). In other words, they increase a brand's probability of being chosen by making it more prominent to consumers. In addition, Mehta et al. (2003) conjecture that display and feature ad help form consideration sets by reducing search costs of price information. We refer to this mechanism as the *consideration set formation effect*.

Both decision mechanisms suggested in the literature are based on thorough theoretical reasoning and have been demonstrated in empirical studies. The objective of this study is not to rule out one in favor of the other, but rather to construct a brand choice model that incorporates both mechanisms in the same framework, and thus enable us to *jointly* assess the extent to which each effect may occur in actual purchase data. In the empirical analysis, we investigate whether the positive impact of display and feature ad on brand choice probabilities are mainly through the price cut proxy effect, the consider set formation effect, or a combination of the two, and whether there are differences among consumers in their tendencies to exhibit these decision processes. Note that the goal of this study is not to measure *how much* the two promotion vehicles increase a brand's chance of being chosen, but to investigate the route through which they may affect the choice decision process. Johnson, Meyer, and Ghose have called for models that are "better representations of decision processes" (1989, p.268). A compensatory model such as the standard multinomial logit or probit model may address the "how much" issue well, but generally it is not well suited to explore the underlying decision mechanisms. The brand choice model we propose in this study is based on the behavioral premises of the price cut proxy and consideration set formation effects and focuses on investigating the alternative mechanisms[1].

Findings from this study will also provide an explanation for some mixed patterns of

[1]See Lemon and Nowlis (2002) for a recent example of studies that focus on measuring the "how much" effects of display, feature ad, and price promotion on brand choice using a compensatory choice model.

promotion interaction effects reported in the literature. Most previous brand choice models that included display and feature ad effects did not measure their interactions with price cut. Those that did reported mixed patterns of the interaction effects. For examples, Gupta (1988) found negative interactions of display and feature ad with price cut, Papatla and Krishnamurthi (1996) found a positive interaction of display and price cut but a negative interaction of feature ad and price cut, while Lemon and Nowlis (2002) reported a negative interaction of feature ad and price cut, but small positive and negative interactions of display and price cut (which vary across brands). It is not clear why display and feature ad exhibited different patterns of interaction effect with price cut. Papatla and Krishnamurthi (1996) expected these interactions to be positive and considered the negative effect of feature and price cut interaction counterintuitive. Gupta (1988) postulated that the negative interactions in his study "suggest a possible overlap or substitutability among different promotional instruments" (p.348) but stopped short of exploring what may be causing the overlap. These three studies employed compensatory multinomial logit or probit models. Of course, their models served the objectives of each study well, and were not constructed with the purpose to explain the cause of the interaction effects. Nonetheless, given the wide usage of the multinomial logit and probit models and the important implication of the sign of these interaction effects on promotion decision making, it is worth finding out what may be causing the mixed patterns.

Built upon the behavioral premises of the underlying decision mechanisms, our model holds the promise to provide a possible explanation. If displays/feature ads mainly serve as price cut proxies, combining price cut with them would add little value to the brand in a consumer's mind. In other words, the joint effect of display/feature ad and price cut would be smaller than the sum of their individual effects, and thus the interaction effect would be negative. On the other hand, if display/feature ad affects brand choice mainly through the consideration set formation effect, which helps a brand to pass the first stage in the decision, then combining it with price cut would reinforce the effectiveness of each other because price cut increases the attractiveness of a brand among those in the consideration set and enhances its chance of being chosen at the second stage of the decision process. This mechanism would suggest a positive interaction effect. We will test these conjectures in the empirical analysis.

2. Model Formulation

We construct a brand choice model based on household scanner panel data. In order to assess the likelihood of undergoing alternative decision mechanisms simultaneously, we allow consumers to use displays and/or feature ads as price cut proxies and/or for consideration set formation in a probabilistic manner in the same model. In other words, with certain probabilities, they may use either or both promotion vehicles as price cut proxies or consideration set formation devices, or they may ignore them and evaluate the entire set of alternatives based on quality and actual pricing information. The model also takes into account the correlation of using display and feature ad for the price cut proxy or consideration set formation effect.

Define: DP_i = 1 if display is used as a price cut proxy by household i, 0 otherwise; FP_i = 1 if feature ad is used as a price cut proxy by household i, 0 otherwise; DC_i = 1 if display is used for forming consideration sets by household i, 0 otherwise; FC_i = 1 if feature ad is used for forming consideration sets by household i, 0 otherwise; f_{DPi} = household i's probability of using display as a price cut proxy; f_{FPi} = household i's probability of using feature ad as a price cut proxy; f_{DCi} = household i's probability of using display for forming consideration sets; f_{FCi} = household i's probability of using feature ad for forming consideration sets.

A consumer who tends to use displays as price cut proxies may also be likely to do so using feature ads. Similarly, the tendencies to use displays and feature ads for consideration set formation may be positively correlated as well. To account for the interdependence of the various decision mechanisms, we include the following covariance terms in the formulation: $s_{DC,FC} = \mathrm{cov}(DC_i, FC_i)$, $s_{DC,FP} = \mathrm{cov}(DC_i, FP_i)$, $s_{DP,FC} = \mathrm{cov}(DP_i, FC_i)$, and $s_{DP,FP} = \mathrm{cov}(DP_i, FP_i)$.

A consumer can use display/feature ad as a price cut proxy, a consideration set formation device, or neither of the two at a given purchase occasion. The probability of the occurrence of each decision mechanism is described in the following chart (the derivation is in the Appendix).

Decision Mechanism		Probability of Occurrence	Conditional brand choice probability
Display	Feature Ad		
1. Consideration set formation	Consideration set formation	$f_{DC} f_{FC} + s_{DC,FC}$	$P_{ikt}^{DC,FC}$
2. Consideration set formation	Price cut proxy	$f_{DC} f_{FP} + s_{DC,FP}$	$P_{ikt}^{DC,FP}$
3. Consideration set formation	No effect	$f_{DC}(1 - f_{FC} - f_{FP})$ $- s_{DC,FC} - s_{DC,FP}$	P_{ikt}^{DC}
4. Price cut proxy	Consideration set formation	$f_{DP} f_{FC} + s_{DP,FC}$	$P_{ikt}^{DP,FC}$
5. Price cut proxy	Price cut proxy	$f_{DP} f_{FP} + s_{DP,FP}$	$P_{ikt}^{DP,FP}$
6. Price cut proxy	No effect	$f_{DP}(1 - f_{FC} - f_{FP})$ $- s_{DP,FC} - s_{DP,FP}$	P_{ikt}^{DP}
7. No effect	Consideration set formation	$(1 - f_{DC} - f_{DP}) f_{FC}$ $- s_{DC,FC} - s_{DP,FC}$	P_{ikt}^{FC}
8. No effect	Price cut proxy	$(1 - f_{DC} - f_{DP}) f_{FP}$ $- s_{DC,FP} - s_{DP,FP}$	P_{ikt}^{FP}
9. No effect	No effect	$(1 - f_{DC} - f_{DP})(1 - f_{FC} - f_{FP})$ $+ s_{DC,FC} + s_{DP,FC}$ $+ s_{DC,FP} + s_{DP,FP}$	P_{ikt}^{0}

For the conditional brand choice probabilities in the above chart, we use superscripts "*DC*" to denote "display consideration set formation", "*FC*" to denote "feature ad consideration set formation", "*DP*" to denote "display price cut proxy", and "*FP*" to denote "feature ad price cut proxy". The subscripts "*ikt*" refer to "household *i*, alternative *k*, purchase occasion *t*". P_{ikt}^{0} represents the conditional brand choice probability when neither display nor feature ad is used in the decision, in which case the consumer chooses from the entire set of available alternatives and evaluate the actual price and price discount of each.

The decision process assumed for the *price cut proxy effect* is that a consumer infers a price cut from a display and/or feature advertising regardless of whether there is an actual reduction in the price. It implies that, in a brand utility function with price cut, display, and feature ad dummy variables, the coefficient of display or feature ad should be the same as the coefficient of the price cut variable, and that the (price cut×display) and (price cut×feature ad) interactions should have the same magnitude but an opposite sign of the price cut coefficient to avoid double-counting by the modeler when an item is on both price discount and display/feature. We will illustrate this in more detail shortly. The decision process assumed in the *consideration set formation effect* is that a consumer relies on display and/or feature advertising to select alternatives and form a consideration set first, and then undergo a thorough evaluation of the alternatives in the consideration set. Like many previous studies on consideration sets (e.g., Roberts and Lattin 1991; Andrews and Scrinivasan 1995; Siddarth, Bucklin, and Morrison 1995; Bronnenberg and Vanhonacker 1996), we assume that a consumer utilizes a compensatory strategy to choose the alternative that maximizes the perceived utility at the second stage of the decision process. We adopt an elimination-by-aspects (EBA) approach to formulating the consideration set formation process. The reader is referred to Fader and McAlister (1990) as an example for details of the EBA model[2].

Let $A_{DF,t}$, $A_{D,t}$, $A_{F,t}$, and A_0 be the set of alternatives defined as: 1) those on display or feature ad at time *t*; 2) only those on display at time *t*; 3) only those on feature ad at time *t*; and 4) the entire set of available alternatives, respectively. The brand utility functions corresponding to the nine conditional brand choice probabilities can be summarized in a general expression as[3]:

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[2] The consideration set formation process can also be captured in a structural model (see Mehta, Rajiv, and Srinivasan 2003). Since a structural formulation of the price cut proxy effect is not available, we choose to adopt a reduced form model as in Fader and McAlister (1990) in order to incorporate the price cut proxy effect in the same model.

[3] Our model can be extended to accommodate the possibility that price cut is used to form consideration sets, in which case there would be 18 decision process scenarios and the same modeling approach applies. We choose to focus on formulating the alternative decision mechanisms of only displays and feature ads to keep the model relatively simple.

$$U_{ikt}^{x,y} = V_{ikt}^{x,y} + e_{ikt}^{x,y} = a_{ik} + g_i I_{ik,t-1} + b_{ap,i} AP_{kt} + b_{pc,i} B_{kt}(x,y) + e_{ikt}^{x,y}, \quad \forall\, k \in A_t(x,y), \tag{1}$$

where $x = \begin{cases} 0, & \text{if display does not affect choice} \\ C, & \text{if display affects choice through consideration set formation} \\ P, & \text{if display affects choice through price cut proxy} \end{cases}$

$$y = \begin{cases} 0, & \text{if feature ad does not affect choice} \\ C, & \text{if feature ad affects choice through consideration set formation} \\ P, & \text{if feature ad affects choice through price cut proxy} \end{cases}$$

$$B_{kt}(x,y) = \begin{cases} PC_{kt}, & \text{if } x = 0 \;\&\; y = 0 \\ PC_{kt} + D_{kt} - PC_{kt} \cdot D_{kt}, & \text{if } x = P \;\&\; y = 0 \\ PC_{kt} + F_{kt} - PC_{kt} \cdot F_{kt}, & \text{if } x = 0 \;\&\; y = P \\ PC_{kt} + D_{kt} + F_{kt} - PC_{kt} \cdot D_{kt} - PC_{kt} \cdot F_{kt}, & \text{if } x = P \;\&\; y = P \end{cases}$$

$$A_t(x,y) = \begin{cases} A_{DF,t}, & \text{if } x = C \;\&\; y = C \\ A_{D,t}, & \text{if } x = C \;\&\; y \neq C \\ A_{F,t}, & \text{if } x \neq C \;\&\; y = C \\ A_0, & \text{if } x \neq C \;\&\; y \neq C \end{cases}$$

For each of the nine decision mechanisms depicted in the above chart, equation (1) reduces to:

$$U_{ikt}^{DC,FC} = V_{ikt}^{DC,FC} + e_{ikt}^{DC,FC} = a_{ik} + g_i I_{ik,t-1} + b_{ap,i} AP_{kt} + b_{pc,i} PC_{kt} + e_{ikt}^{DC,FC}, \;\forall\, k \in A_{DF,t}; \tag{1a}$$

$$U_{ikt}^{DC,FP} = V_{ikt}^{DC,FP} + e_{ikt}^{DC,FP} = a_{ik} + g_i I_{ik,t-1} + b_{ap,i} AP_{kt} + b_{pc,i}(PC_{kt} + F_{kt} - PC_{kt} \cdot F_{kt}) + e_{ikt}^{DC,FP}, \;\forall\, k \in A_{D,t}; \tag{1b}$$

$$U_{ikt}^{DC} = V_{ikt}^{DC} + e_{ikt}^{DC} = a_{ik} + g_i I_{ik,t-1} + b_{ap,i} AP_{kt} + b_{pc,i} PC_{kt} + e_{ikt}^{DC}, \;\forall\, k \in A_{D,t}; \tag{1c}$$

$$U_{ikt}^{DP,FC} = V_{ikt}^{DP,FC} + e_{ikt}^{DP,FC} = a_{ik} + g_i I_{ik,t-1} + b_{ap,i} AP_{kt} + b_{pc,i}(PC_{kt} + D_{kt} - PC_{kt} \cdot D_{kt}) + e_{ikt}^{DP,FC}, \;\forall\, k \in A_{F,t}; \tag{1d}$$

$$U_{ikt}^{DP,FP} = V_{ikt}^{DP,FP} + e_{ikt}^{DP,FP} = a_{ki} + g_i I_{ik,t-1} + b_{ap,i} AP_{kt} + b_{pc,i}(PC_{kt} + D_{kt} + F_{kt} - PC_{kt} \cdot D_{kt} - PC_{kt} \cdot F_{kt}) + e_{ikt}^{DP,FP}, \;\forall\, k \in A_0; \tag{1e}$$

$$U_{ikt}^{DP} = V_{ikt}^{DP} + e_{ikt}^{DP} = a_{ki} + g_i I_{ik,t-1} + b_{ap,i} AP_{kt} + b_{pc,i}(PC_{kt} + D_{kt} - PC_{kt} \cdot D_{kt}) + e_{ikt}^{DP}, \;\forall\, k \in A_0; \tag{1f}$$

$$U_{ikt}^{FC} = V_{ikt}^{FC} + e_{ikt}^{FC} = a_{ik} + g_i I_{ik,t-1} + b_{ap,i} AP_{kt} + b_{pc,i} PC_{kt} + e_{ikt}^{FC}, \;\forall\, k \in A_{F,t}; \tag{1g}$$

$$U_{ikt}^{FP} = V_{ikt}^{FP} + e_{ikt}^{FP} = a_{ki} + g_i I_{ik,t-1} + b_{ap,i} AP_{kt} + b_{pc,i}(PC_{kt} + F_{kt} - PC_{kt} \cdot F_{kt}) + e_{ikt}^{FP}, \;\forall\, k \in A_0; \tag{1h}$$

$$U_{ikt}^{0} = V_{ikt}^{0} + e_{ikt}^{0} = a_{ki} + g_{i} I_{ik,t-1} + b_{ap,i} AP_{kt} + b_{pc,i} PC_{kt} + e_{ikt}^{0}\,,\ \forall\ k \in A_{0}\,; \tag{1i}$$

where a_{ki} = alternative-specific constant; $I_{ik,t-1}$ = 1 if alternative *k* was chosen by household *i* at purchase occasion (*t-1*), and 0 otherwise; AP_{kt} = alternative *k*'s actual price at *t*, i.e., regular price minus price discount if there is any; PC_{kt} = 1 if alternative *k* is on a price discount at *t*, and 0 otherwise; D_{kt} = 1 if alternative *k* is on display at *t*, and 0 otherwise; F_{kt} = 1 if alternative *k* is on feature advertising at *t*, and 0 otherwise; $V_{ikt}^{DC,FC}$, $V_{ikt}^{DC,FP}$, V_{ikt}^{DC}, $V_{ikt}^{DP,FC}$, $V_{ikt}^{DP,FP}$, V_{ikt}^{DP}, V_{ikt}^{FC}, V_{ikt}^{FP}, and V_{ikt}^{0} are the systematic component in each utility function; and $e_{ikt}^{DC,FC}$, $e_{ikt}^{DC,FP}$, e_{ikt}^{DC}, $e_{ikt}^{DP,FC}$, $e_{ikt}^{DP,FP}$, e_{ikt}^{DP}, e_{ikt}^{FC}, e_{ikt}^{FP}, and e_{ikt}^{0} are the random term in each utility function. Parameter g_i captures a household's degree of state dependence. Finally, parameter $b_{ap,i}$ represents a household's sensitivity to the *actual* price paid, and parameter $b_{pc,i}$ represents the effect of an *actual* price discount on the household's brand choice.

In the above utility functions, when a consideration set formation effect takes place, only alternatives that satisfy the consideration set formation condition are evaluated and the others have a zero chance of being chosen. When a price cut proxy effect takes place, the coefficient of display/feature ad is the same as that of the price cut dummy variable, and the interaction term is subtracted to avoid double-counting by the modeler. For example, equation (1d) describes the utility function when a consumer uses feature ads to form consideration sets and treats displays as price cut proxies. Under this decision process, only alternatives that are on feature ad enter the consideration set and are compared against each other, and the consumer equates a display to a sign for price cut when evaluating those alternatives. If alternative *k*, $\forall\ k \in A_{F,t}$, is on price cut only or on display only, the term $(PC_{kt} + D_{kt} - PC_{kt} \cdot D_{kt})$ = (1 + 0 – 0) or (0 + 1 - 0) = 1 and the effect on the brand utility is $b_{pc,i}$. If the alternative is on both price cut and display, the effect should still be

$b_{pc,i}$, and this is reflected by the term $(PC_{kt} + D_{kt} - PC_{kt} \cdot D_{kt})$ = (1 + 1 – 1) = 1.

Assuming that the random terms in the utility functions each follow an IID Type-I extreme value distribution with location parameter 0 and scale parameter 1, we get the standard logit formulation of the conditional probability of choosing an alternative under each of the decision mechanisms described above. We express the conditional probabilities in a general form:

$$P_{ikt}^{*} = \begin{cases} \exp(V_{ikt}^{*}) / \sum_{j \in A^{*}} \exp(V_{ijt}^{*}), & if\ k \in A^{*} \\ 0, & otherwise \end{cases}, \tag{2}$$

where $P_{ikt}^{*} \in \{ P_{ikt}^{DC,FC}, P_{ikt}^{DC,FP}, P_{ikt}^{DC}, P_{ikt}^{DP,FC}, P_{ikt}^{DP,FP}, P_{ikt}^{DP}, P_{ikt}^{FC}, P_{ikt}^{FP}, P_{ikt}^{0} \}$, $V_{ikt}^{*} \in \{ V_{ikt}^{DC,FC}, V_{ikt}^{DC,FP}, V_{ikt}^{DC}, V_{ikt}^{DP,FC}, V_{ikt}^{DP,FP}, V_{ikt}^{DP}, V_{ikt}^{FC}, V_{ikt}^{FP}, V_{ikt}^{0} \}$, and $A^{*} \in \{ A_{DF,t}, A_{D,t}, A_{F,t}, A_{0,t} \}$.

The unconditional probability of choosing alternative *k* by household *i* at purchase occasion *t* is obtained by multiplying the conditional choice probability under each decision process by the probability of its occurrence as described in the above chart, and then taking the sum. Specifically,

$$\begin{aligned} P_{ikt} = & [f_{DCi} f_{FCi} + s_{DC,FC}] P_{ikt}^{DC,FC} + [f_{DCi} f_{FPi} + s_{DC,FP}] P_{ikt}^{DC,FP} + [f_{DCi}(1 - f_{FCi} - f_{FPi}) - s_{DC,FC} - s_{DC,FP})] P_{ikt}^{DC} \\ & + [f_{DPi} f_{FCi} + s_{DP,FC}] P_{ikt}^{DP,FC} + [f_{DPi} f_{FPi} + s_{DP,FP}] P_{ikt}^{DP,FP} + [f_{DPi}(1 - f_{FCi} - f_{FPi}) - s_{DP,FC} - s_{DP,FP})] P_{ikt}^{DP} \\ & + [(1 - f_{DCi} - f_{DPi}) f_{FCi} - s_{DC,FC} - s_{DP,FC})] P_{ikt}^{FC} + [(1 - f_{DCi} - f_{DPi}) f_{FPi} - s_{DC,FP} - s_{DP,FP})] P_{ikt}^{FP} \\ & + [(1 - f_{DCi} - f_{DPi})(1 - f_{FCi} - f_{FPi}) + s_{DC,FC} + s_{DP,FC} + s_{DC,FP} + s_{DP,FP})] P_{ikt}^{0} \end{aligned} \tag{3}$$

The unconditional choice probability function also depends on the category level promotion situation at a given purchase occasion. Equation (3) applies to those purchase occasions for which there is at least one alternative on display and at least one alternative on feature ad in the category at the purchase occasion. When there is no alternative on display in the category, the display price cut proxy and consideration set formation effects and their covariance with feature ad would not be relevant, in which case equation (3) would reduce to:

$$P_{ikt} = f_{FCi} P_{ikt}^{FC} + f_{FPi} P_{ikt}^{FP} + (1 - f_{FCi} - f_{FPi}) P_{ikt}^{0}. \tag{4}$$

When there is no alternative on feature ad in the category, the feature ad price cut proxy and consideration set formation effects and their covariance with display would not be relevant, in which case equation (3) would reduce to:

$$P_{ikt} = f_{DCi} P_{ikt}^{DC} + f_{DPi} P_{ikt}^{DP} + (1 - f_{DCi} - f_{DPi}) P_{ikt}^{0} . \tag{5}$$

Finally, when there is no alternative on display or on feature ad in the category, all four decision mechanisms are irrelevant and the household has to choose from the entire set of available alternatives and evaluate each based on its actual price. In this case, equation (3) would reduce to:

$$P_{ikt} = P_{ikt}^{0} . \tag{6}$$

To ensure that the estimates of the occurrence probabilities fall between 0 and 1 and the sum of the conditional probabilities equals to their corresponding marginal probabilities, we need to re-parameterize the probability and covariance terms[4]. The detail is provided in the Appendix.

The model has been constructed at the individual household level so far. We adopt a latent class approach to capturing unobserved consumer heterogeneity (see Kamakura & Russell 1989), in which parameters are segment-specific, denoted by subscript $g = 1, \ldots, G$. The log-likelihood function is given by:

$$LL = \sum_{i=1}^{N} \log \left(\sum_{g=1}^{G} q_g \prod_{t=1}^{T_i} \prod_{k=1}^{K} [P_{iktg}]^{I_{ikt}} \right) \tag{7}$$

where q_g is the probability of belonging to segment g, T_i is the number of total purchases by household i, and N is the number of households in the sample. The number of latent segments is determined empirically by comparing the Bayesian Information Criterion (BIC) of models with different G and the one that yields the lowest BIC is selected. When estimating each model, we use 40 sets of starting values to minimize the chance that the procedure ends at a local optimum.

[4] Our formulation involves eight parameters for the nine occurrence probabilities. Alternatively, one could directly estimate these probabilities also using eight parameters. The drawback of the latter approach is that one does not get estimates of the probabilities of the price cut proxy and consideration set formation effects, which are the focus of this study.

We compare the proposed model to a multinomial logit model (MNL) with main effects and interactions of display and feature ad with price cut. The variables used in both models are exactly the same. For the MNL model, we also adopt the latent-class formulation to handle unobserved consumer heterogeneity. The segment-specific brand utility function is:

$$U_{ikt} = a_{kg} + g_g I_{ik,t-1} + b_{ap,g} AP_{kt} + b_{pc,g} PC_{kt} + b_{d,g} D_{kt} + b_{f,g} F_{kt} + b_{pd,g} PC_{kt} \cdot D_{kt} + b_{pf,g} PC_{kt} \cdot F_{kt} + e_{ikt}. \tag{8}$$

Our proposed model is constructed based on the behavioral premises of the price cut proxy and consideration set formation effects. It imposes certain constraints on the relationships among the effects of the price cut, display and feature ad variables according to the underlying decision mechanisms. Since the parameter of each variable in the MNL model is estimated freely, our theory-based model which uses the same variables but with constraints is unlikely to provide a better fit to the data. These two types of models serve different research purposes. The issue at hand is whether the proposed model performs well relative to the MNL model in terms of fit to the data and predictive power, while providing a better understanding of the underlying decision mechanisms at the same time. See Johnson and Meyer (1984), Johnson, Meyer, and Ghose (1989), and Fader and McAlister (1990) for more discussion on the value of decision-process-based models.

3. Empirical Analysis

3.1. Data Description

We calibrate the model using A. C. Nielsen's scanner panel data on single-wrap cheese slices. This category is chosen because it has relatively frequent price discounts, displays, and feature ads, as well as fairly high variation in these promotion activities among brands. The data were collected in a mid-west market during a 104-week period (January 1992 to December 1993). The top six brand-size combinations are included in the analysis: Kraft 12 oz., Kraft 16 oz., Velveeta 12 oz., Borden 12 oz., private label 12 oz., and private label 16 oz. These six items accounted for 77.1% of total category purchases. We use data of the first 52 weeks for model estimation and treat the second 52 weeks as the holdout period. There are 369 households in the data. Table 1 presents descriptive statistics of the estimation data. Note that both display and feature ad were often accompanied by a price cut, and it occurred more frequently for feature ad (81.7%-100%) than for display (42.7%-84.3%) in the data.

[Insert Table 1 here]

3.2. Model Estimation Results

A three-segment model appears to be the best one for the MNL and proposed models based on BIC (for models with one, two, three, and four segments, BIC is 2611.9, 2476.8, 2455.7, and 2483.7 for the MNL model, and 2652.6, 2516.3, 2494.9, and 2513.9 for the proposed model, respectively)[5]. The estimation and holdout prediction results of the two models are reported in Tables 2 and 3. As expected, the MNL model provides a better fit to the data. Nonetheless, the log-likelihood of our model, which imposes constraints on the relationships among variables, is close to that of the MNL model (-2332.9 vs. -2309.2). In terms of holdout prediction, the MNL model yields a log-likelihood of -3096.2 and a hit rate of 64.5%, while our model generates an almost identical log-likelihood of -3096.6 and a slightly better hit rate of 65.2%.

The two models depict a similar segment structure in terms of segment sizes and estimates of the alternative-specific constants, state dependence parameter, and actual price coefficient within each segment. But, the MNL model yields several counter-intuitive inferences on the price cut, display and feature ad effects. For example, in segment two, the price cut coefficient is negative and significant. In addition, the effect of offering display and price cut together (0.083) is smaller than the effect of display alone (1.218). In segment three, the effect of offering feature ad and price cut together (0.297) is smaller than the effect of feature ad alone (1.725), and the effect of offering display and price cut together is estimated to be even negative (-0.782). Note that a negative interaction effect of display/feature ad and price cut *per se* is not a problem. The counter-intuitive inferences discussed here result from a combination of a negative price cut coefficient and a negative interaction term[6]. These problematic estimates are likely due to multicollinearity of the variables[7]. Although the MNL model provides somewhat better fit to the estimation data, there are no counter-intuitive effects in our proposed model as will be described shortly, which is a major advantage of our approach for the purpose of making promotion decision recommendations.

[Insert Tables 2 and 3 here]

We now focus on the results of the proposed model. The parameter estimates reveal three distinct segments with regard to their tendencies to use displays and feature ads as price cut proxies versus consideration set formation devices. Segment one is the largest in size (51.7%). It has the lowest degree of state dependence (0.394) and the largest effect of an actual price cut (0.161). Consumers of this segment seem to use display and feature ad for forming consideration sets sometimes, with probabilities of 16.2% and 34.9% respectively, but never treat them as price cut proxies. Segment two is the middle segment in terms of size (26.5%) and degree of state dependence (1.211), and has a price coefficient similar to segment one and a price cut coefficient similar to segment three. This segment appears to be primarily influenced by in-store promotion activities. Consumers of this segment tend to see displays as price cut proxies fairly often (with a

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[5] The model with segment-specific $q_{DC,FC}$, $q_{DP,FC}$, $q_{DC,FP}$, and $q_{DP,FP}$ (i.e., the parameters for computing the covariance terms) does not offer significant improvement over the one with a common set of these parameters and therefore the latter is presented. Note that the resulting covariance terms are still segment-specific (see the Appendix for the detail).

[6] A similar problem would occur if either of the positive main effects of price cut and display/feature ad is smaller than the magnitude of the negative interaction effect.

[7] Using alternative variables, such as “display only (without feature ad and price cut)”, “feature ad only (without display and price cut)”, “price cut only (without display and feature ad)”, could reduce collinearity among variables to some extent, but does not seem to resolve the problems caused by multicollinearity completely. See, for examples, Gupta (1988) and Lemon and Nowlis (2002).

probability of 68.3%) and sometimes use them to form consideration sets (with a probability of 31.7%). They very occasionally use feature ads to form consideration sets (with a probability of 3.7%), but seem to never treat them as proxies for price cuts. Segment three is the smallest in size (21.8%). It exhibits the highest degree of state dependence (2.773) and is least sensitive to the actual price of an item. Unlike the first two segments, consumers of segment three appear to almost always treat display and feature ad as price cut proxies (with estimated probabilities of 100% and 98.9%, respectively), and rarely use them to form consideration sets. Finally, the signs of the covariance terms between using display/feature as consideration set formation devices and price cut proxies are all as expected. Several of them turn out to be close to zero, which is consistent with their corresponding probability estimates of nearly 0 or 1 in a certain segment. In other words, the covariance approaches zero when there is little variation (i.e., either yes or no) in the occurrence of one of the events involved. The non-zero covariance terms indicate that there is a positive correlation of using displays and feature ads to form consideration sets, and a negative correlation between using displays for price cut proxies and feature ads to form consideration sets.

The estimation results reveal some interesting patterns of the association between consumer characteristics and the tendencies to undergo different decision processes. It appears that consumers who are the least state-dependent and are more sensitive to the actual price and price discount (i.e., segment one) tend to use displays and feature ads to form consideration sets. Consumers who are most state dependent and least sensitive to the actual price and price cut (i.e., segment three) tend to treat displays and feature ads as proxies for price cuts. Consumers who have an intermediate level of state dependence and sensitivity to actual price discounts show a combination of the consideration set formation and price cut proxy effects. A plausible cause for this pattern is that the state-dependence, price and price discount coefficients may reflect how much effort consumers pay in processing information on actual prices and price discounts at a given purchase occasion. Consumers in segment one (the least state dependent one) are likely to be more involved in evaluating pricing and promotion information, and thus know whether a display and feature ad is accompanied by an actual price discount and are not likely to confuse them when they do not occur together. For these consumers, sometimes displays and feature ads may be used as heuristics to form consideration sets, which points to a conscious strategy to save cognitive effort and simplify purchase decisions, instead of unknowingly equating displays and feature ads to price cuts. But most of the time (with a probability of 65.1%) they tend to evaluate the entire set of alternatives based on their actual price and discount information. Consumers in segment three (the most state dependent one) tend to rely on past purchase outcomes and are likely to be least involved in processing actual price and promotion information, and thus seem to almost always take displays and feature ads as proxies for price cuts. This is consistent with the finding by Inman et al. (1990) that consumers with low need-for-cognition tend to see promotional signs as a cue for a price cut even when there is no actual reduction in the price. Consumers in segment two appear to be in between the other two in terms of their involvement in the purchase decisions and thus may use displays and feature ads for both consideration set formation and price cut proxies. In summary, we have found support for both the price cut proxy and consideration set formation effects, and they tend to occur to consumers of different characteristics. Even for consumers who are aware of and sensitive to actual prices, the mere fact that a brand is on display or feature ad can increase its choice probability by influencing their consideration set formation process. This phenomenon cannot be explained by the price cut proxy effect.

To further examine the characteristics of the segments identified by our model, we classify the households into one of the three segments based on their posterior segment probabilities in the estimation data. Segment-specific descriptive information is presented in Table 4. Segment one has the highest percentage of purchases made on price discount and feature ad, the highest percentage of switching purchases, and the second highest percentage of purchase made on display. Segment two lies in the middle on these measures except that it has the highest percentage of purchases made on display, which implies that this segment is the most responsive one to in-store display promotions. Segment three is the least responsive to price discounts, displays, and feature ads, and also has the lowest percentage of switching purchases. These patterns are consistent with our model estimation results.

[Insert Table 4 here]

The different patterns across consumer segments also provide an explanation for the mixed patterns of promotion interaction effects in the literature. As speculated in Section 1, if display/feature ad affects brand choice mainly through the price cut proxy effect, the interaction term of display/feature ad and price cut in a compensatory model should be negative, because the joint effect would be smaller than the sum of the two individual effects. On the other hand, if display/feature ad are mainly used to form consideration sets, the interaction effect is likely to be positive because a display/feature ad helps an item get into the consideration set, which is the first stage of the decision process, while a price cut helps it stand out among the remaining alternatives at the evaluation stage, and thus they reinforce the effectiveness of each other in the entire brand choice process. This conjecture is supported by a comparison of the estimation results from the MNL model and the proposed model which offer a similar segment structure of the brand constants, state dependence, and actual price coefficients. For segment one, our model indicates that display and feature ad are used to form consideration sets, while their interactions with price cut are both positive in the MNL model. For segment two, feature ad is used to form consideration sets according to our model and its interaction with price cut is positive in the MNL model, while display is more than twice likely to be a price cut proxy than a consideration set formation device accordingly to our model (68.3% vs. 31.6%), and correspondingly, its interaction with price cut is negative in the MNL model. For segment three, the predominant effects of display and feature ad are price cut proxies based on our model, and the interaction terms in the MNL model turn out to be both positive. The matching pattern between the MNL and our models suggests that *a positive interaction effect of display/feature ad and price cut in a compensatory brand choice model is likely due to the consideration set formation mechanism, while a negative interaction effect is likely attributable to the price cut proxy mechanism*. It implies that the mixed patterns of the interaction effects reported previously may simply be a result of which mechanism dominates at the aggregate level for a particular data sample. This explanation may help bring a closure to an unsolved puzzle in some previous studies.

4. Implications for Promotion Decisions

Having a better understanding on the underlying decision mechanisms of how in-store displays and feature ads affect consumers' brand choice behavior has important implications for promotion decisions. It is a common practice by retailers to frequently combine temporary price reductions with displays and feature ads, which is also the case in our data. Yet this common practice would often contradict with recommendations based on a MNL model that yields negative interaction effect(s) of price cut with display and/or feature ad. Previous studies as well as the current one indicate that compensatory brand choice models frequently generate negative interaction effects. For example, the MNL model estimated from our data predicts a negative overall interaction effect of display and price cut (averaged across segments), which implies that the retailers should not have offered price discounts with in-store displays for the category analyzed here. Yet it occurred in 43%-84% of the cases when an item was on display in the data.

Findings from this study, however, reveal a very different picture. If a negative interaction effect is due to the price cut proxy mechanism, as corroborated by our empirical analysis, it would be unwise to eliminate price reductions from displays or feature ads. The price cut proxy effect is caused by a lack of motivation or interest to engage in careful information processing. Its occurrence relies on consumers' lack of accurate or complete information contained in a display or feature ad. This effect would disappear once consumers realize that a display or feature ad is never accompanied by an actual price discount. It implies that, if a retailer completely eliminates price discounts from displays and feature ads, they will no longer have any effect (including the main effect) on brand choice in the long run for consumers who primarily use them as price cut proxies, because their signaling effect would erode over time. Rather, some but not all of displays and feature ads should be accompanied by price discounts to induce the usage of them as cues for price cuts, yet still taking advantage of the phenomenon that some consumers see them as signs for discounts even when there are no actual price reductions. It would be beneficial to combine price discounts with displays/feature ads if the consideration set formation mechanism dominates. (This recommendation is likely to be supported by a MNL model as well.)

Results from our model also indicate that it makes sense to bundle price cuts with feature ads more frequently than with displays for this category, which is exactly the case in the current data, because the overall probability (averaged across segments) of using feature ads to form consideration sets is greater than that of using displays to form consideration sets (19.0% vs. 16.8%), while the overall probability of using displays as price cut proxies is greater than that of using feature ads as price cut proxies (39.9% vs. 21.6%). In summary, although retailers may not know the detailed decision mechanisms underlying consumers' brand choice processes, they seem to have the right intuition for frequently offering price discounts with displays and feature ads. The model we propose in this study offers an analytical tool to help them assess the tendencies to undergo various decision mechanisms by different consumers based on actual purchase data, and our empirical results provide a rationale for a common practice employed by many retailers.

Appendix Derivation and Re-parameterization of the Occurrence Probabilities

For ease of exposition, the subscripts i and g are omitted in this section.

$\because$ $$E(DC,FC) = 1\cdot \Pr(DC=1, FC=1) + 0 \cdot [1-\Pr(DC=1, FC=1)] = \Pr(DC=1, FC=1)$$

and $$\mathrm{cov}(DC,FC) = E(DC,FC) - E(DC)\cdot E(FC)$$

$\therefore$ $$\Pr(DC=1, FC=1) = E(DC)\cdot E(FC) + \mathrm{cov}(DC,FC) = f_{DC} f_{FC} + s_{DC,FC} \tag{A1}$$

Similarly, $$\Pr(DC=1, FP=1) = E(DC)\cdot E(FP) + \mathrm{cov}(DC,FP) = f_{DC} f_{FP} + s_{DC,FP} \tag{A2}$$

And, $$\begin{aligned}\Pr(DC=1, FC=0, FP=0) &= f_{DC} - (f_{DC} f_{FC} + s_{DC,FC}) - (f_{DC} f_{FP} + s_{DC,FP}) \\ &= f_{DC}(1 - f_{FC} - f_{FP}) - s_{DC,FC} - s_{DC,FP}\end{aligned} \tag{A3}$$

Applying the same logic, we get the occurrence probabilities of the other decision mechanisms. To ensure that the probability estimates fall between 0 and 1 and that the sum of the conditional probabilities equals to their corresponding marginal probabilities, we re-parameterize the probability and covariance terms as follows.

$$f_{DC} = \frac{\exp(d_{DC})}{1+\exp(d_{DC})+\exp(d_{DP})},\ f_{DP} = \frac{\exp(d_{DP})}{1+\exp(d_{DC})+\exp(d_{DP})},$$

$$f_{FC} = \frac{\exp(d_{FC})}{1+\exp(d_{FC})+\exp(d_{FP})},\ f_{FP} = \frac{\exp(d_{FP})}{1+\exp(d_{FC})+\exp(d_{FP})},$$

$$\Pr(DC=1, FC=1) = f_{DC} f_{FC} \frac{\exp(q_{DC,FC})}{f_{FC}\exp(q_{DC,FC}) + f_{FP}\exp(q_{DC,FP}) + 1}, \tag{A4}$$

$$\Pr(DC=1, FP=1) = f_{DC} f_{FP} \frac{\exp(q_{DC,FP})}{f_{FC}\exp(q_{DC,FC}) + f_{FP}\exp(q_{DC,FP}) + 1}, \tag{A5}$$

$$\Pr(DC=1, FC=0, FP=0) = f_{DC} \frac{1}{f_{FC}\exp(q_{DC,FC}) + f_{FP}\exp(q_{DC,FP}) + 1}, \tag{A6}$$

$$\Pr(DP=1, FC=1) = f_{DP} f_{FC} \frac{\exp(q_{DP,FC})}{f_{FC}\exp(q_{DP,FC}) + f_{FP}\exp(q_{DP,FP}) + 1}, \tag{A7}$$

$$\Pr(DP=1, FP=1) = f_{DP} f_{FP} \frac{\exp(q_{DP,FP})}{f_{FC}\exp(q_{DP,FC}) + f_{FP}\exp(q_{DP,FP}) + 1}, \quad \text{(A8)}$$

$$\Pr(DP=1, FC=0, FP=0) = f_{DP} \frac{1}{f_{FC}\exp(q_{DP,FC}) + f_{FP}\exp(q_{DP,FP}) + 1}, \quad \text{(A9)}$$

$$\Pr(DC=0, DP=0, FC=1) = f_{FC}[1 - \frac{f_{DC}\exp(q_{DC,FC})}{f_{FC}\exp(q_{DC,FC}) + f_{FP}\exp(q_{DC,FP}) + 1} - \frac{f_{DP}\exp(q_{DP,FC})}{f_{FC}\exp(q_{DP,FC}) + f_{FP}\exp(q_{DP,FP}) + 1}], \quad \text{(A10)}$$

$$\Pr(DC=0, DP=0, FP=1) = f_{FP}[1 - \frac{f_{DC}\exp(q_{DC,FP})}{f_{FC}\exp(q_{DC,FC}) + f_{FP}\exp(q_{DC,FP}) + 1} - \frac{f_{DP}\exp(q_{DP,FP})}{f_{FC}\exp(q_{DP,FC}) + f_{FP}\exp(q_{DP,FP}) + 1}], \quad \text{(A11)}$$

$$\Pr(DC=0, DP=0, FC=0, FP=0) = 1 - f_{FC} - f_{FP} - \frac{f_{DC}}{f_{FC}\exp(q_{DC,FC}) + f_{FP}\exp(q_{DC,FP}) + 1} - \frac{f_{DP}}{f_{FC}\exp(q_{DP,FC}) + f_{FP}\exp(q_{DP,FP}) + 1}, \quad \text{(A12)}$$

where d_{DC}, d_{DP}, d_{FC}, d_{FP}, $q_{DC,FC}$, $q_{DC,FP}$, $q_{DP,FC}$, and $q_{DP,FP}$ are parameters to be estimated. It can be shown that:

(A4) + (A5) + (A6) = f_{DC}, (A7) + (A8) + (A9) = f_{DP}, (A10) + (A11) + (A12) = $1 - f_{DC} - f_{DP}$,

(A4) + (A7) + (A10) = f_{FC}, (A5) + (A8) + (A11) = f_{FP}, (A6) + (A9) + (A12) = $1 - f_{FC} - f_{FP}$.

In addition, the covariance terms can be obtained by:

$$s_{DC,FC} = f_{DC} f_{FC}[\frac{\exp(q_{DC,FC})}{f_{FC}\exp(q_{DC,FC}) + f_{FP}\exp(q_{DC,FP}) + 1} - 1], \quad \text{(A13)}$$

$$s_{DC,FP} = f_{DC} f_{FP}[\frac{\exp(q_{DC,FP})}{f_{FC}\exp(q_{DC,FC}) + f_{FP}\exp(q_{DC,FP}) + 1} - 1], \quad \text{(A14)}$$

$$s_{DP,FC} = f_{DP} f_{FC}[\frac{\exp(q_{DP,FC})}{f_{FC}\exp(q_{DP,FC}) + f_{FP}\exp(q_{DP,FP}) + 1} - 1], \quad \text{(A15)}$$

$$s_{DP,FP} = f_{DP} f_{FP}[\frac{\exp(q_{DP,FP})}{f_{FC}\exp(q_{DP,FC}) + f_{FP}\exp(q_{DP,FP}) + 1} - 1]. \quad \text{(A16)}$$

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Table 1 Descriptive Statistics

Price and Promotion Information

Alternative	Average Price (cents/ounce)	% occasions with Price Cut[a]	% occasions on Display[a]	% occasions on Feature Ad[a]	% Displays with a PC[a]	% feature ads with a PC[a]
1: Kraft 12 oz.	18.8	46.5%	11.5%	21.8%	64.4%	98.9%
2: Kraft 16 oz.	20.1	19.7%	3.3%	3.6%	47.2%	100%
3: Velveeta 12 oz.	16.3	29.8%	11.2%	6.7%	42.7%	85.1%
4: Borden 12 oz.	18.1	33.2%	0.8%	21.6%	62.5%	81.7%
5: Private label 12 oz.	14.6	56.3%	11.2%	19.8%	84.3%	98.7%
6: Private label 16 oz.	15.5	27.9%	0.9%	9.4%	65.7%	94.7%

[a]: Total number of purchase occasions in the sample = 2240.

Purchase Information

Alternative	# of Purchases	Share	Purchases made On display[b]	Purchase made on feature ad[b]
1: Kraft 12 oz.	678	30.3%	143 (21.1%)	400 (59.0%)
2: Kraft 16 oz.	154	6.9%	31 (20.1%)	39 (25.3%)
3: Velveeta 12 oz.	335	15.0%	70 (20.9%)	25 (7.5%)
4: Borden 12 oz.	261	11.7%	4 (1.5%)	91 (34.9%)
5: Private label 12 oz.	569	25.4%	125 (22.0%)	246 (43.2%)
6: Private label 16 oz.	243	10.9%	9 (3.7%)	74 (30.5%)

[b]: Purchases that were made when the chosen alternative was on display/feature ad, with percentage of the total purchases of that alternative in parentheses.

Table 2 The Multinomial Logit Model

Variables/Parameters	Segment 1	Segment 2	Segment 3
Constants (baseline: Private label 16 oz.)			
Kraft 12 oz.	0.895 ***	3.833 ***	0.904 ***
Kraft 16 oz.	-0.263	3.013 ***	0.357
Velveeta 12 oz.	-0.951 ***	2.535 ***	0.599 **
Borden 12 oz.	0.102	3.267 ***	-0.891 **
Private label 12 oz.	0.553 ***	1.248 ***	-0.209
State dependence (g)	0.324 ***	1.112 ***	2.799 ***
Actual price (b_{ap})	-0.293 ***	-0.329 ***	-0.113 ***
Price cut indicator (b_{pc})	0.284 **	-0.435 **	-0.161
Display (b_D)	-0.088	1.218 ***	1.178 **
Feature ad (b_F)	0.158	-0.116	1.725 **
Price cut * Display (b_{PD})	0.604 *	-0.700 **	-1.799 ***
Price cut * Feature ad (b_{PF})	0.661 *	1.305 **	-1.267 **
Segment size	43.1%	35.0%	21.9%
Log-likelihood		-2309.2	
# parameters		38	
Holdout log-likelihood		-3096.2	
Holdout hit rate		64.5%	

Table 3 The Proposed Model

Variables/Parameters	Segment 1	Segment 2	Segment 3
Constants (baseline: Private label 16 oz.)			
Kraft 12 oz.	1.263 ***	4.871 ***	0.705 **
Kraft 16 oz.	-0.056	4.107 ***	0.235
Velveeta 12 oz.	-0.402 **	3.111 ***	0.589 **
Borden 12 oz.	0.204	4.372 ***	-0.910 *
Private label 12 oz.	0.663 ***	1.288 ***	-0.216
State dependence (g)	0.394 ***	1.211 ***	2.773 ***
Actual price (b_{ap})	-0.317 ***	-0.422 ***	-0.085 **
Price cut indicator (b_{pc})	0.161 ***	0.137 **	0.092 **
Pr{consideration set formation: display} (f_{DC})	0.162	0.317	0.000
Pr{ consideration set formation: feature} (f_{FC})	0.349	0.037	0.010
Pr{price cut proxy: display} (f_{DP})	0.000	0.683	1.000
Pr{price cut proxy: feature} (f_{FP})	0.000	0.000	0.989
Cov(DC,FC)	0.105	0.035	0.000
cov(DC,FP)	-0.000	-0.000	-0.000
cov(DP,FC)	-0.000	-0.031	-0.000
cov(DP,FP)	0.000	0.000	0.000
Segment size	51.7%	26.5%	21.8%
Log-likelihood		-2332.92	
# parameters		42	
Holdout log-likelihood		-3096.6	
Holdout hit rate		65.2%	

Note: *** P-value < 0.01, ** P-value < 0.05, * P-value < 0.10, except for the probability and covariance terms which are computed from d_{DC}, d_{FC}, d_{DP}, d_{FP}, $q_{DC,FC}$, $q_{DC,FP}$, $q_{DP,FC}$, and $q_{DP,FP}$.

Table 4 Segment-Specific Descriptive Information Based on the Proposed Model

	Segment 1	Segment 2	Segment 3
# households	204 (55.3%)	89 (24.1%)	76 (20.6%)
# purchases	1141	617	482
% purchases on price cut	75.0%	58.8%	34.4%
% purchases on display	19.1%	20.8%	7.5%
% purchases on feature ad	50.3%	40.2%	11.0%
% of switching purchases	66.0%	53.3%	19.9%