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# Individual Differences in Response to Consumer Promotions

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# Individual differences in response to consumer promotions

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This research hypothesizes important individual differences in response to promotions and tests for them using a cross-sectional multinomial logit choice model. Our hypotheses suggest interactions between individual brand preference and the effects of current promotion and past promotional purchase. To test for these interactions, we introduce a new method of measuring brand preference from past purchase data. The new method seeks to incorporate competitive purchase conditions as modifiers to observed brand purchase behavior in estimating consumer brand preference. We account for heterogeneity in the cross-sectional model by using two measures of loyalty: one to capture differences across individuals and one to capture the time-varying changes within an individual. Our empirical results, based on scanner panel data for instant caffeinated coffee, support our hypotheses and our model specification. We conclude that accounting for consumer heterogeneity both in response to promotion and in brand and size loyalty improves both fit and predictive ability.

## 1. Introduction

Sales promotions continue to play a major role in the marketing efforts of consumer-products companies. A survey of sixty-eight major consumer-goods marketers indicates that 64.8% of the companies' marketing dollars were allocated to trade and consumer promotions (Donnelley Marketing's 10th Annual Survey of Promotional Practices, 1988). Correspondingly, marketing practitioners and academicians have focused considerable attention on consumer response to promotions, and in particular the effect of promotional activities on *brand choice* (e.g. Guadagni and Little, 1983; Fader and McAlister, 1988; Lattin and Bucklin, 1989; Currim et al., 1988). The availability of scanner panel data facilitates this research; the purchase behavior and store environment information collected can be used to calibrate brand choice models at the individual and aggregate level.

One such model, developed by Guadagni and Little (1983), offers a parsimonious characterization of item choice, where item refers to a unique combination of brand and size. In the model, choice is a function of the utilities of the items. Utilities, in turn, are a function of a number of explanatory variables reflecting consumer tastes (i.e. brand and size loyalty, which are exponentially weighted averages of past purchase behavior), and marketing mix activity (including promotion). Guadagni and Little use panel data to estimate a single coefficient for each of the variables in the utility function. Thus, while utility levels may differ across individuals depending upon brand and size loyalty, the impact of promotion or of a lagged promotional purchase on utility is the same.

The work presented in this paper extends the Guadagni and Little model in three important ways. First, we hypothesize that individuals differ with respect to the impact of promotions on utility, depending on their brand preferences. We expect that promotions by a particular brand will have the

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strongest impact on utility when the panelist prefers a number of brands, including the brand in question. The impact of promotion on utility will be less when the individual does not prefer the brand or, conversely, when the individual prefers the brand very strongly (and does not prefer other brands). We also expect that a prior promotional purchase of the brand will have the greatest negative impact on utility when the panelist does not prefer the brand. A lagged promotional purchase should have little or no impact on the utility of the panelist who strongly prefers the brand.

Second, we introduce a new method for measuring brand preference from the scanner panel data, in order to test our hypotheses. The measure, $PREF^*$, is similar to loyalty in that it measures the strength of preference from the past purchase history. It is a better measure of preference, however, because it takes into account the competitive promotional conditions that potentially influence purchase behavior. For example, with $PREF^*$, we assume that a purchase of brand A made at regular price when promoted alternatives are available is a stronger indication of preference for brand A than a purchase of brand A made on promotion. This measure of preference, $PREF^*$, is used in the model to characterize the individualized impact of promotions on utility.

Third, we propose a different way of accounting for heterogeneity in the cross-sectional choice model. Guadagni and Little use a single measure of loyalty, based on an exponentially weighted average of the past choice behavior by the individual. We decompose this loyalty measure into two components: a static term to capture differences across individuals and a dynamic term to capture the time-varying changes within an individual.

We assess the value-added of the extended model in a number of ways. Most importantly, if our hypotheses have merit, then the parameter estimates for the added explanatory variables should be statistically significant and appropriately signed. This will show if our view of individualized promotion response is supported by the data. Similarly, if the decomposition of loyalty is appropriate in capturing heterogeneity, we should find significant differences in the coefficients of the static and dynamic terms. We can also claim added value if the extended model not only fits but also predicts choice behavior better than a model without individualized promotion response. This is evidence of the model's predictive validity.

We first present the modeling framework underlying brand choice. After summarizing the Guadagni and Little approach, we then present our three extensions. Next, we discuss the scanner panel data used for model calibration and the measurement of the model constructs. We then present the results of the model calibration of the extended model; a model consistent with the Guadagni and Little form is used as a benchmark for evaluation. We conclude with a discussion of the next steps in the program of research.

## 2. Models of item choice

### 2.1. The Homogeneous Promotions Effects Model

One model of item choice (where the term item refers to a unique combination of brand and size, e.g. the 4 oz. size of Folgers instant coffee) has been proposed by Guadagni and Little (1983). The model parsimoniously accommodates the effects of price and promotion, brand and size loyalty, item-specific factors, and past promotional purchase (see Shoemaker and Shoaf, 1977; Dodson et al., 1978). Guadagni and Little begin by specifying that individual choice follows a multinomial logit model. According to the assumptions of that model, the probability of choosing an item is given by a non-linear function of the individual's utility for that item and all other available items: a particular strength of this model is that it explicitly acknowledges that the choice of an item depends not only upon the characteristics of the given item, but also upon the characteristics of the other items available. As shown in Fig. 1, when other item utilities are held constant, the multinomial logit choice probability is S-shaped with respect to the item's own utility.

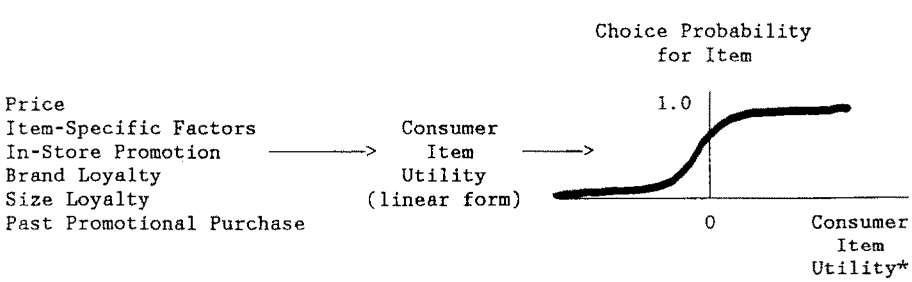
Item utility is modeled as a linear function of the explanatory variables specified above. Thus, choice is related to the explanatory variables through utility as shown in Fig. 1. The model specified by Guadagni and Little assumes homogeneity in the population with respect to utility in that the impact of each of the explanatory variables on utility is assumed identical for all panelists. While the levels of item utility across individuals may differ depending on the values of brand and size loyalty, the impact of variables such as promotion and past promotional purchase is the same for each panelist.

Note that the impact of promotion and price variables *on choice* may still differ across individuals depending upon where the individual is placed on the S-shaped curve that links utility to choice. For example, for an individual with high brand loyalty (and hence high utility), choice will be less strongly influenced by a promotion than for an individual with medium brand loyalty. This is so because the loyalty variables position the two individuals differently on the S-shaped curve.

Guadagni and Little calibrate the model using scanner data for the regular ground (caffeinated) product class. They find high statistical significance for the loyalty, price, and promotion variables; furthermore the model is shown to predict well to a hold-out sample of purchases. A model consistent with the Guadagni and Little formulation will be used as the reference model for evaluating the extended model presented below. The reference model will be referred to as the "Homogeneous Promotion Effects Model", the new model as the "Heterogeneous Promotion Effects Model".

### 2.2. *The Heterogeneous Promotion Effects Model*

The Heterogeneous Promotion Effects Model extends the Homogeneous Promotion Effects Model above in three ways. Most importantly, in-store promotion and past promotional purchase effects are characterized at the individual level. For that characterization, we introduce a new method for measuring brand preference from past purchase data, one that assumes that the strength of preference revealed by a purchase is indicated by the promotional environment in which the purchase took place. Additionally, *for both*




*Other item utilities held constant.

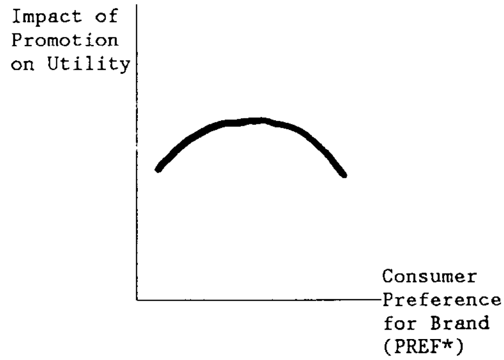
Fig. 1. Item utility modeled as a linear function of explanatory variables.

*models*, we decompose the loyalty effects to discriminate the cross-sectional from time-varying changes in loyalty.

*Extension 1: Individualized response to promotions*

**In-store promotion**. The Homogeneous Promotion Effects Model uses a single coefficient to describe the impact of in-store promotions. The benefit of this assumption is that it permits a simple, cross-sectional specification of the model, thus facilitating calibration, interpretation, and prediction. The drawback of this assumption is that the model, as specified, cannot address important individualized promotion effects. One way to overcome this weakness is to conduct individual-level analyses, then examine the parameters describing individual promotion response (e.g. Currim et al., 1988; Fader and McAlister, 1988). Unfortunately, there is unlikely to be sufficient data to permit reliable calibration of the model at the individual level. We adopt a different approach by providing a specific form for individual differences in promotion impact. We specify a form to describe how we expect promotion response to differ across consumers, then use the data to test our specification.

In particular, we hypothesize that promotion response is mediated by the consumer's preference for the brand as shown in Fig. 2a. Promotions are expected to have greater impact when a consumer likes a number of brands instead of strongly preferring one particular brand over the others. In the context of Fig. 2a, an individual is low on the preference scale when she so dislikes the brand that it is never considered as a possible purchase. Similarly, she is high on the scale if it is so preferred that it is the *only* brand considered for purchase. Between the two extremes, one can think of a consumer who has a number of favorite brands, all of which are considered on any given purchase occasion. In a two-brand case, for example, if the individual has




$$\text{Impact} = \theta_1 + \theta_2 \, PREF^* + \theta_3 \, PREF^{*2}$$

$$\theta_1 > 0, \ \theta_2 > 0, \ \theta_3 < 0$$

Fig. 2a. Heterogeneous Promotion Effects Model: current promotion.

low preference for one brand, she will have high preference for the other. Conversely, if she has mid-range preference for the one brand, she will also have mid-range preference for the other. [1]

The rationale for this specification is based upon the notion that the consumer, making a packaged goods decision, will simplify the decision-making process by selectively attending to promotional stimuli in the store environment. To explain this, we appeal to the notion of felt involvement articulated by Celsi and Olson (1988), referring to a consumer's subjective feeling of personal relevance. Specifically, we argue that the packaged goods decision is of low personal relevance because of its relatively low purchase price and routine nature. As a result, consumers will experience lower felt involvement with this type of purchase and following the work of Petty et al. (1983) and Greenwald and Leavitt (1984), this should result in low effort, attention, and comprehension.

[1] We will assume that the measure of preference is scaled so that $PREF^* > 0$ and $\Sigma_k PREF^* = 1$, where $k$ indexes the set of all items. The measurement of brand preference will be presented in Extension 2.

This argument is supported by Dickson and Sawyer (1986) who found that consumers across four types of packaged goods, spent less than 15 seconds making a purchase decision. In addition, they found that in the supermarket setting, consumers showed little evidence of active processing of in-store information as indicated by low recall of the promotional status of brands chosen.

Because of the increasingly cluttered store environment and consumers' low felt involvement, we expect selective attention to, and comprehension of, promotional stimuli. Attention will depend upon the individuals' underlying preferences across brands. When the consumer considers a number of brands acceptable, promotions of those brands are likely to be relevant cues in determining which brand to purchase: the promotion of one of the nearly equally preferred brands serves as the tiebreaker and therefore it makes sense for the consumer to spend time watching for those brands' promotions. Consequently, if the brand in question is one of the set of relatively equally preferred brands and therefore the consumer has mid-range preference for it, we expect stronger impact of promotion on utility as shown in Fig. 2a. Conversely, if the brand is disliked or is the only favorite brand, the consumer will be at either of the two extremes on the preference scale and will save time and effort by ignoring the promotional stimuli that are largely irrelevant to the purchase. Correspondingly, at the two extremes, we expect a lesser impact of promotion.

This approach differs from that taken by Fader and McAlister (1988), who hypothesize that promotion response takes the form of choice restriction, and that individuals differ with respect to their propensity to restrict choice to promoted brands. We argue that an individual's response to promotion will depend upon her preference for the brand being promoted and that impact of promotion will be greatest when it "breaks the tie" among a number of relatively equally preferred brands.

Given this specification for the impact of promotion on brand choice, the relationship shown in Fig. 2a must be formally incorporated into the model. The heterogeneous impact of promotion in Fig. 2a is captured in the utility form through a utility weight that is quadratic with respect to brand preference. The inverted-U structure is validated if the corresponding weights exhibit the correct sign

Table 1
Forms of utility weights and expected signs

| Explanatory variable | Homogeneous Promotion Effects Model | | Heterogeneous Promotion Effects Model | |
|---|---|---|---|---|
| | Utility weight | Expected sign | Utility weight | Expected sign |
| Price | $\gamma$ | $\gamma<0$ | $\gamma$ | $\gamma<0$ |
| Item-specific effect | $\beta_k$ | – | $\beta_k$ | – |
| Promotion | $\theta$ | $\theta>0$ | $\theta_1+\theta_2$ preference $+\theta_3$ (preference) [a] | $\theta_1>0$ $\theta_2>0$ $\theta_3<0$ |
| Lagged promotional purchase | $\lambda$ | $\lambda<0$ | $\lambda_1+\lambda_2$ preference | $\lambda_1<0$ $\lambda_2>0$ $\lambda_1+\lambda_2=0$ |
| Brand loyalty | Panel differences = $\alpha_{B_1}$ | $\alpha_{B_1}>0$ | Panel differences = $\alpha_{B_1}$ | $\alpha_{B_1}>0$ |
| | Individual differences = $\alpha_{B_2}$ | $\alpha_{B_2}>0$ | Individual differences = $\alpha_{B_2}$ | $\alpha_{B_2}>0$ |
| Size loyalty | Panel differences = $\alpha_{S_1}$ | $\alpha_{S_1}>0$ | Panel differences = $\alpha_{S_1}$ | $\alpha_{S_1}>0$ |
| | Individual differences = $\alpha_{S_2}$ | $\alpha_{S_2}>0$ | Individual differences = $\alpha_{S_2}$ | $\alpha_{S_2}>0$ |

[a] See footnote 2.

and are statistically significant. Table 1 provides the utility weights for the model and indicates the expected signs of the utility weights that capture the quadratic form. The inverted-U effect shown in Fig. 2a is consistent with $\theta_1 > 0$, $\theta_2 > 0$, and $\theta_3 < 0$. [2]

Because the S-shaped curve translating utility to choice results in less promotion impact on choice at low and high levels of loyalty, the choice model already incorporates the phenomenon described above. However, we believe that beyond this effect, individuals will value promotions more, and they will be a more important determinant of utility for a brand, when the individual finds a number of brands acceptable and therefore has mid-range preference for the brand in question. Since the logit model structure already incorporates a similar response pattern, we are subjecting our hypotheses to a more stringent test.

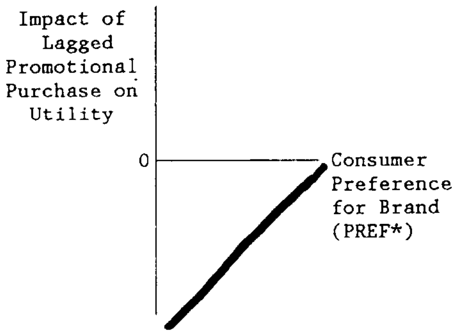
**Lagged promotional purchase**. The Homogeneous Promotion Effects Model also uses a single coefficient to describe the impact of a prior promotional purchase. According to attribution theory (Dodson et al., 1978; Scott, 1976) and behavioral learning theory (Rothschild and Gaidis, 1981), the sign of the coefficient should be negative. Attribution theory specifies that consumers infer their attitudes from their behavior and that promotional discounts impact utility negatively because the consumer attributes the purchase to the incentive and not to an underlying preference for the brand purchased. Behavioral learning theory assumes that consumers develop purchase habits which their current behavior either reinforces or extinguishes. A promotional purchase, by reinforcing the purchase on deal habit, should also impact utility in a negative way.

[2] Note that if $\theta_1 > 0$ and $\theta_2$ and $\theta_3$ are not significantly different from zero, then the generalized model reduces to the Homogeneous Promotion Effects Model.

We re-interpret these explanations, introducing brand preference as an intervening variable. If the consumer has stronger preference for the brand, then under the attribution theory argument, there should be less need to justify the purchase by referring to the promotion and the lagged promotional purchase should have a less negative impact. Under the behavioral learning theory argument, if the consumer strongly prefers the brand, it has probably been regularly purchased and thus it is less likely that this regular purchase habit will be converted to a deal orientation through one promotional purchase.

A third framework, price/quality signalling, suggests the same observed effect. To the extent that consumers are unable to directly assess a product's quality, they may infer it from price (Gabor and Granger, 1966; Monroe, 1979; Spence, 1974; Huber and McCann, 1982; Gerstner, 1985; Urbany et al., 1988). The lower price generated by the promotional discount signals lower quality most particularly to the consumer with little direct experience due to a low preference for the brand. Since stronger preference suggests greater direct knowledge of the brand, the negative shock due to a price/quality inference should dampen as preference increases.

Taken together, these three frameworks indicate that the common negative utility weight for past promotional purchase in the Homogeneous Promotion Effects Model should more appropriately be an effect moderated by brand preference as shown in Fig. 2b. This increasing (from negative to zero) relationship is consistent with $\lambda_1 < 0$, $\lambda_2 > 0$ and $\lambda_1 + \lambda_2 = 0$. The latter relationship, $\lambda_1 + \lambda_2 = 0$ indicates that at maximum preference (i.e. $PREF^* = 1$), lagged promotional purchase should have no effect on utility or the current purchase. Thus, we look to the estimated signs and their relative magnitudes and significance for empirical support of the model as specified.




$$\text{Impact} = \lambda_1 + \lambda_2 \text{ PREF*}$$

$$\lambda_1 < 0, \lambda_2 > 0$$

$$\lambda_1 + \lambda_2 = 0$$

Fig. 2b. Heterogeneous Promotion Effects Model: lagged promotional purchase of the brand.

*Extension 2: Characterizing brand preference*

This measure is critical to the promotion effects (current and lagged) specified in the Heterogeneous Promotion Effects Model. One appropriate measure of preference is a *survey* measure, one in which the panelist is asked his or her relative preferences across brands (Silk and Urban, 1978). Unfortunately, most sources of scanner data (including ours) do not provide for such a direct measure of preference. Consequently, we seek an indirect, purchase-based measure of preference. One such measure of preference, loyalty, as described above, treats all purchases of the brand the same in terms of their indication of underlying preference. As a result, the loyalty measure ignores potentially relevant information about panelist preference that is provided by the promotional environment in which the purchase took place. We propose an alternative purchase-based preference measure that accounts for the competitive promotional conditions at the time of purchase. Our objective with this measure is to evaluate strength of preference as it is revealed by behavior given the promotional environment. For example, if brand A is purchased at regular price when brand B is on deal, then this is a stronger indication of the consumer's brand A preference than if brand A were purchased on deal while brand B were available only at the regular nondeal price.

More formally, with two brands A and B, the focal brand A can be purchased (or not purchased) under the four different promotional scenarios outlined in Table 2. When brand A is purchased, strongest preference is indicated under the most severe competitive conditions for brand A; i.e., when brand A is regularly priced and brand B is on promotion (scenario IV). On the other hand, the weakest indicator of preference for brand A would be when brand A is purchased on promotion while brand B is regularly priced (scenario I) – these are the least severe competitive conditions for brand A purchase. In between these two extremes are scenarios II and III, which are indistinguishable in terms of the information provided about brand A preference, but both are considered to be a stronger indicator of brand A preference than scenario I and a

Table 2
PREF* promotional sceranios

| | Scenario | | | |
|---|---|---|---|---|
| | I | II | III | IV |
| Brand A | On promotion | On promotion | Regular price | Regular price |
| Brand B | Regular price | On promotion | Regular price | On promotion |
| (Index) | 1 | 2 | 2 | 3 |
| (Dummy variable) | $D_1$ | $D_2$ | $D_2$ | $D_3$ |

weaker indicator of brand A preference than scenario IV.

When brand A is not purchased, weakest preference for brand A is indicated when brand A faces the least severe competitive conditions (i.e. when brand A is promotionally priced while brand B is regularly priced (scenario I)). When competitive conditions are most severe for brand A (scenario IV), failure to purchase brand A is the weakest indicator of a consumer's low preference for brand A. Falling between the two extremes again are scenarios II and III.

The four scenarios can be combined to construct three time-varying indices from which an overall measure of preference (*PREF**) is developed. Each index represents observed behavior over the previous purchase occasions, the behavior being purchase or failure to purchase the focal brand under the appropriate set of competitive conditions. The indices are constructed in a manner similar to that used by Guadagni and Little in their construction of loyalty. Each index takes a value between 0 and 1, and is updated according to an exponential smoothing model (an index is not updated if no new information is revealed by the purchase occasion). After updating the appropriate index or indices, the overall measure of preference (*PREF**) for the next purchase occasion is given by the average value of the three indices. Specifically the *PREF** measure is constructed as follows:

*Step 1*: Determine which of the three indices applies to the current purchase occasion and focal brand. Assign a value (1 = purchase or 0 = no purchase) to the dummy variable associated with the index ($D_1$, $D_2$, $D_3$ for indices 1, 2, and 3 respectively). Note that when we observe behavior applicable to one of the indices, we may also be able to infer what behavior would have been with other indices. For example, if the consumer buys brand A at regular price and brand B is promoted (scenario IV, index 3, $D_3$), we can also infer that she would have bought brand A under the less severe competitive conditions of scenarios I–III. Consequently, given that observation, we can update all three indices. Thus, if a purchase of brand A is made under scenario IV, then $D_3 = 1$ and we may infer $D_2 = D_1 = 1$. Further, if a purchase of brand A is made under scenario II or III, then $D_2 = 1$ and we may infer $D_1 = 1$. Table 3 presents the scheme by which these inferences are drawn. As shown in Table 3, the converse holds for nonpurchase of brand A.

Table 3
Constructing *PREF**: Assignment of values to dummy variables

| | $D_1$ | $D_2$ | $D_3$ |
|---|---|---|---|
| 1. *Severe competitive conditions* | | | |
| Brand A is at regular price and some other brand is on promotion. | | | |
| Brand A purchased | 1 | 1 | 1 |
| Brand A not purchased | * | * | 0 |
| 2. *Mid-range competitive conditions* | | | |
| All brands are at regular price or brand A is on promotion and some other brand is on promotion. | | | |
| Brand A purchased | 1 | 1 | * [a] |
| Brand A not purchased | * | 0 | 0 |
| 3. *Weakest competitive conditions* | | | |
| Brand A is on promotion and all other brands are at regular price. | | | |
| Brand A purchased | 1 | * | * |
| Brand A not purchased | 0 | 0 | 0 |

[a] An asterisk implies that we do not have sufficient information to determine the value of the indicator on this particular occasion. When brand A is purchased in mid-range competitive conditions, we infer that the purchase will also be made under the weakest competitive conditions (hence, $D_1 = 1$). We cannot, however, infer whether or not brand A would have been purchased under severe competitive conditions (hence $D_3$ is indeterminate). We treat these cases as missing data, which has the effect of carrying over the information from the previous purchase occasion.

*Step 2*: Use the dummy variables to update the indices using an exponential smoothing model. Some indices cannot be updated given the current purchase occasion information. Leave them as is.

*Step 3*: Sum the three indices and divide by three. This value represents the $PREF^*$ measure that will be used on the next occasion.

To show the differences between an exponential smoothing model of brand loyalty and our more elaborate measure $PREF^*$, consider the example outlined in Table 4. Based on the sequence of purchases, brand loyalty ($BLOY$) measure equals 0.56 at the final purchase. This is true regardless of the promotion environment during the choice history. The measure $PREF^*$, on the other hand, will depend upon the prevailing promotional activity by the two brands. History 1 consists of purchases made under less severe conditions (A is on promotion every time it is purchased). History 2, on the other hand, consists of purchases made under more severe competitive conditions, as shown by the number of brand A purchases when A was not on promotion but B was. This difference is reflected in the final values of $PREF^*$: 0.48 in history 1, and 0.70 in history 2. In history 2, the value for preference is greater because those purchases are made under more severe competitive conditions. The consumer shows stronger preference in this case because she is purchasing A at regular price when a promoted alternative is available.

The preference measure described above is admittedly crude in its consideration of the competitive conditions surrounding purchase in a number of ways. First, under scenario I, we do not distinguish between purchasing the brand at regular price when only one other brand is promoted and when many other brands are promoted nor do we account for which brands are on promotion. Intuitively, it would seem that stronger preference is indicated in scenario I if a number of other brands are being promoted and/or if the brands being promoted are particularly attractive brands. Second, we arbitrarily average the three indices instead of differentially weighting them in constructing the overall measure. Though the measure is somewhat arbitrary, we believe that intuitively it provides a step in the right direction towards the development of scanner-based preference measures that more accurately reflect the competitive environment surrounding purchase behavior.

*Extension 3: Specification for brand and size loyalty*

Guadagni and Little recognized the importance of accounting for individual differences

Table 4
$PREF^*$ purchase history example

| Chosen brand | $BLOY_A$ | Promotion history 1 | | | Promotion history 2 | | |
|---|---|---|---|---|---|---|---|
| | | $Prom_A$ | $Prom_B$ | $PREF^*$ for A | $Prom_A$ | $Prom_B$ | $PREF^*$ for A |
| A | 1.00 | Y | N | 0.33 | N | Y | 1.00 |
| A | 1.00 | Y | Y | 0.67 | N | Y | 1.00 |
| B | 0.70 | N | Y | 0.67 | Y | Y | 0.80 |
| B | 0.49 | Y | N | 0.47 | N | Y | 0.73 |
| A | 0.64 | Y | Y | 0.53 | Y | N | 0.73 |
| A | 0.75 | Y | N | 0.55 | N | Y | 0.81 |
| B | 0.53 | N | N | 0.47 | N | Y | 0.75 |
| B | 0.37 | N | Y | 0.47 | N | Y | 0.70 |
| A | 0.56 | Y | N | 0.48 | Y | N | 0.70 |

in utility for an item. They constructed measures of brand and size loyalty using an exponentially weighted average of the individual's past purchase history (see Guadagni and Little, 1983, for a complete description of the brand and size loyalty measures). The loyalty measures used by Guadagni and Little are designed to capture two sources of variation in the panel data:

- differences in loyalty *across consumers* (loyalty for consumer 1 at time $n$ versus loyalty for consumer 2 at time $n$),
- differences in loyalty *within individual over time* (loyalty for consumer 1 at time $n$ versus loyalty for consumer 1 at time $n+1$).

The simple brand (and size) loyalty measure used by Guadagni and Little does not allow for the separate estimation of these two sources.

We generalize loyalty by separately capturing these two sources of variance (see also Lattin, 1987). To account for *inter-individual* differences in loyalty, we construct a static share-of-purchases measure for brand and size, using data from an initialization period. We let $\overline{BLOY(k, i)}$ denote the static component of brand loyalty for individual $i$ toward item $k$, and let $\overline{SLOY(k, i)}$ denote the static component of size loyalty. To account for *intra-individual* differences, we construct a difference measure by subtracting the static measure from the exponential smoothing model proposed by Guadagni and Little. Thus, we let

$$BLOY^*(k, i, n) = BLOY(k, i, n) - \overline{BLOY(k, i)}$$

denote the dynamic component of brand loyalty for individual $i$ toward item $k$ on occasion $n$, and let

$$SLOY^*(k, i, n) = SLOY(k, i, n) - \overline{SLOY(k, i)}$$

denote the dynamic component of size loyalty.

The utility function coefficients for these variables are shown in Table 1. Instead of including one variable each for brand and size loyalty in the utility form ($BLOY$ and $SLOY$), we include two: $\overline{BLOY}$ and $\overline{SLOY}$ for the share of purchase measure and $BLOY^*$ and $SLOY^*$ for the dynamically updated measure. The utility weights for the four variables are all expected to be positive as shown in Table 1; that is, greater loyalty attributed to either source is expected to increase utility. Furthermore, if the utility weight for the brand share variable ($\overline{BLOY}$) is equal to that of the individual differences variable ($BLOY^*$), then the two variables reduce to the one variable specification and our generalization will not have provided additional insight.

### 2.3. Summary

Table 1 provides a complete list of the explanatory variables for the two models described above. The variables are listed along with the utility weight coefficients for each of the two models and their expected signs. In the model calibration below, the Homogeneous Promotion Effects Model is the null model against which we test the generalized Heterogeneous Promotion Effects Model.

It should be noted that the reference model is in the spirit of the Guadagni and Little formulation in that it does not include individualized promotion response as characterized above. It differs from Guadagni and Little's original formulation in two ways. First, we include only one promotion indicator variable while the original formulation included the indicator and a promotion price cut variable. In initial analysis of the data, these two variables were included, but the high collinearity across the promotion variables prohibited estimation of the more elaborate model described above. Thus, to enable nested model comparisons, we kept the single promotion indicator variable in each model. Similarly, for purposes of making nested model comparisons, both models include loyalty variables that are decomposed into panel versus individual differences in loyalty.

One might question our decision to use the brand loyalty variables $\overline{BLOY}$ and $BLOY^*$ instead of the preference measure $PREF^*$, since our measure should do a better job of using the purchase information to infer preference. We did not specify this formulation because we wanted the Homogeneous Promotion Effects Model to reflect the Guadagni and Little formulation as closely as possible, given the data constraints and constraints due to the nested model configuration. However, as will be reported in the empirical results section, we did estimate the model using preference in place of loyalty and found substantively the same results. (A reason for this close correspondence is that the $PREF^*$ measure and the Guadagni and Little $BLOY$ measure were highly correlated (0.94) in our data.)

## 3. Data and measures of explanatory variables

### *3.1. Data*

To calibrate the two models, we use IRI purchase panel data for instant caffeinated coffee. We have selected only heavy users (at least 15 purchases over a two-year period) from a single geographic region served by six supermarkets. Our focus on heavy users is to ensure that the purchase-based measures requiring an initialization set of purchases (like brand and size loyalty) have a reasonable number of observations. One hundred panelists were chosen for calibration of the models. [3] Of the large number of distinct items available in the product category, we chose only those 13 items with greater than 2.5% market share from among all panelists. The 13 items chosen consisted of five brands across six sizes. Model calibration was conducted on panelists' purchases made between week 31 and week 75. The first 31 weeks of purchases were used to calculate the static share of purchases measures ($\overline{BLOY}$ and $\overline{SLOY}$) and to initialize the dynamically updated measures ($BLOY^*$, $SLOY^*$, and $PREF^*$). We chose the first 31 weeks as the initialization period as this seemed a reasonable time period to provide a stable initial estimate; most published studies (e.g. Guadagni and Little, 1983; Gupta, 1988; Lattin and Bucklin, 1989) have used roughly one-half year of data for initialization.

[3] An additional 75 panelist histories were available for the predictive tests conducted on the two models.

### *3.2. Measures*

*Price* is the observed purchase price of the item on the purchase occasion. The purchase price may include a promotional discount.

*Item-specific effect* is a dummy variable that takes on the value one for the item in question, zero otherwise.

*Promotion* is a dummy variable that takes on the value one if the item is offered at special price or specially displayed or featured in a store advertisement or flyer, zero otherwise.

*Lagged promotional purchases* is a dummy variable that takes on the value one if the panelist purchased the brand of the item on promotion (without the use of a coupon) on the previous purchase, zero otherwise.

*Brand loyalty*

*Inter-Individual* ($\overline{BLOY}$) is the brand's share of the panelists' purchases over the initialization set of purchases (weeks 1–30).

*Intra-Individual* ($BLOY^*$) is $BLOY - \overline{BLOY}$, where $BLOY$ is an exponentially weighted average of the panelists' past purchases, using a smoothing constant of 0.70. [4]

*Size loyalty*

*Inter-individual* ($\overline{SLOY}$) is the size's share of the panelists' purchases over the initialization set of purchases.

*Intra-individual* ($SLOY^*$) is $SLOY - \overline{SLOY}$, where $SLOY$ is an exponentially weighted average of the panelists' past purchases using a smoothing constant of 0.70.

*Brand preference* ($PREF^*$) is as described above, with the same weighting factor.

## 4. Empirical results

The Heterogeneous Promotion Effects Model incorporates three interaction variables that reflect the individualized promotion effects described in Section 2. Empirical validation of the proposed model is conducted by:

- Checking the relevant parameters in the Heterogeneous Promotion Effects Model for appropriate sign and significance: Support for Figs. 2a and 2b is shown if:

  $$\begin{cases}\theta_1 > 0\\ \theta_2 > 0\\ \theta_3 < 0\end{cases} \quad \text{and} \quad \begin{cases}\lambda_1 < 0\\ \lambda_2 > 0\\ \lambda_1 + \lambda_2 = 0\end{cases}$$

  and all estimates except $\lambda_1 + \lambda_2 = 0$ have significant $t$-values.
- Conducting likelihood ratio tests and comparing $U^2$ across the two nested models [5], Homogeneous Promotion Effects Model, and Heterogeneous Promotion Effects Model. These tests indicate whether the more complex model offers a significant improvement in fit over the simpler model.
- Determining if the Heterogeneous Promotion Effects Model predicts well to hold-out samples (relative to the Homogeneous Promotion Effects Model).

In addition, we have proposed a generalization to Guadagni and Little's loyalty specification that distinguishes between panel differences in loyalty (cross-sectional) and individual differences in loyalty (time series). The value of this extension is indicated if

$$\alpha_{B_1} \neq \alpha_{B_2} \quad \text{and} \quad \alpha_{S_1} \neq \alpha_{S_2}.$$

We check the estimates of both models to determine if the decomposition of effects is empirically justified.

Table 5 presents parameter estimates and corresponding $t$-ratios for the nested models, the Homogeneous Promotion Effects Model, and the Heterogeneous Promotion Effects Model. Table 5 omits the item-specific effects as they are not directly relevant to the interpretation of the models or to the testing of our hypotheses. Also provided are the log-likelihoods and $U^2$ for the two models, and the chi-square test for nested models.

### 4.1. Significance tests for parameter estimates

Before addressing the promotion parameter estimates given in Table 5, it is useful to note that the other estimates are of the predicted sign and have significant $t$-values. The price coefficient is negative and statistically significant for both models, and all four brand and size loyalty coefficients are positive and statistically significant (the loyalty coeffi-

[4] In choosing the exponential decay constant, we began by setting $\rho = 0.70$ a priori, calculating the loyalties and $PREF^*$, and calibrating the model. We then increased and decreased $\rho$, recalculated the loyalties and $PREF^*$ and recalibrated the model. In each case, the model fit deteriorated slightly and $t$-statistics diminished. While this was not equivalent to a full grid search over all possible values for $\rho$ (which would be prohibitively expensive), we took it as evidence that 0.70 was a reasonable choice for $\rho$.

[5] With nested models, the chi-quared test assesses the improvement in log-likelihood from the more complex model, given the additional degrees of freedom used. $U^2$ is analogous to $R^2$ and uses a null model consisting of only item-specific effects. If a model explains nothing over and above the null model, $U^2 = 0$; if it explains everything, $U^2 = 1$. $U^2$ in the range of 0.4 to 0.5 are generally considered as indications of excellent fit.

Table 5
Empirical results

| Variable | Coefficient and expected sign | Homogeneous promotion effects [a] | Heterogeneous promotion effects [a] |
|---|---|---|---|
| Price | $\gamma < 0$ | −7.04 (−3.91) | −6.75 (−3.66) |
| Promotion | $\theta > 0$ | 1.36 (10.30) | |
| | $\theta_1 > 0$ | | 0.71 (3.19) |
| | $\theta_2 > 0$ | | 2.71 (3.11) |
| | $\theta_3 < 0$ | | −1.96 (−2.33) |
| Lagged promotional purchase | $\lambda < 0$ | −0.06 (−0.31) | |
| | $\lambda_1 < 0$ | | −1.61 (−2.19) |
| | $\lambda_2 > 0$ | | (2.23) (2.16) |
| Brand loyalty | $\alpha_{B_1} > 0$ | 3.02 (21.25) | 2.62 (16.05) |
| | $\alpha_{B_2} > 0$ | 2.29 (11.97) | 2.05 (10.32) |
| Size loyalty | $\alpha_{S_1} > 0$ | 3.02 (21.61) | 3.05 (21.49) |
| | $\alpha_{S_2} > 0$ | 2.24 (12.05) | 2.27 (12.09) |
| Log-likelihood | | −1278.8 | −1268.8 |
| $U^2$ | | 0.490 | 0.496 |
| Chi-square test | | | $\chi_3^2 = 20$ |

[a] Results are given as parameter estimate (*t*-statistic).

cients will be discussed in more detail below). For the Homogeneous Promotion Effects Model, the promotion coefficient, $\theta$, is positive and statistically significant. On the other hand, the lagged promotional purchase coefficient, $\lambda$, is negative, and is not statistically significant. This result for $\lambda$ is consistent with the empirical results of Guadagni and Little (1983). They found that the first previous lagged promotional purchase coefficient was negative, but was not statistically significant, and that the second previous promotional purchase coefficient was both negative and significant.

As for the promotion estimates for the Heterogeneous Promotion Effects Model, Table 5 shows that both $\theta_1$ and $\theta_2$ (0.71 and 2.71, respectively) are positive and $\theta_3$ is negative (−1.96), as expected, and all are statistically significant.

Thus, the empirical analysis is consistent with our hypotheses regarding the mediating effect of preference on the impact of an in-store promotion on utility.

As *PREF** increases to 0.69, there is an increase in the promotion's impact. Thereafter, the impact diminishes as *PREF** approaches 1.0. The decrease in impact at high levels of *PREF** is not substantial as may be seen by computing the promotional impact for various values of *PREF**:

| *PREF** | Overall impact of promotion |
|---|---|
| 0 | 0.71 |
| 0.69 | 1.65 |
| 1.00 | 1.46 |

These calculations also show that approximately $(1.65 - 0.71)/1.65 = -57\%$ of the total maximum estimated promotion effect on utility is impacted by incorporating heterogeneous promotion effects. Hence, the heterogeneous promotional effects are substantial as well as statistically significant.

Table 5 also shows that $\lambda_1$ is negative (−1.61) and $\lambda_2$ is positive (2.23), as expected, and both are statistically significant. The sum $\lambda_1 + \lambda_2$, while positive, is not significant with a *t*-value of 1.55. These results are consistent with the hypothesized linear relationship in Fig. 2b.

Consequently, the empirical analysis is consistent with our hypotheses regarding the mediating effect of preference on the impact of a lagged promotional purchase on utility.

Interestingly, though not a significant result, our estimates for $\lambda_1$ and $\lambda_2$ suggest that there may be a positive impact of a lagged promotional purchase at high levels of brand preference. While this result was not anticipated and certainly should be regarded with caution, it does suggest that perhaps a different phenomenon is occurring. Work by Tybout and Scott (1983) suggests that (a) when immediate sensory data are available, internal knowledge is well-defined and attitude formation will involve an information aggregation process, and (b) when immediate sensory data are unavailable, well-defined internal knowledge is lacking and attitude formation entails a self-perception process. Using this explanation, if information aggregation is used for preference formation, as is most likely the case for a high-preference consumer who has frequent and probably recent experience with the brand, the promotional incentive increases the already favorable information and consequently it reinforces brand preference. Conversely, if self-perception is used for preference formation, as is most likely the case for a low-preference consumer with little and probably distant experience with the brand, the promotional incentive provides an external reason for the purchase which leads to the negative impact on preference. We interpret these data with caution, however, noting that this relationship, while suggestive, was not statistically significant.

As noted above, since the *PREF** measure makes greater intuitive sense as a measure of underlying brand preference, one might argue that it should serve as the brand loyalty measure also. Thus, the individual panelist and, over time, individual difference versions of the *PREF** measure, would replace their current brand loyalty counterparts. This model estimation was conducted with the following results: $\theta_1$, $\theta_2$, and $\theta_3$ all had the expected signs (their values were 0.90, 1.83, and $-1.27$, respectively) but only $\theta_1$ and $\theta_2$ were statistically significant. The two lagged promotional purchase estimates, $\lambda_1$ and $\lambda_2$, also had the expected signs, but neither was statistically significant (their values were $-0.73$ and 1.28, respectively). Thus, our results hold with this adjustment in model specification, though statistical significance of the results deteriorated.

### 4.2. Goodness-of-fit tests

The chi-squared likelihood ratio test and a comparison of the $U^2$ of the estimated models indicate whether the Heterogeneous Promotion Effects Model provides a statistically significant improvement in model fit to the purchase data over the generally nested Homogeneous Promotion Effects Model. [6]

Table 5 shows that the Heterogeneous Promotion Effects Model does provide a statistically significant improvement in model fit over the Homogeneous Promotion Effects Model with a $\chi^2$ of 20 on three degrees of freedom. The improvement in $U^2$ is small (from 0.490 to 0.496). [7]

### 4.3. Model validation

To assess the validity of the model findings, we use a predictive test based on the final 32 weeks of purchase data (weeks 76–107). Our goal is to test the predictive performance of the less parsimonious Heterogeneous Promotion Effects Model to determine if it deteriorates relative to the Homogeneous Promotion Effects Model due to capitalization on chance within the calibration sample. We use the estimated coefficients from Table 5 (for both models) to predict future purchase

[6] It should be noted that the Homogeneous Promotion Effects Model provided a statistically significant improvement in model fit over another nested model, one consisting only of the item-specific variables. This model is used as the null model for computing $U^2$. With a $\chi^2$ of 2462 and seven degrees of freedom, and a $U^2$ of 0.490, the Homogeneous Promotion Effects Model was a significantly better fit to the data than the item-specific variables model.

behavior for two groups of panelists: the same 100 consumers used above for the model calibration and a hold-out group of 75 consumers. Our tests on these two groups enable us to assess the generalizability of the model structure into the future *and* across different households.[8]

Predictive accuracy is assessed using the log-likelihood function and the $U^2$ values. For both models, $U^2$ values from the hold-out data exceeded $U^2$ values from the calibration data, indicating no evidence of deterioration in fit due to idiosyncratic sample error. Furthermore, for both sets of hold-out data, the Heterogeneous Promotion Effects Model predicts choice behavior better than the Homogeneous Promotion Effects Model. These test results suggest that the relationship between preference and promotion embedded in the Heterogeneous Promotion Effects Model has some predictive validity and does not simply reflect capitalization on chance in the calibration period.

### 4.4. Decomposition of brand and size loyalty

The generalization of brand and size loyalty to distinguish *inter- from intra-individual* differences in loyalty is appropriate if the parameter estimates of the two distinct components ($\overline{BLOY}$ and $BLOY^*$ for brand and $\overline{SLOY}$ and $SLOY^*$ for size) are significantly different in value. The $t$-values for the two models are given below:

| Homogeneous Promotion Effects Model | |
|---|---|
| $\alpha_{B_1} \neq \alpha_{B_2}$, | $t = 4.04$ |
| $\alpha_{S_1} \neq \alpha_{S_2}$, | $t = 4.38$ |

| Heterogeneous Promotion Effects Model | |
|---|---|
| $\alpha_{B_1} \neq \alpha_{B_2}$, | $t = 3.12$ |
| $\alpha_{S_1} \neq \alpha_{S_2}$, | $t = 3.95$ |

All four $t$-values are statistically significant, indicating that it is important to distinguish across-panelist from within-panelist differences in loyalty. Looking at Table 5, for both models the static measure of loyalty ($\overline{BLOY}$ and $\overline{SLOY}$) has a greater impact on utility than the dynamic measure of loyalty ($BLOY^*$ and $SLOY^*$). Thus, loyalty effects due to differences across consumers seem to have greater impact on choice than within-consumer differences in loyalty for both brand and size loyalty.

## 5. Conclusion

### 5.1. Summary of results

The research presented in this paper originates from the notion that individual differences are important and can be parsimoniously incorporated into a cross-sectional

[7] The Heterogeneous Promotion Effects Model was also estimated with the dynamic brand loyalty measure, *BLOY*, replacing $PREF^*$ as the measure of preference that mediates promotion response. This was done to determine if the additional information about brand preference provided by the competitive promotional conditions (in $PREF^*$) added value in terms of the statistical fit of the model to the scanner panel data. Furthermore, this additional empirical analysis allowed us to check the robustness of the predicted relationships between the promotion variables, brand preference, and brand choice. In the model estimation replacing $PREF^*$ with *BLOY*, all estimates for the promotion variables were in the predicted direction. More specifically, the three promotion estimates, $\theta_1$, $\theta_2$, and $\theta_3$, all had the expected signs with $\theta_1$ and $\theta_2$ being statistically significant. The estimate for $\theta_3$, $-1.63$, was not statistically significant at the 0.05 level. The two lagged promotional purchase estimates, $\lambda_1$ and $\lambda_2$ also had the expected signs but neither was statistically significant. The model estimation that replaced $PREF^*$ with *BLOY* did not provide as good a fit to the data as the original model specification. The revised model that used *BLOY* produced a log-likelihood of $-1275.4$ ($\chi^2$ of 6.8) as compared to the log-likelihood of $-1268.8$ for the original model specification that used $PREF^*$ ($\chi^2$ of 20). Consequently, on the basis of model fit, $PREF^*$, the measure of brand preference that incorporated competitive promotional conditions seems justified.

[8] Both models contain explanatory variables which must be updated with actual purchase behavior as it unfolds (loyalties, $PREF^*$, and lagged promotional purchase). As a result, our predictive tests consist of a sequence of single step ahead predictions with the explanatory variables being updated at each step to reflect actual choice.

model of choice. We have extended the incorporation of individual response within aggregate brand choice models in three ways.

First, we have incorporated individualized response to promotions through the addition of the individual and brand-specific utility parameters. We have shown empirically that the addition of such individualized response adds significantly and substantially to the cross-sectional characterization of choice. Furthermore, the signs of the parameter estimates and the significant $t$-values have supported our distinct specification of individualized response; consumers with the weakest preference for a brand *are* less sensitive to the brand's promotions than consumers with moderate preference for the brand, as predicted by our underlying behavioral framework. In fact, our results have shown that incorporating individualized response to promotions indicate the promotion effect on utility for the most promotion-sensitive panelists (1.65) to be over twice the promotion effect for the least promotion-sensitive panelists (0.71). These results suggest that it may be optimistic to expect an in-store promotion to induce consumers with low preference for the brand to buy it. Furthermore, even if induced to buy the promotion, consumers with low preference for the brand are unlikely to repeat buy.

Second, we have proposed an alternative way of capturing individual preference from scanner panel purchase data. Our measure explicitly acknowledges the importance of the competitive promotional conditions in determining the preference revealed by a purchase history. In product classes with frequent in-store promotions, substantial information about consumer preference is lost with measures that solely use item purchase as the raw data. This is important for those managers and market researchers who only use observed purchase behavior to study their customer base and its response to marketing variables. With just these data, managers and researchers must infer preference from observed behavior. Our measure, $PREF^*$, while limited, begins to incorporate the richness of the promotional environment into the measure of preference and therefore is more conceptually complete than its predecessors.

Finally, we have shown the importance of distinguishing between two separate conceptualizations of individual differences in the formulation of loyalty variables in a cross-sectional model: differences in loyalty within an individual over time and differences in loyalty across individuals. Our empirical results have shown that it is appropriate to separate these two effects in a brand choice model as each factor contributes differently to the aggregate model of choice. This finding is consistent with the stream of research that addresses cross-section vs. time series differences in aggregate choice models (see Massy, Montgomery, and Morrison's, 1970, stochastic choice models and, more recently, Lattin and Bucklin's, 1989, model of the dynamic effects of price and promotion).

### 5.2. *Future research*

A program of future research should center on a couple of important topics. First is the issue of omitted variables from the brand choice model. Horowitz (1980) suggests that error due to an omitted variable can affect the integrity of the parameter estimates and the choice probability estimates. One such omitted variable from most models of brand choice that use scanner panel data is coupon availability. The scanner data typically gives coupon redemptions but not coupon availability. With coupon distribution reaching 215 billion in 1987 (Bowman, 1988), couponing may be a critical missing variable. Thus, an important contribution to scanner panel research on brand choice would be the development of a method of inferring coupon distribution from the aggregate coupon redemptions in the panel data.

A second topic of future research is a comprehensive investigation of measures of preference derived from scanner panel purchase data. Such an undertaking would compare a purchase-based measure of preference like loyalty and *PREF** to other measures such as a survey measure of preference for example. The magnitude and significance of the coefficients of measures like loyalty in a model of brand choice highlight the importance of such an investigation.

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