



Reports

E-S-QUAL: A Multiple-Item Scale for Assessing Electronic Service Quality (04-112)

A. Parasuraman, Valarie A. Zeithaml, and Arvind Malhotra

The Effect of Retailer Reputation and Response on Postpurchase Consumer Reactions to Price-Matching Guarantees (04-113)

Hooman Estelami, Dhruv Grewal, and Anne L. Roggeveen

Modeling a Brand's Customer-Mix (04-114)

Yung-Hsin Chien, Edward I. George, and Leigh McAlister

Effects of Export Assistance on Pricing Strategy Adaptation and Export Performance (04-115)

Luis Filipe Lages and David B. Montgomery

The S-Curve of Technological Evolution: Strategic Law or Self-Fulfilling Prophecy? (04-116)

Ashish Sood and Gerard J. Tellis

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S E R I E S

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Modeling a Brand's Customer-Mix

Yung-Hsin Chien, Edward I. George, and Leigh McAlister

A brand's customer-mix is a key element of retailer positioning and manufacturer sales strategies. This model offers new insight into which customers purchase a particular brand, and how that customer-mix changes in response to the market environment.

Report Summary

Understanding more about a brand's customer-mix and how that mix changes in response to the environment is important for retailers and manufacturers.

Here, Chien, George, and McAlister develop a customer-mix model that improves upon previous models in three ways: (1) it does not require base rate information regarding the number of consumers in each different response segment in order to provide a customer-mix distribution, (2) it can estimate customer-mix without reference to other brands, and (3) it is not limited to defining customer types by brand-choice-probability-profiles.

The model focuses on a particular brand and a set of customer types who buy the brand, and defines a brand's customer-mix by the expected proportion of that brand's purchases made by each customer type.

Using supermarket data, customer types are defined by basket size (the number of items in the customer's basket at checkout). Each brand's customer-mix distribution (i.e., the expected proportion of that brand's purchases made by customers of each basket size) is modeled for a variety of different brands. In addition, the model considers the influence of the brand's promotional status and whether the shopping was done on a weekday or a weekend.

By estimating the model for 16 brands, the authors are able to compare customer-mix distributions across non-competing brands. Their model sheds light on the relative concentration of large basket shoppers in different brands' customer-mixes and the way a brand's customer-mix changes when the brand is on-promotion and when the brand is bought on weekends. ■

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Introduction

Understanding more about a brand's customer-mix (the proportion of a brand's purchases made by a customer type) and how that mix changes in response to the environment is important for retailers and manufacturers.

Consider the perspective of the retailer who is trying to position the store for upscale customers. This retailer will be more sympathetic to brand b 's requests for more/better shelf space if he or she knows that brand b 's customer-mix contains a high concentration of upscale customers. Further, the retailer's willingness to promote brand b will be greater if he or she knows that, in response to a promotion on b , the mix of shoppers buying b shifts to include an even higher concentration of upscale customers.

Such insights are also useful to the manufacturer who has to sell a product to the retailer. If the manufacturer can demonstrate that his or her brand has a customer-mix that is consistent with the retailer's positioning strategy and that, when promoted, the brand's customer-mix becomes an even better match with the retailer's strategy, the manufacturer will find it easier to gain shelf space and merchandising support from that retailer.

In addition, in evaluating alternative marketing tactics, it would be useful for a brand manager to know that tactic 1 enhanced the proportion of target customers in the brand's customer-mix while tactic 2 shifted the brand's customer-mix away from its target.

In this study, for a particular brand and a collection of customers that can be grouped into a set of customer types, we provide a theoretically grounded, parsimonious model that fits the brand's "customer-mix" as defined by the expected proportion of that brand's purchases made by each customer type. The parameters of the model for a particular brand provide insight into that brand's customer-mix and the ways that mix changes in response to environmental influences.

Background

Our paper is not the first to consider the customer-mix for the brand. Previous work has approached the issue of customer-mix for a brand by combining demographic customer information with logit brand choice models. For example, Krishnamurthi and Raj (1988), by including customer income in a customer's utility function, obtain brand-specific income coefficients that capture the extent to which customers' incomes influence brand choice probabilities among directly competing brands. For three particular competing brands (b_1, b_2, b_3), they found that high income customers were less likely to choose b_3 . From such information, one can infer that the customer-mix of b_3 includes fewer high income customers than the customer-mixes of b_1 and b_2 . However, one cannot infer that the customer-mix of b_3 contains a majority of low income customers because it could be that very few low income customers are attracted to this category.

Krishnamurthi and Raj (1988) allow us to identify the probability that a customer of type c will purchase brand b rather than some other directly competing brand ($P(\text{purchase brand } b | \text{customer type } c) = P(b|c)$). Our customer-mix model allows us to identify the probability that a given purchase of brand b was made by a customer of type c rather than by a customer of some other type ($P(\text{customer type } c | \text{purchase brand } b) = P(c|b)$). Bayes rule relates Krishnamurthi and Raj's (1988) formulation to our formulation: $P(c|b) \propto P(b|c)P(c)$. That is, one needs the base rate frequencies for different customer types, $P(c)$, in order to translate the Krishnamurthi and Raj probabilities into a customer-mix distribution.

Further, Krishnamurthi and Raj (1988) can only determine that $P(b|c)$ differs across customer types, c , if $P(b|c)$ also differs across directly competing brands, b . If each customer type responds in the same way to all directly competing brands, then these directly competing brands will have identical customer-

mixes and a model like Krishnamurthi and Raj (1988) will be unable to identify differences in $P(b|c)$ across different customer types.

To see that knowing a brand's customer-mix may be relevant even if that brand's mix doesn't differ from the mixes of other directly competing brands, consider again the retailer who wants to position the store as upscale. This retailer would find it useful to know that brand b of olive oil is bought primarily by upscale customers even if it is the case that all other directly competing brands of olive oil are also bought primarily by upscale customers. The model we propose allows one to estimate brand b 's customer-mix without reference to other brands.

Other examples of such previous work use logit brand choice models to group a brand's customers into segments with homogeneous brand-choice-probability-profiles, and then consider the demographic characteristics of those segments. This work grows out of the literature on latent class analysis models of market structure (Grover and Srinivasan 1987, 1989, 1992; Kamakura and Russell 1989). For example, Bucklin and Gupta (1992) obtain probabilities of customer membership in such segments and assign customers to those segments for which their membership probability is highest. For each segment, they then run a logistic regression to relate demographic characteristics to segment membership probabilities. Gupta and Chintagunta (1994) also relate demographic variables to segment membership probabilities, but do so during the step in which segment membership probabilities are determined.

Given a set of directly competing brands, these latent class logit brand choice models focus on each customer's vector of brand choice probabilities across those directly competing brands. These models create groups of customers whose brand-choice-probability-profiles are similar. In some sense, these models define a "customer type" by the vector of brand choice probabilities that characterize that group. Similar to the

interpretation of Krishnamurthi and Raj (1988), one can interpret these latent class logit brand choice models as defining, for a customer with brand-choice-probability-profile c , the probability of buying brand $b = P(\text{purchase brand } b | \text{customer type defined by brand-choice-probability-profile } c) = P(b|c)$. As with Krishnamurthi and Raj (1988), one needs base rate information, in this case base rate information on the frequencies of different brand-choice-probability-profiles ($P(c)$), in order to translate latent class logit brand choice probabilities into a customer-mix distribution. Note also that such customer-mix distributions can *only* be specified over brand-choice-probability-profile-defined customer types. While these models relate a customer's demographic descriptors to the probability that that customer might have a particular brand-choice-probability-profile, there is no direct way to specify $P(\text{customer of type } c \text{ did the choosing} | \text{brand } b \text{ was chosen})$ for any customer descriptor other than brand-choice-probability-profile.

In summary, existing logit brand choice models that incorporate customer descriptors would have to be augmented with base rate information on customer types in order to provide customer-mix distributions like those we estimate directly. Further, logit brand choice models incorporating demographic variables as descriptors (like Krishnamurthi and Raj 1988) are necessarily silent about the relationship between customer characteristics and brand choice probabilities if all directly competing brands have the same customer-mix. In addition, latent class logit brand choice models are limited to defining a customer types by brand-choice-probability-profiles.

The customer-mix model we propose, unlike either the Krishnamurthi and Raj (1988) logit brand choice model or the latent class logit brand choice models, does not have to be augmented with base rate information in order to provide a customer-mix distribution. Further, unlike the Krishnamurthi and Raj (1988) logit brand choice model, our customer-mix model can be

estimated even if customer-mix does not differ across directly competing brands. And, unlike the latent class logit brand choice models, our customer-mix model is not limited to defining customer types by brand-choice-probability-profiles.

In what follows we develop a theoretically grounded model for $P(c|b)$, the probability that a randomly selected purchase of brand b was made by a customer of type c . We interpret $P(c|b)$ as the expected proportion of brand b 's purchases made by customers of type c . We refer to the distribution over customer types, c , of $P(c|b)$ as brand b 's customer-mix distribution.

We illustrate the proposed customer-mix model using supermarket scanner data that contains information on complete shopping baskets. Because our shopping basket data does not contain information that identifies the specific consumer who bought that basket, we treat each shopping basket as a distinct customer. We use basket size (the number of items in a customer's basket at check-out) to define customer types. For a variety of different brands, we model each brand's customer-mix distribution (i.e., the expected proportion of that brand's purchases made by customers of each basket size) and consider the influence on that distribution of the brand's promotional status and whether the shopping was done on a weekday or a weekend.

We use basket size to define customer types in the study because retailers use this customer characteristic to distinguish their "best" shoppers (those whose shopping baskets contain many items at time of checkout) from other shoppers. As testimony to the level of retailer interest in this customer characteristic, manufacturers now include basket-size information¹ in virtually every selling pitch made to leading retailers (Chien, George, and McAlister 2001). Further testimony to the importance of this customer characteristic was provided by Al Carey, President of PepsiCo Sales, when he highlighted PepsiCo's use of basket size information in his featured practitioner talk at the

"Operationalization—Marketing Analytics" plenary session of the 2003 Marketing Science Conference at The University of Maryland.

Customer-Mix Model

Consider a set of purchase transactions, T , made by a set of customer types, C , from a set of brands, B . We assume that;²

(1) The attraction that customer $t \in T$ has to brand $b \in B$, a_{tb} , is:

$$a_{tb} = v_{tb} + \varepsilon_{tb}$$

where:

v_{tb} = the deterministic component of t 's attraction to brand b , to be calculated from observed variables, and

ε_{tb} = the random component of t 's attraction to brand b , varying across customer types and across brands, possibly as a result of unobserved variables.

(2) Given that brand b is chosen, we assume that the probability that b was chosen by customer t is:

$$P(t|b) = P(a_{tb} \geq a_{jb}, j \in T)$$

(3) the ε_{tb} are independently distributed random variables with a double exponential (Gumbel type II extreme value) distribution:

$$P(\varepsilon_{tb} \leq \varepsilon) = e^{-e^{-\varepsilon}}, -\infty < \varepsilon < \infty$$

Given assumptions 1-3, it can be shown (Theil 1969; McFadden 1974) that the probability that a randomly selected purchase of brand b was made by customer t is:

$$P(t | b) = \frac{e^{v_{tb}}}{\sum_{j \in T} e^{v_{jb}}} \quad (1)$$

The deterministic component of customer t 's attraction to brand b will be expressed as a func-

tion of observable variables. Some of these observable variables might be attributes of the customer (e.g., basket size, income, education). Other attributes might be related to the brand being bought (e.g., promotional status, price, or quality of the brand). Letting M represent the set of attributes whose values we observe, we get:

$$v_{tb} = \sum_{m \in M} w_{mb} x_{mbt} \quad (2)$$

where:

x_{mbt} = function of the observed value of attribute m of brand b for customer t

w_{mb} = attraction weight of attribute m for brand b .

Equations 1 and 2 present a model that describes the strength with which customer t is attracted to brand b . But we are defining our customer-mix distribution over a set of customer types, not over all individual customers. Since customer descriptor variables take on the same values for all customers of a given customer type, we can restate Equation 2 by recognizing that $v_{t_1b} = v_{t_2b} = v_{cb}$ for all customers t_1 and t_2 who are of customer type c . Given that there are q_{cb} customers of type c who buy brand b , we define brand b 's customer-mix by the probability distribution, defined over customer types $c \in C$, as:

$$P(c | b) = \frac{q_c e^{v_{cb}}}{\sum_{j \in C} q_j e^{v_{jb}}} \quad (3)$$

The probability $P(c|b)$ can be interpreted as the probability that any given purchase of brand b was made by a customer of type c .

The data to fit this model will consist of the observed transactions and corresponding attributes. We set b as the target brand and observe, for each transaction t , the customer type (i.e., the basket size), whether brand b was included in that basket, and the attribute values x_{mbt} . This data can then be used to provide a likelihood for the unknown attribute weights w_{mb} . Letting $T_b \subset T$ be the subset of transactions that were

observed to include brand b , the likelihood of the attribute weights for brand b is obtained as:

$$L(w_{mb} : m \in M) = \prod_{T_b} P(c | b) \quad (4)$$

Note that because the model defined by equations 2 and 3 is conditioned on the event that brand b was chosen, the product in Equation 4 is restricted to T_b (those transactions which included brand b). This likelihood can be used for inference, such as maximum likelihood estimation of the attribute weights w_{mb} .

Benchmark models

In order to gauge the ability of the proposed model to reflect changes in customer-mix driven by environmental influences, we propose two models that ignore environmental influence and benchmark against those models. The most basic model against which we might compare performance holds that the probability that brand b is bought by customer t depends neither on the specific brand under consideration nor on t 's customer type. This benchmark suggests that all customers are equally attracted to brand b . That is, letting $|T|$ represent the total number of customers:

$$P'(t|b) \equiv \frac{1}{|T|}$$

Aggregating these probabilities by customer type, the above equation implies that:

$$P'(c | b) = \frac{q_c}{\sum_{j \in C} q_j} = \frac{q_c}{|T|} \quad (5)$$

We refer to this model as the “equally likely customers” benchmark model.

In our second benchmark model, we continue to assume no difference across brands, but we do allow influence by customer type. In particular, in this benchmark model we let t 's attraction to brand b be proportional to the number of items in t 's basket. (That is, for a given

purchase of b , the probability that that purchase was made by t is proportional to the number of items in t 's basket.) If we let n_c = number of items in the basket of a customer t who is of customer type c , our second benchmark model holds that:

$$P''(t|b) \propto n_c$$

Given that there are q_c customers of the same type as customer t , the above implies:

$$P''(c_i|b) \propto q_c n_c$$

and we structure our second benchmark model to be:

$$P^n(c|b) = \frac{q_c n_c}{\sum_{j \in C} q_j n_j} \quad (6)$$

If we think of the basket of a customer of type c as having n_c "slots" to be filled, then across all customer types there are $\sum_C q_c n_c$ available slots to be filled. Since, under this second benchmark model, any particular brand is equally likely to have been bought for any of the available slots, we refer to Equation 6 as the "equally likely slots" benchmark model. The probability that a customer of type c bought any particular randomly selected brand is proportional to $q_c n_c$, the number of slots in all baskets of customers of type c .

Application

To illustrate our proposed formulation, we applied it to estimate $P(c|b)$ for 16 brands over seven weeks of purchase history in one supermarket. These brands were selected by the retailer who provided the data because they represent the range of packaged food items typically considered for merchandising support. During the period of observation, a total of 1,562,434 items in 110,289 shopping baskets were purchased, and the brands contained in each basket were recorded. Baskets sizes n_c ran from 1 item up to 130 items. Because the iden-

tity of the customers was not recorded in our data, we treated each basket as a distinct customer. For each purchase, we also observed whether the transaction occurred when the brand was on promotion, and whether the transaction occurred on a weekend. Given this data we considered the special case of equations 2 and 3 where

$$\begin{aligned} v_{bt} &= \ln n_{c_t} + \omega_{1b} \ln n_{c_t} + \omega_{2b} D_{bc_t} + \omega_{3b} D_{bc_t} \quad (7) \\ (\ln n_{c_t} - m_{bD}) &+ \omega_{4b} W_{c_t} + \omega_{5b} W_{c_t} (\ln n_{c_t} - m_W) \end{aligned}$$

and

$D_{bc_t} = 1$ if b was on promotion when t shopped, and 0 otherwise,

$m_{bD} = \frac{1}{|T_{bD}|} \sum_{T_{bD}} \ln n_{c_t}$ where $T_{bD} \subset T$ is the subset of transactions that occurred when brand b was on promotion, and $|T_{bD}|$ is the number of transactions in T_{bD}

$W_{c_t} = 1$ if t shopped on a weekend and 0 otherwise, and

$m_W = \frac{1}{|T_W|} \sum_{T_W} \ln n_{c_t}$ where T_W is the subset of transactions that occurred on a weekend, and $|T_W|$ is the number of customers in T_W .

In Equation 7 we insert the isolated term $\ln n_{c_t}$ and use the natural log of basket size ($\ln n_{c_t}$) rather than basket size itself (n_{c_t}) so that the benchmark models are each nested within the proposed customer-mix model. To see that this nesting occurs, note that when $\omega_{1b} = -1$ and $\omega_{2b} = \omega_{3b} = \omega_{4b} = \omega_{5b} = 0$, the customer-mix model collapses into the "equally likely customers" benchmark model:

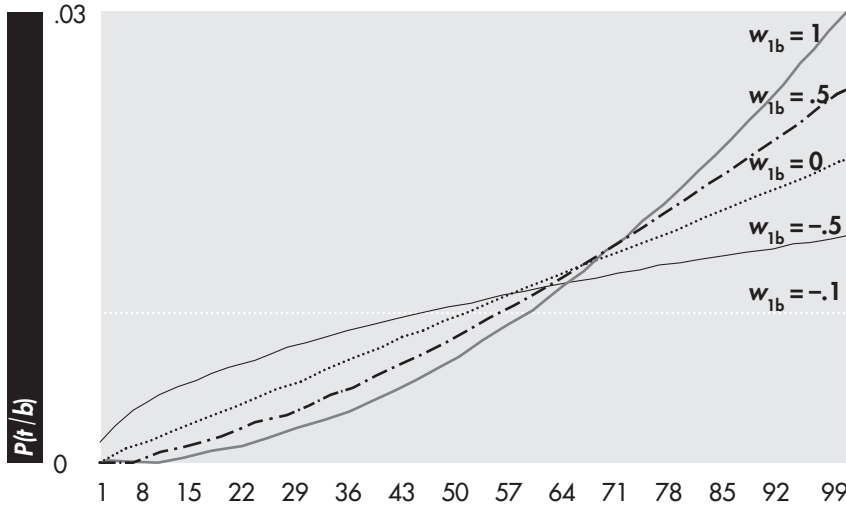
$$P(c|b \text{ and } \omega_{1b} = -1 \text{ and } \omega_{2b} = \dots = \omega_{5b} = 0) = P'(c|b) = \frac{q_c}{\sum_{j \in C} q_j}$$

Further, when $\omega_{1b} = \omega_{2b} = \omega_{3b} = \omega_{4b} = \omega_{5b} = 0$, the customer-mix model collapses into the "equally likely slots" benchmark model:

$$P(c|b \text{ and } \omega_{1b} = \omega_{2b} = \dots = \omega_{5b} = 0) = P''(c|b) = \frac{q_c n_c}{\sum_{j \in C} q_j n_j}$$

Figure 1

$P(t|b, w_{2b} = \dots = w_{5b} = 0)$ for $w_{1b} = -1, -.5, 0, .5, 1$



We now motivate our choice of these five attributes for Equation 7 with discussions of the interpretation of the attribute weights w_{1b}, \dots, w_{5b} .

Basket size effects

Consider the term $w_{1b} \ln n_{c_i}$ in Equation 7. To focus on the effect of our customer type descriptor (basket size) suppose that $w_{2b} = w_{3b} = w_{4b} = w_{5b} = 0$. In this case:

$$P(t|b, w_{2b} = \dots = w_{5b} = 0) = \frac{\exp\{(1 + w_{1b}) \ln n_{c_i}\}}{\sum_{j \in T} \exp\{(1 + w_{1b}) \ln n_{c_j}\}} = \frac{n_{c_i}^{(1+w_{1b})}}{\sum_{j \in T} n_{c_j}^{(1+w_{1b})}}$$

Figure 1 plots the values of $P(t|b, w_{2b} = \dots = w_{5b} = 0)$ vs. n_{c_i} for $w_{1b} = -1, -.5, 0, .5, 1$ to give a feel for the impact of this parameter on the relative strength with which customers of different types are attracted to brand b . In addition, this figure gives a feel for the nature of the two benchmark models. Recall that $w_{1b} = -1$ corresponds to the “equally likely customers” benchmark model and $w_{1b} = 0$ corresponds to the “equally likely slots” benchmark model.

When $w_{1b} = 0$, plotting $P(t|b, w_{2b} = \dots = w_{5b} = 0) = \frac{n_{c_i}}{\sum_{j \in T} n_{c_j}}$ against basket size yields a straight

line with positive slope, as illustrated in Figure 1.

This indicates that t 's attraction to b is exactly proportional to t 's basket size, which is what the “equally likely slots” benchmark model implies. When $w_{1b} > 0$, t 's attraction to b is more than proportional to t 's basket size for large baskets and less than proportional to t 's basket size for small baskets. That is, $w_{1b} > 0$ implies that brand b is comparatively more likely to be bought by customers with large baskets. When $w_{1b} < 0$, the opposite is true; brand b is comparatively more likely to be bought by customers with smaller baskets. When $w_{1b} = -1$, plotting $P(t|b, w_{2b} = \dots = w_{5b} = 0) \equiv 1/|T|$ against basket size yields a straight line with slope = 0. This indicates that t 's attraction to b is the same for all customers, which is what the “equally likely customers” benchmark model implies.

Thus w_{1b} is a measure of the relative strength of the attraction to brand b experienced by customers with many vs. few items in their shopping baskets. In addition, in the case when all other importance weights = 0; if $w_{1b} = -1$, we have the “equally likely customers” benchmark model, if $w_{1b} = 0$ we have the “equally likely slots” benchmark model.

Promotion effects

Our model (Equation 7) contains two terms that involve the promotion indicator D_{bc_i} , namely $w_{2b} D_{bc_i}$ and $w_{3b} D_{bc_i} (\ln n_{c_i} - m_{bD})$. To understand the effect of including these terms, consider the promotion-shift ratio:

$$Dshift_{bc_i} \equiv \frac{P(c_i, D_{bc_i} = 1, W_{c_i} | b)}{P(c_i, D_{bc_i} = 0, W_{c_i} | b)} = \exp\{w_{2b}\} \exp\{w_{3b} (\ln n_{c_i} - m_{bD})\}$$

which we have labeled $Dshift_{bc_i}$. When D_{bc_i} goes from 0 to 1 (i.e., when b is on-promotion rather than off-promotion) while W_{c_i} remains fixed, the change in t 's attraction to b is the product of two components: $\exp\{w_{2b}\} \exp\{w_{3b} (\ln n_{c_i} - m_{bD})\}$. Let us consider each of these components in turn.

The constant component, $\exp\{w_{2b}\}$, of $Dshift_{bc_i}$ is the mean shift in $P(t|b)$ when brand b is on-promotion, in the sense that

$$\left(\prod_{T_{bD}} Dshift_{bc_i} \right)^{1/|T_{bD}|} = \exp\{\tau_{2b}\}.$$

Note that the expression above is the harmonic mean, as opposed to the arithmetic mean, and is appropriate here because $Dshift_{bc_i}$ is a multiplicative rather than an additive effect. Note also that both the interpretation and the maximum likelihood estimate of $\exp\{\tau_{2b}\}$ would remain the same if the second promotion term $\omega_{3b} D_{bc_i} (\ln n_{c_i} - m_{bD})$ were dropped from Equation 7.

Based on what we know about the power of promotion to increase brand choice probabilities (e.g., Guadagni and Little 1983; Blattberg, Briesch and Fox 1995), we anticipate that t would feel a stronger attraction to b when b is on-promotion than when b is off-promotion. Hence we expect $\tau_{2b} > 0$, a conclusion that is strongly supported by our empirical results.

The main effect of promotion, $\exp\{\tau_{2b}\}$, indicates an identical increase in attraction to promoted brand b for every customer, t . To allow for the possibility that t 's promotion-driven increase in attraction for b is related to t 's basket size, n_{c_i} , we included the term $\omega_{3b} D_{bc_i} (\ln n_{c_i} - m_{bD})$ in Equation 7. This yields the interaction effect $\exp\{\tau_{3b} (\ln n_{c_i} - m_{bD})\}$ in $Dshift_{bc_i}$, which allows the degree of t 's promotion-enhanced attraction to b to depend on the size of t 's basket, n_{c_i} . When $\omega_{3b} > 0$, b 's promotion increases large basket customers' attraction to b more than it increases small basket customers' attraction to b . When $\omega_{3b} < 0$, the opposite is true.

Following the literature, values of $\omega_{3b} < 0$ (suggesting that b 's promotion causes a relatively larger increase in small basket customers' attraction to b) would be consistent with promotion drawing "cherry pickers."³ Values of $\omega_{3b} > 0$ (suggesting that b 's promotion causes a relatively larger increase in large basket customers' attraction to b) would be consistent with promotion serving to reward the store's best shoppers.

Weekend effects

Analogously to our development in the previous section, understanding the effects of including the weekend terms and $\omega_{4b} W_{c_i}$ and $\omega_{5b} W_{c_i} (\ln n_{c_i} - m_W)$ in Equation 7 is facilitated by considering the ratio

$$Wshift_{bc_i} \equiv \frac{P(c_i, D_{bc_i}, W_{c_i} = 1 | b)}{P(c_i, D_{bc_i}, W_{c_i} = 0 | b)} =$$

$$\exp\{\tau_{4b}\} \exp\{\tau_{5b} (\ln n_{c_i} - m_W)\}$$

which we have labeled $Wshift_{bc_i}$. This ratio reveals that when W_{c_i} goes from 0 to 1 (i.e., t shops on a weekend rather than on a weekday) while D_{bc_i} remains fixed, the shift in t 's attraction to b is described by the product of two components $\exp\{\tau_{4b}\} \exp\{\tau_{5b} (\ln n_{c_i} - m_W)\}$. The interpretation of each of these components is similar to their $Dshift_{bc_i}$ counterparts.

The constant component, $\exp\{\tau_{4b}\}$, of $Wshift_{bc_i}$ is the (harmonic) mean shift in t 's attraction to b when t shops on a weekend rather than a weekday,

$$\left(\prod_{T_W} Wshift_{bc_i} \right)^{1/|T_W|} = \exp\{\tau_{4b}\}.$$

Similarly to $\exp\{\tau_{2b}\}$ both the interpretation and the maximum likelihood estimate of $\exp\{\tau_{4b}\}$ would remain the same if the second weekend term $\exp\{\tau_{5b} (\ln n_{c_i} - m_W)\}$ were dropped from Equation 7. However, unlike the promotion effect τ_{2b} , the literature does not provide us with a likely sign for τ_{4b} . That is, we have no reason to think that the contrast of weekday to weekend will reveal a consistent shift upward or downward in t 's attraction to brand b .

The interaction effect $\exp\{\tau_{5b} (\ln n_{c_i} - m_W)\}$ in $Wshift_{bc_i}$ allows the difference between t 's weekday and weekend attraction to brand b to vary by t 's basket size. When $\tau_{5b} > 0$, the increase in t 's attraction to b going from weekday to weekend is greater for large basket customers than for small basket customers. When $\tau_{5b} < 0$, the opposite is true.

Table 1

Parameter Estimates, Improvement in Fit

Brand	w_{1b} Basket Size Effect	w_{2b} Promotion Main Effect	w_{3b} Interaction between Promotion and Basket Size	w_{4b} Weekend Main Effect	w_{5b} Interaction between Weekend and Basket Size	Chi- squared for Likelihood Ratio Test against (5), "Equally Likely Customers"	Chi- squared for Likelihood Ratio Test against (6), "Equally Likely Slots"	Number of transactions that include this brand
Mazola Corn Oil	.50*	1.52*	-.41*	.16	.23	1,430*	330*	586
Kraft Mac 'n Cheese	.19*	.53*	-.24*	.05	.00	2,940*	116*	1,829
Ragu Spaghetti Sauce	.17*	.57*	-.04	.02	.24**	1,495*	85*	836
Kellogg's Cereals	.08	1.03*	-.09	-.16	.17	1,129*	149*	665
Libby Canned Fruit	.06	1.67*	-.01	-.02	.04	931*	297*	464
Minute Maid OJ	.05	.31*	-.03	-.24*	.14	1,549*	37*	1,062
Nabisco Cookie/Cracker	-.07**	.31*	-.05	-.05	.09	1,915*	25*	1,582
Gold Medal Flour	-.10	---	---	.08	-.02	378*	4	1,245
Clorox	-.10**	1.07*	-.25*	.04	.04	1,230*	270*	1,066
Budget Gourmet	-.11	.35**	.05	.09	-.02	384*	11	348
Snickers	-.24*	2.40*	-.18*	-.08	.06	3,105*	2,461*	1,664
Dr. Pepper	-.30*	.60*	-.02	.16*	.01	3,154*	658*	3,965
Coke	-.34*	.42*	-.03	.13*	.00	3,952*	1,160*	5,964
Baird Bread	-.34*	.64*	-.05	.10**	.07**	2,780*	732*	3,739
Pepsi	-.35*	.84*	-.08	.13**	-.02	890*	347*	1,248
Marlboro Cigarettes	-1.02*	---	---	.02	.08**	5	3,310*	2,242

* indicates $p < .01$ ** indicates $p < .05$

All chi-squared tests for Gold Medal and Marlboro have 3 degrees of freedom. All other chi-squared tests have 5 degrees of freedom.

An equivalent way to state the interpretation of $w_{5b} > 0$, is to say that the increase in t 's attraction to b , going from *weekend to weekday*, is greater for *small* basket customers than for large basket customers. That is, for a brand with $w_{5b} > 0$, small basket shoppers would be relatively more attracted to that brand on weekdays than on weekends. Hence such a brand would hence expect to have a relatively higher concentration of small basket shoppers on weekdays than on weekends. We suggest that this higher concentration of small basket shoppers on weekdays is consistent with a brand being a "trip generator," where we use the term "trip generator" to refer to a product which is typically bought as a part of the planned "major" shopping trip on week-

ends, but which can trigger "quick trips" on weekdays when a customer exhausts his/her home supply of that product.⁴ The interaction effect $\exp\{w_{5b}(\ln n_c - m_w)\}$ gives our model the flexibility to reflect such shopping behavior by setting $w_{5b} > 0$.

Estimation and Empirical Results

We use maximum likelihood based on Equation 4 to estimate the model parameters w_{1b}, \dots, w_{5b} in equations 3 and 7. This estimation process was performed independently for each of the 16 brands listed in Table 1. Note that neither Gold Medal flour nor Marlboro

cigarettes were promoted during the period of observation, so we could not estimate the promotion-related coefficients w_{2b} and w_{3b} for Gold Medal or Marlboro. The benchmark “equally likely customers” (Equation 5) and “equally likely slots” (Equation 6) models were also estimated for each of the 16 brands. The sixth and seventh columns of Table 1 report the significance level of the likelihood ratio tests evaluating the improvement in fit provided by the proposed model (equations 3 and 7) over the two benchmark models.

Empirical results

Begin by noting that for all brands except Marlboro, the likelihood ratio test comparing the proposed model (equations 3 and 7) to the “equally likely customers” benchmark model (Equation 5) suggests that the proposed model fits the observed customer-mix data significantly better than this benchmark. The lack of significant increase in fit for Marlboro suggests that the probability of a transaction including Marlboro cigarettes is not related to the number of items included in that transaction nor is it related to whether it is a weekday or a weekend. (Recall, we did not have data for weeks in which Marlboro cigarettes were promoted so we cannot comment on the responsiveness of Marlboro’s customer-mix to promotion.)

For all brands except Budget Gourmet and Gold Medal Flour, the likelihood ratio test comparing the proposed model (equations 3 and 7) to the “equally likely slots” benchmark model (Equation 6) suggests that the proposed model fits the observed customer-mix data significantly better than this benchmark. The lack of significant increase in fit for Budget Gourmet and Gold Medal Flour suggests that a customer’s attraction to one of these brands is proportional to the number of items in that customer’s basket.

Turning now to parameters estimated for each brand’s model we see that, as one would predict based on historical analyses of promotion response, Table 1 shows us that \hat{w}_{2b} is significantly positive for all of the brands. For each of

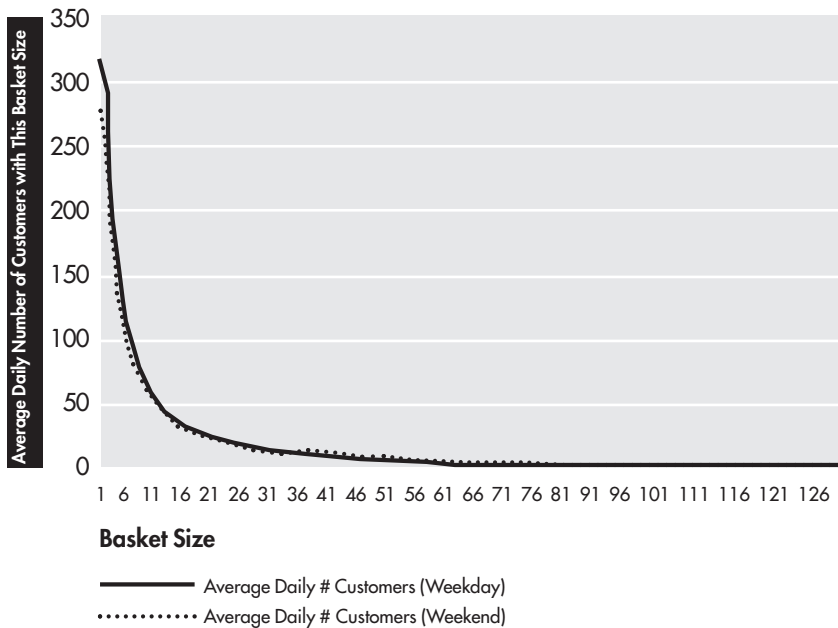
the brands that experiences promotion, all customers find themselves more attracted to the brand when it is on-promotion than when it is off-promotion. For four of the brands, \hat{w}_{3b} (the coefficient of the interaction between promotion and basket size) is significantly negative, suggesting that the promotion-driven attraction is greater for small basket customers than for large basket customers. These four brands may be drawing cherry pickers with their promotions.

For the weekday/weekend effects, \hat{w}_{4b} is significantly positive for four brands (suggesting that customers are more attracted to these four brands on a weekend than on a weekday) and significantly negative for one brand (suggesting that customers are more attracted to this brand on a weekday than on a weekend). For each of the three brands for which \hat{w}_{5b} (the coefficient of the interaction between weekend and basket size) is significantly positive, small basket customers’ attraction to these brands is higher on weekdays than on weekends. These three brands may be “trip generators.”

To interpret the \hat{w}_{1b} estimates in the first column of Table 1, consider the set of purchases where $D_{bc} = 0$ (brand b was off-promotion) and where $W_{c_i} = 0$ (the purchase was made on a weekday). Note that \hat{w}_{1b} is not significantly different from 0 for five of the brands. Thus, for each of these brands, we cannot reject the hypothesis that their customer-mixes follow the “equally likely slots” distribution when off-promotion on a weekday. For each of the three brands for which \hat{w}_{1b} is significantly positive, customers with larger baskets are relatively more attracted to the brand. For each of the eight brands for which \hat{w}_{1b} is significantly negative, customers with smaller baskets are relatively more attracted to the brand.

More generally, the relationship between basket size and $P(t|b)$ is estimated by $(\hat{w}_{1b} + \hat{w}_{3b}D_{bc} + \hat{w}_{5b}W_{c_i})$ which will include the impact of basket size interactions with promotion when $D_{bc} = 1$ and with weekend purchase when $W_{c_i} = 1$. For example, consider Kraft Mac ’n Cheese where

Figure 2
Basket Size Distribution



$\hat{\omega}_{1,Kraft} = .19$ is significantly positive. When off-promotion on weekdays (i.e., $D_{Kraft,c_i} = 0$ and $W_{c_i} = 0$), customers with larger baskets are relatively more attracted to Kraft, in the sense described above. However, when Kraft is promoted on weekdays ($D_{Kraft,c_i} = 1$ and $W_{c_i} = 0$), customers with smaller baskets are relatively more attracted to Kraft since the net effect is $\hat{\omega}_{1,Kraft} + \hat{\omega}_{3,Kraft} = (.19 - .24) = -.05$. Because $\hat{\omega}_{5,Kraft} = 0$, the above relationships between basket size and $P(t|b)$ for Kraft are estimated to be the same on weekdays and weekends.

Customer-mix distributions

Figure 1 reports the relationship between basket size (i.e., customer type) and $P(t|b)$ for various values of the parameter ω_{1b} . It is important to remember that $P(t|b)$ has to be aggregated across all customers, t , who are of customer type c_i , in order to get the customer-mix model $P(c|b)$ as defined by Equation 3. When the distribution of customers across customer types is not uniform, the shape of the customer-mix distribution can be very different from the shape of the curves in Figure 1.

Defining customer type by basket size, it is definitely *not* the case that we have an approximately equal number of customers of each customer type. The distribution of basket sizes (i.e., customer types) across all of the transactions in our data is highly skewed as can be seen in Figure 2 where sixty percent of the baskets contain fewer than ten items. It is useful to note that the basket size distribution is quite stable. As can be seen in Figure 2, the distribution of basket sizes on weekdays is virtually identical to that distribution on weekends. Similarly (though it is not illustrated in Figure 2), the distribution of basket sizes is stable week to week.

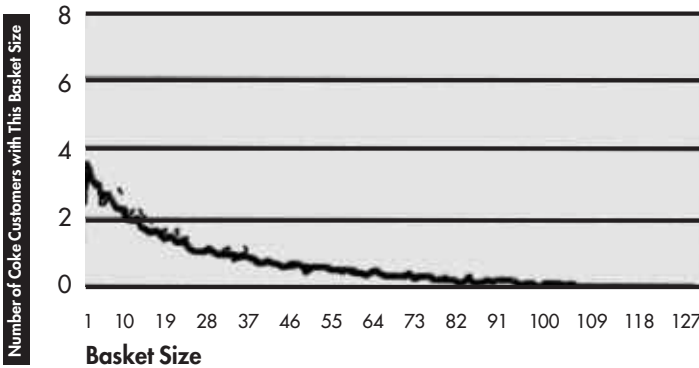
We illustrate the plotting of customer-mix distributions in our application for three of our brands: Coke, Kraft Mac 'n Cheese, and Ragu Spaghetti Sauce. For each brand, we fit $P(c|b)$ in equations 3 and 7 under each of the four settings of (d,w) : Off-Promotion Weekday (0,0), On-Promotion Weekday (1,0), Off-Promotion Weekend (0,1), and On-Promotion Weekend (1,1).

Figure 3 provides a separate graph for each of the four (d,w) settings for Coke. In each graph, the dashed line is a plot of the observed customer-mix distribution, namely the actual number customers whose baskets included Coke for each basket size, and the solid line is a plot of our fitted values, namely the predicted number of customers expected to buy Coke for each basket size. Figures 4 and 5 provide analogous plots for Kraft Mac 'n Cheese and for Ragu Spaghetti Sauce.

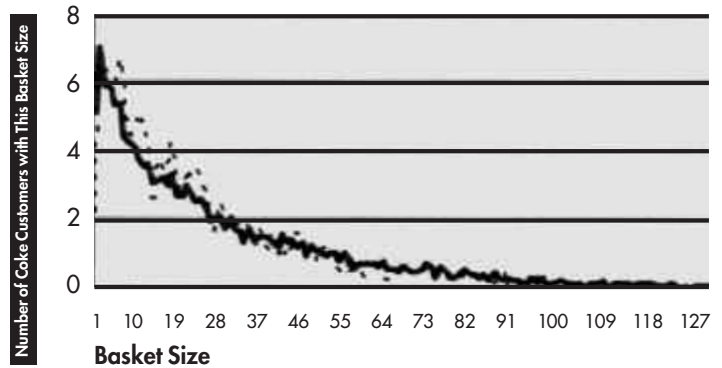
Scanning figures 3-5, we see that the model (equations 3 and 7) fits the observed customer-mix distributions reasonably well. Visually, one can see that in each setting, the fitted model tracks the mean of the observed values, considerably smoothing out the variation. Not surprisingly, the models appear to fit less well for those settings where they are estimated with fewer data points. Most of the brands in this study had data for 30 off-promotion weekdays, 11 off-promotion weekend days, 5 on-promo-

Figure 3
Coke's Customer-Mix Distribution

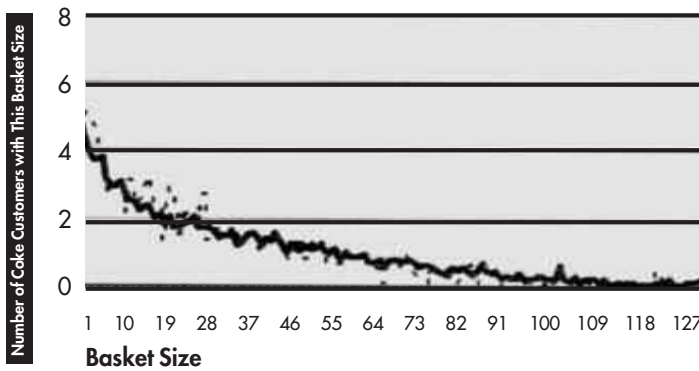
3a: Coke Weekdays, Off-Promotion



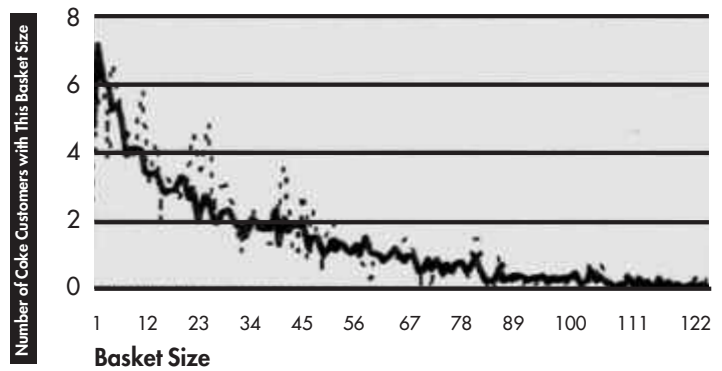
3b: Coke Weekdays, On-Promotion



3c: Coke Weekends, Off-Promotion



3d: Coke Weekends, On-Promotion



— Predicted
..... Actual

tion weekdays, and 2 on-promotion weekend days. Further, the total number of purchases varied across brands. Coke was chosen by 5,964 customers, Kraft by 1,829 customers, and Ragu by only 836 customers.

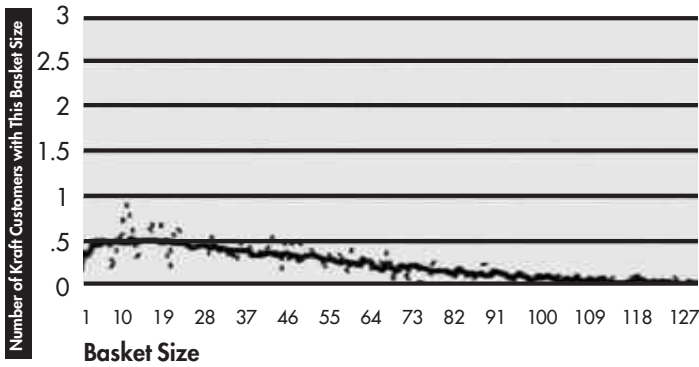
For Coke in Figure 3 the positive value $\hat{w}_{2,Coke} = .42$ manifests itself as more area under the on-promotion plots (figures 3b and 3d) than the off-promotion plots (figures 3a and 3c). Similarly, the positive value $\hat{w}_{4,Coke} = .13$ is manifested by more area under the weekend plots (figures 3c and 3d) than the weekday plots (figures 3a and 3b). In both of these cases, the increase in area corresponds directly to the

increased number of Coke customers, giving a clear picture of the extent of the promotion and the weekend effects.

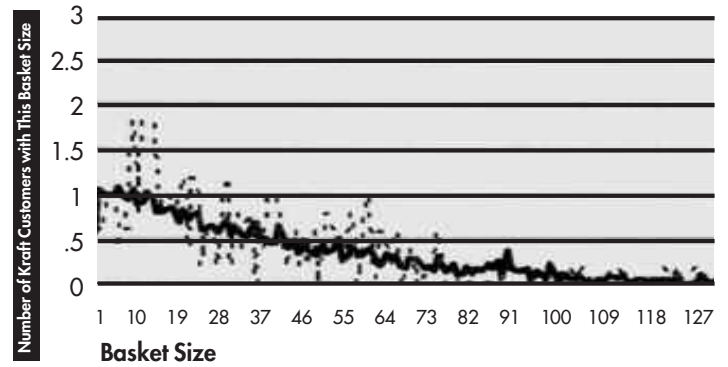
Turning to Kraft in Figure 4, the positive value $\hat{w}_{2,Kraft} = .53$ also manifests itself as more area under the on-promotion plots (figures 4b and 4d) than the off-promotion plots (figures 4a and 4c). However, the negative value for the interaction of promotion and basket size, $\hat{w}_{3,Kraft} = -.24$, serves to disproportionately increase the small basket customers' attraction to Kraft when Kraft is on-promotion, thereby further increasing the concentration of small basket customers in the on-promotion plots (figures 4b and 4d).

Figure 4
Kraft's Customer-Mix

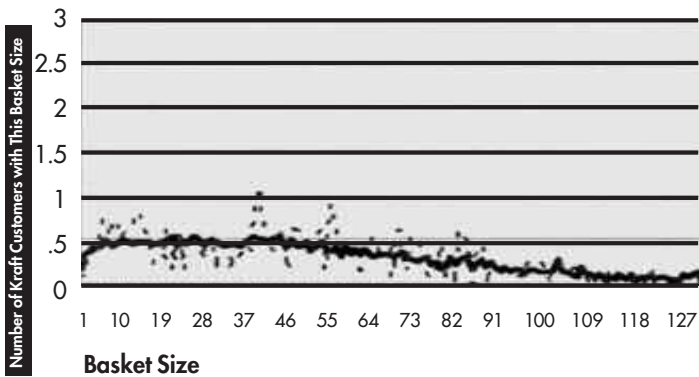
4a: Kraft Weekdays, Off-Promotion



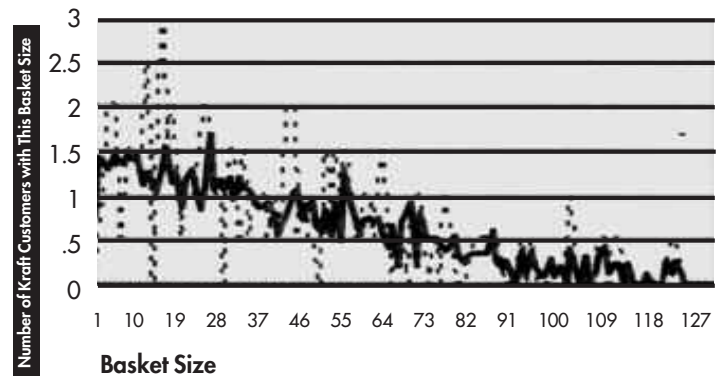
4b: Kraft Weekdays, On-Promotion



4c: Kraft Weekends, Off-Promotion



4d: Kraft Weekends, On-Promotion



— Predicted
..... Actual

This is precisely what would occur if Kraft were drawing more cherry pickers when promoted.

Finally, turning to Ragu in Figure 5, the positive value $\hat{w}_{2,Ragu} = .57$ again manifests itself as more area under the on-promotion plots (figures 5b and 5d). However, in this case, the positive value for the interaction of weekend and basket size, $\hat{w}_{5,Ragu} = .24$, serves to disproportionately increase the small basket customers' attraction to Ragu on weekdays (figures 5a and 5b) compared to weekends (figures 5c and 5d). The resulting higher concentration of small basket customers on weekdays is consistent with the hypothesis that Ragu is a trip generator brand.

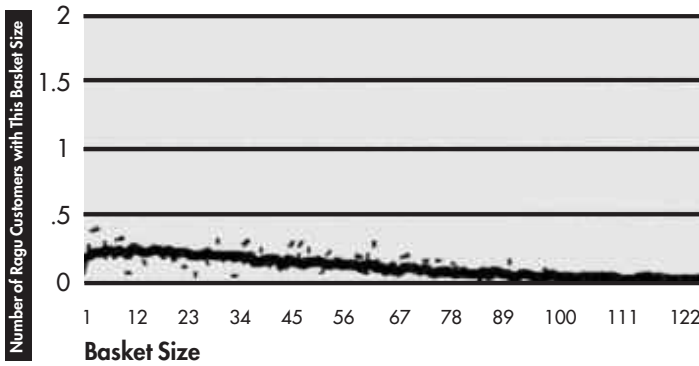
Managerial Implications and Directions for Future Research

In this paper we proposed a theoretically grounded, parsimonious model of a brand's customer-mix, $P(c|b)$, that reports the expected proportion of brand b 's customers that will be of type c . This model, estimated for 16 brands, was able to fit each brand's customer-mix reasonably well and the parameters of a brand's model were shown to provide insight into that brand's customer-mix and the way that mix changed when the brand was promoted or bought on a weekend.

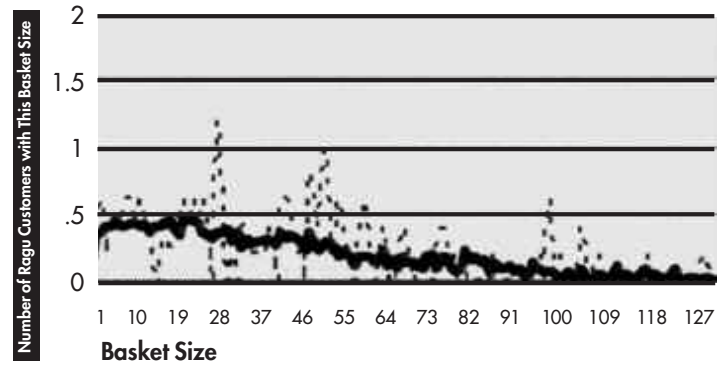
The proposed model provides parameters that

Figure 5
Ragu's Customer-Mix

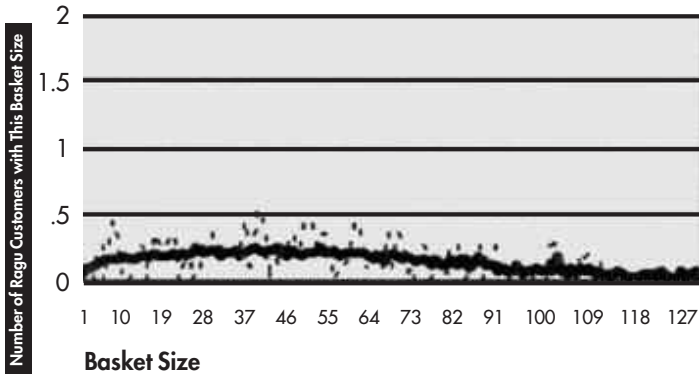
5a: Ragu Weekdays, Off-Promotion



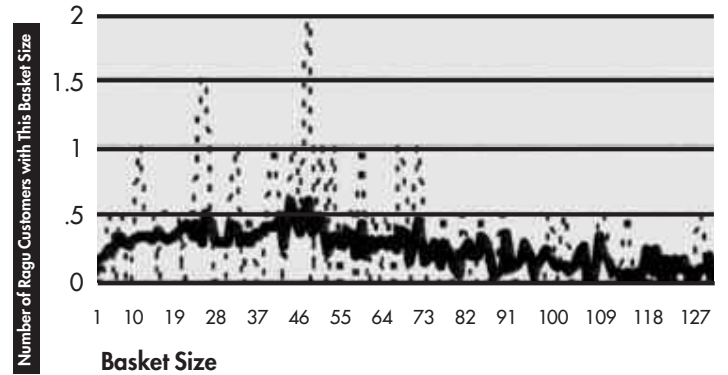
5b: Ragu Weekdays, On-Promotion



5c: Ragu Weekends, Off-Promotion



5d: Ragu Weekends, On-Promotion



— Predicted
..... Actual

can be compared across all brands in a store. Because the brands in Table 2 are arranged according to the value of the $\hat{\omega}_{1b}$ parameter, the retailer can infer that (on weekdays, when unpromoted) the brands at the top of the list are likely to be bought by customers who, on average, have more items in their baskets while the brands at the bottom of the list are likely to be bought by customers who, on average, have fewer items in their baskets.

Also note that the proposed model is able to identify differences in attraction to brand b across customer types even when those differences in attraction across customer types don't

vary across directly competing brands. Consider parameter estimates for Coke, Pepsi, and Dr. Pepper. With $\hat{\omega}_{1,Coke} = -.34$, $\hat{\omega}_{1,Pepsi} = -.35$, and $\hat{\omega}_{1,DrPepper} = -.30$, and there are no significant basket size interactions for any of these three brands. The similarity of these parameter estimates suggests that there is very little difference in the customer-mix distributions for these brands. All three of these brands' customer-mixes tend to have high concentrations of small basket shoppers. While useful to a retailer, this insight would not be discoverable with brand choice logit models like that proposed by Krishnamurthi and Raj (1988). Because the customer-mix does not differ markedly across

these three directly competing brands, the logit brand choice model would not be able to associate differences in this customer descriptor with differences in brand choice probabilities across the three brands.

Finally, our empirical results help build confidence in our model for the customer-mix of a brand. As would be expected from previous studies of promotion response, our significantly positive \hat{w}_{2b} estimates indicated that customers are more attracted to a brand when that brand is on-promotion than when it is off-promotion. Further, significantly negative \hat{w}_{3b} estimates are evidence that, when Mazola Corn Oil, Kraft Mac 'n Cheese, Clorox, and Snickers are promoted, small basket customers are disproportionately attracted, which is consistent with cherry pickers being drawn to these brands by promotion. By considering the difference between weekday and weekend shopping behavior, we note that customers are more attracted to some brands on weekends and customers are more attracted to other brands on weekdays. Retailers can use an understanding of the resulting week-part specific differences in customers' attraction to a brand to highlight relevant brands during selected week-parts. The estimated coefficient of the interaction between weekend and basket size, \hat{w}_{5b} , provides further guidance to retailers. A significantly positive \hat{w}_{5b} for a brand is evidence that small basket customers are relatively more attracted to this brand on weekdays than on weekends. We argued earlier that the resulting buying patterns would be consistent with what one would expect of brands that are "trip generators." The ability to identify those brands that are, in fact, trip generators would allow retailers to shape their communication and pricing strategies in ways that would allow them to capture more of their customers' mid-week quick trips.

In addition, by producing a graphical representation of a brand's customer-mix (as we did in figures 3-5), we give brand managers, manufacturers' sales people, and retailers a visual tool for understanding and communicating the

customer-mix of a brand. This tool also allows these managers to see the impact of various marketing actions on a brand's customer-mix.

Further research questions arise in trying to understand the sometimes substantial differences between parameter estimates across brands. For some brands, \hat{w}_{1b} was significantly positive and for others, it was significantly negative. To what extent do marketing activities cause the basic customer franchises of these brands to skew towards larger or smaller basket customers? We found that promotion was more effective for Snickers ($\hat{w}_{2,Snickers} = 2.40$) than for Minute Maid Orange Juice ($\hat{w}_{2,MinuteMaid} = .31$). Research to understand the differences in promotion-enhanced attractiveness across brands would be useful. Perhaps more interestingly, we notice differences in the coefficients of the interaction term between promotion and basket size. Do these differences in fact indicate differences in the brands' propensities to draw cherry pickers when promoted? If so, why do some brands have a greater tendency than other brands to draw cherry pickers when promoted?

Differences in the weekday vs. weekend parameters also suggest further research opportunities. Why are customers more attracted to some brands on weekdays while customers are more attracted to other brands on weekends? And, again, perhaps more interestingly, we notice differences in the coefficients of the interaction between weekend and basket size. Are brands with positive \hat{w}_{5b} really trip generator brands? If so, what makes these brands trip generators? How can we identify a general class of trip generator brands?

And, of course, research needs to consider a wider spectrum of customer descriptor variables and different product categories. The model of $P(c|b)$ in Equation 3 can accommodate a wide variety of specifications for v_{bc} . Once the parameters of v_{bc} have been estimated using the likelihood (Equation 4), customer-mix distributions can be specified for any customer descriptor variable. For simplicity, we have

restricted attention to likelihood procedures such as maximum likelihood. However, for future development, it would be straightforward to add prior distributions and consider Bayesian inference. In particular, it would be interesting to consider a hierarchical Bayes approach which modeled the parameters of similar brands as exchangeable. It might also be of interest to consider nonparametric versions of our general approach to allow increased flexibility.

In this paper we have defined a brand's customer mix by the expected proportion of that brand's purchases made by each customer type. The customer-mix model is built on the assumptions that a customer's attraction to a brand has both a deterministic and a probabilistic component, that the customer with the strongest attraction to the brand buys it, and that the random component of a customer's attraction to the brand has a double exponential distribution. We illustrated the model using supermarket data, defining customer types by the number of items in the customer's basket at checkout. Models estimated separately for 16 brands

allow one to compare customer-mix distributions across non-competing brands. Models' parameters shed light on the relative concentration of large basket shoppers in different brands' customer-mixes and the way a brand's customer-mix changes when the brand is on promotion and when the brand is bought on weekends. ■

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Notes

1. In using shopping basket size information, manufacturers sometimes report statistics based on the number of items in a basket and other times report statistics based on the dollar value of the basket. Unsurprisingly, number of items in a basket is highly correlated with dollar value of the basket. We opt to use number of items in a basket as the customer descriptor in this analysis because it lends itself to a straightforward definition for the customer types. Given that the sizes of the baskets in this dataset run from 1 item in the basket to 130 items in the basket, we will define 130 different customer types based on the number of items in a customer's basket at checkout. If we used dollar value of the basket to define customer types, we would have to arbitrarily define dollar value ranges for each customer type.

2. This model development section is patterned after the model development section in Guadagni and Little (1983).

3. Customers who make small purchases at several stores, focusing purchases on each store's promoted brands, see Dreze (1994), Urbany, Dickson and Kalapurakal (1996), and Fox and Hoch (2003).

4. Kahn and Schmittlein (1989) distinguish "quick trips" (those made randomly through the week to pick up a few items) from "major trips" (those made on the same day each week to pick up many items). They suggest that quick trips might be driven by "spur-of-the-moment stock-outs [at home] necessitating a quick run to the store." (p. 58.) They also note that for the majority of shoppers, "major trips" happen on weekends. Hence, stock-out driven "quick trips" are likely to happen on weekdays. If brand b is a "trip generator," then these weekday "quick trips" would make brand b more likely to be purchased by small basket customers on weekdays than on weekends. Note that one could get a much better fix on whether, in fact, the increase in the proportion of small baskets was the result of at-home stock-outs if one had data linking a customer's baskets through time.

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