THE IMPACT OF PRICE PROMOTIONS ON A BRAND'S MARKET SHARE, SALES PATTERN AND PROFITABILITY*

by
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Working Paper # 1622-85
February 1985

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Preliminary Draft: Please Do Not Quote

* The author would like to thank Carnation and Rudolph Struse for providing financial support for this research, thank Selling Areas Marketing, Inc. (SAMI), Peter Guadagni and John D.C. Little for providing data and acknowledge Peter Fader's valuable contributions in analyzing the data. Others who have contributed include Alden Clayton, Michael Dermody, John Hauser, Jim Lattin, Scott Neslin, John Roberts, Diane Schmalensee, Subrata Sen, Richard Staelin, Glen Urban and Lester Young.

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THE IMPACT OF PRICE PROMOTIONS ON A BRAND'S MARKET SHARE, SALES PATTERN AND PROFITABILITY

ABSTRACT

A model of market response to price promotions reflecting consumer heterogeniety in preferences and promotion responsiveness shows that a brand's market share is effected by the relative frequency of its own promotions and by its preference profile among consumers: widely accepted, smaller preference brands are more likely to gain long run market share through promotion than are widely accepted higher preference brands, ceteris paribus. If consumers respond to promotions by stockpiling, a brand's unpromoted "baseline" sales are depressed by its own promotions. If consumers respond to promotions by increasing the probability of choosing the promoted brand, a brand's unpromoted "baseline" sales are depressed by competitive brands' promotions. The overall profitability of offering price promotions is shown to depend upon the mix of consumers in the marketplace. Consumers who do not respond to promotions and those who respond to promotions by stockpiling the brand they would have chosen anyway decrease the overall profitability of offering promotions. Consumers who respond to promotions by switching to the promoted brand or by buying and consuming more of the promoted brand than they would have had there been no promotion tend to increase the overall profitability of offering promotions. The model is operationalized using UPC scanner panel data on coffee purchases.

INTRODUCTION

Expenditures for promotions (price deals, coupons, rebates, etc.) have grown dramatically in recent years, reaching an estimated $60 billion in 1982 (Bowman 1981). Industry reactions to this trend are mixed. Hertz' chair, Olson, finds such expenditures counter profitable.[1] 7-Up's chair, Winter, finds them essential and productive.[2] By-standers attribute the confused spending in part, at least, to the management of promotion dollars. An Ad Age article titled "Room at the Top in Promotions," suggest that promotion management has remained clerical despite the fact that promotion expenditures have grown from 5% to 60% of a typical marketing budget. In "Sales Promotion - Fast Growth, Faulty Management," Strang (1976) suggests that promotion expenditures have been used by brand managers to optimize their career paths rather than their firms' profits.

The magnitude of this problem and the relative confusion surrounding it has given rise to some interesting academic research. This paper adds to that body a model of market response to price-off promotional offers. The model is built up from a collection of models of individual response to promotional offers which reflect heterogeniety in consumers tastes and in their response to promotional offers. The aggregated model is explored to develop intuition concerning the impact of price promotions on a brand's market share, sales pattern and profitability. The approach is applied to UPC coffee purchase panel data to derive insights and suggest guidelines for managing promotional expenditures in that product class.

Literature Review

Several studies have acknowledged and explored the heterogeniety in consumers tastes and in their responses to promotions[3] (Blattberg and Sen 1974, 1976; Blattberg, Peacock and Sen 1978). Roughly following the categorization schemes in those studies, we suggest that consumers might respond to promotions in one of

several ways. A consumer might buy more units of a brand than she normally would (i.e., stockpile) because the brand is promoted (Blattberg, Eppen, and Lieberman 1981, Neslin, Quelch and Henderson 1983). Alternatively, a consumer might increase the probability of choosing a particular brand because it is on promotion. (Guadagni and Little 1983, Fraser 1983, Narasimhan 1984). A consumer might also do both: increase the probability of choosing a promoted brand and stockpile when buying a promoted brand. Finally, a consumer might be enticed by the promotion to make a purchase (or to buy and consume more) from the product category.

We restrict ourselves to the modeling of consumer response to the promotion of mature products. We operationalize this restriction by assuming that a consumer's response to a promotion for a brand does not effect that consumer's subsequent preferences among brands. (One function of promotion for new products is to stimulate trial and bring about awareness. In that situation, subsequent preferences and hence purchase probabilities very likely are altered.)

By assuming the choice of a promoted brand does not effect the consumer's subsequent preference, we have assumed away two types of effects. First, we eliminate the traditional time series effects of "learning" (e.g. Keuhn 1958) and "variety seeking" (e.g., McAlister and Pessemier 1982) that have to do with the brand chosen but not with whether that brand was on promotion or not. We assume those to be second order effects in this problem. Second, we eliminate the change in purchase probabilities (a manifestation of changed preference) that arises because the brand chosen was on promotion. Several researchers have investigated such effects. Rothchild and Gaidis (1981) draw on behavioral learning theory to suggest that well designed promotions can serve as reinforcers and can increase a brand's repurchase rate. Cotton and Babb (1978) found that post-promotion purchase rates for dairy products were generally higher than pre-promotion purchase rates. In contrast, Shoemaker and Shoaf (1977) found that the probability of repurchasing

a brand actually dropped if the previous purchase was on promotion. Scott (1976) and Dodson, Tybout and Sternthal (1978) propose self-perception theory as an explanation of this phenomenon. That theory suggests that the probability of repurchase is lowered because the individual is uncertain whether her selection of the promoted product is attributable to preference for the purchased product or to a desire to take advantage of the promotion.

We opted for the assumption that, with mature products, long run preferences are not altered by promotions for several reasons. First there is no consensus as to the force driving or even the direction of such changes in preference. Theoretical and empirical evidence can be marshalled for either increases or decreases. Second, promotions on almost all brands occur so frequenlty that, should long range preference changes exist, such effects may cancel one another out. Finally, the magnitudes of the demonstrated long run preference changes are very small compared to the magnitude of the demonstrated short run change in probability of purchase that occurs at the time the promotion is offered (Guadagni and Little 1983). It is this short run change in the probability of purchase that occurs at the time of the promotion on which we focus.

We further restrict ourselves to the modeling of consumer response to a particular type of promotion. Studies of short term price reductions by the retailer (Massy and Frank 1965, Guadagni and Little 1983), premiums (Seipel 1971), in-store display (Chevalier 1975), and coupons (Irons, Little and Klein 1983, Neslin and Shoemaker 1983, Narasimhan 1984) illustrate the differences that exist among promotional instruments. The instrument we have chosen is a short term price reduction by a retailer. We further assume that a brand is "on promotion" or is "not on promotion". Clearly, price reductions of different magnitudes should elicit different magnitudes of response. The assumption we make is tantamount, therefore, to assuming that the promotional price reductions in the product class

that we consider are all of the same magnitude. It is not uncommon for such uniformity of promotional price cuts to occur (e.g., Guadagni and Little 1983). One could relax this assumption within the modeling context of this paper by parameterizing consumer response with depth of price reduction. We avoid that parameterizing in the interest of analytical simplicity. For a similar reason we do not consider the possible interaction effect of advertising with promotion (Brown 1974, Sunoo and Lin 1978).

Finally, it is important to point out that we consider the response of consumers to promotions offered by a retailer. An understanding of such response has important implications for a manufacturer. However, such understanding does not completely solve the manufacturer's problem of managing promotion expenditures. The manufacturer must also understand the ways in which retailers respond to promotional offers made by manufacturers (Chevalier and Curhan 1976, Ibraham and Lodish 1984).

MODEL

We model individual choice behavior as a probabilistic process. We assume that an individual chooses from among a set of "relevant" brands with probabilities proportional to her preferences for those brands (Luce 1959). We consider separately the choice behavior of "regular consumers" of the product class and "category expansion consumers." A "regular consumer" has a fixed consumption rate but may respond to promotions by altering brand choice or purchase timing. A "category expansion consumer" responds to promotions by altering her consumption rate as well as by possibly altering brand choice or purchase timing.

When a regular consumer is not responding to promotions, all brands that she finds "acceptable" (ever purchases) are "relevant." When a regular consumer is responding to promotions, all acceptable brands that are on promotion are

"relevant". The regular consumer's propensity to respond to promotions is also modeled probabilistically. With probability γ_i $(0 \leq \gamma_i \leq 1)$, regular consumer i will restrict her choice to those acceptable brands on promotion. With probability $1-\gamma_i$ regular consumer i will ignore promotions and choose from among all acceptable brands.

Category expansion consumers may be enticed by a promotion to make purchases in the product class that they would not have made had there been no promotion. Consumers exhibiting two types of choice behavior are aggregated here. First we have the consumers who would not buy in the product class at all if there were no promotion. Second, we have those consumers who regularly buy in the product class but who increase their consumption rate because of the promotion. The <u>extra units</u> that this type of consumer buys and consumes immediately are considered purchases by a category expansion consumer. (The units whose consumption is not attributable to promotion are considered purchases by a "regular consumer" of the product class.)

Our model of market response to promotions is made up of two components. The first component describes the response of "category expansion consumers". The second component describes the response of "regular consumers" of the product class. Depending upon the values taken on by individual specific parameters, this second component can represent a consumer who is indifferent to promotions $(\gamma_i=0)$ a consumer who reponds to promotions by stockpiling $(\gamma_i \geq 0$ and $n_i > 1)$, a consumer who responds to promotions by restricting choice to promoted brands $(\gamma_i > 0, \pi_{ij} < 1$ for all brands j) or a consumer who responds with a combination of the above behaviors. We consider the profit implications for brand B_1 of the likely buying behavior of a collection of consumers described by such models. We first present the notation to be used and then develop the two components of the model.

Notation

J = Number of brands in the marketplace

B_j = $j^{\underline{th}}$ brand; $j=1, 2, \ldots, J$

γ_i = Probability that consumer i responds to a promotion given that a promotion is available on some brand acceptable to consumer i

π_{ij} = Consumer i's preference for B_j, $\sum_{j=1}^{J} \pi_{ij} = 1$, $\pi_{ij} \geq 0$ for all j

e_i = The set of consumer i's acceptable brands (those brands with with $\pi_{ij} > 0$)

w_i = Number of units that regular consumer i of the product class uses per purchase cycle

= average number of units that regular consumer i of the product class buys per purchase cycle

w_i' = Number of units that category expansion consumer i buys because of a promotion that she would not have bought had there been no promotion.

I = The set of "regular consumers" of the product class.

I' = The set of "category expansion consumers" of the product class.

$$P_{jt} = \begin{cases} 1 \text{ if } B_j \text{ is on promotion at time } t \\ 0 \text{ if } B_j \text{ is not on promotion at time } t \end{cases}$$

α_j = $E_t\,[P_{jt}]$ = Expected value of P_{jt} over time

= Probability that a consumer finds B_j on promotion during an arbitrary shopping trip

= Fraction of time that B_j is on promotion

G_{it} = Profit that B_1 expects from "regular consumer" i at time t

$G_{i\bullet}$ = $E_t\,[G_{it}]$ = Expected value over time G_{it}

= Expected profit to B_1 from "regular consumer" i per purchase cycle

G'_{it} = Profit that B_1 expects from "category expansion consumer" i at time t.

$G'_{i\bullet}$ = $E_t\,[G'_{it}]$ = Expected value over time of G'_{it}

= Expected profit to B_1 from "category expansion consumer" i per purchase cycle.

n_i = Factor by which a stockpiling consumer increases the number of units purchased in response to a promotion, $n_i \geq 1$.

β_{i1} = $E_t[\prod_{\substack{k \neq 1 \\ k \in e_i}} (1-P_{kt})]$ = Probability that no brand that consumer i views as competitive to B_1 is on promotion at an arbitrary point in time.

k_{i1} = $E_t[\frac{1}{\pi_{i1} + \sum_{\substack{k \neq 1 \\ k \in e_i}} P_{kt}\pi_{ik}}]$ = the factor by which B_1 expects its promotion to inflate the probability that consumer i will choose B_1.

M_N = Profit margin that B_1 receives from each unpromoted purchase

M_P = Profit margin that B_1 receives from each promoted purchase, $0 < M_P < M_N$.

Category Expansion Conumers

If B_1 is not on promotion at time t ($P_{1t}=0$), then category expansion consumer i will not buy B_1. If B_1 is on promotion at time t ($P_{1t}=1$), then category expansion consumer i will buy w_i units of B_1 with probability $\pi_{i1}/(\sum_{j \in e_i} P_{jt}\pi_{ij})$ yielding M_P per unit to the manufacturer of B_1.

$$G'_{it} = P_{1t} \left(\frac{w'_i \pi_{i1}}{\pi_{i1} + \sum_{\substack{j \neq 1 \\ j \in e_i}} P_{jt} \pi_{ij}} \right) M_P \tag{1}$$

And, assuming the independence of P_{jt}'s across j,

$$G_{i.} = E_t[G'_{it}] = \alpha_1 \pi_{i1} w'_i k_{i1} M_P \tag{2}$$

where k_{i1} is

$$k_{i1} = E_t \left[\frac{1}{\pi_{i1} + \sum_{\substack{k \neq 1 \\ k \in e_i}} P_{kt} \pi_{ik}} \right]$$

$$\simeq \frac{1}{\pi_{i1} + \sum_{\substack{k \neq 1 \\ k \in e_i}} \alpha_k \pi_{ik}} + \frac{\sum_{\substack{k \neq 1 \\ k \in e_i}} \pi_{ik}^2 (\mathrm{Var}_t P_{kt})}{(\pi_{i1} + \sum_{\substack{k \neq 1 \\ k \in e_i}} \alpha_k \pi_{ik})^3}$$

Regular Consumers of the Product Class

Since a regular consumer of this product class may respond to promotions by stockpiling (buying $w_i n_i$ units rather than w_i units) we must consider the implications of the promotion in the period it is offered and in the subsequent n_i-1 periods in which the stockpiling consumer uses up her inventory and makes no further purchases. We consider the n_i periods between t and $t+n_i-1$. We assume that, in period t, consumer i goes to the market to buy w_i or possibly $w_i n_i$ units from the product class to which brand B_1 belongs. The profit that the manufacturer of B_1 expects from consumer i across the n_i periods is given by equation (3).

$$\int_{\tau=t}^{t+n_i-1} G_{it} = P_{1t}\{\gamma_i[w_i n_i(\frac{\pi_{i1}}{\pi_{i1}+\sum_{\substack{k\neq 1\\ k\varepsilon e_i}} P_{kt}\pi_{ik}})M_P+(n_i-1)0]$$

$$+ (1-\gamma_i)[\pi_{i1}w_i M_P+(n_i-1)G_{i\bullet}]\}$$

$$+(1-P_{1t})\{\gamma_i (\prod_{\substack{k\neq 1\\ k\varepsilon e_i}} (1-P_{kt}))[\pi_{i1}w_i M_N+(n_i-1)G_{i\bullet}]$$

$$+(1-\gamma_i)[\pi_{i1}w_i M_N+(n_i-1)G_{i\bullet}]\} \qquad (3)$$

This equation can be explained as follows. On her shopping trip in period t, consumer i either does ($P_{1t} = 1$) or does not ($P_{1t} = 0$) find brand B_1 on promotion. If she does find B_1 on promotion she may or may not react to promotions by restricting her choice to those brands on promotion and buying $w_i n_i$ units (γ_i = probability she will react). If B_1 is on promotion and consumer i reacts to promotions, then with probability $\pi_{i1}/(\pi_{i1}+\sum_{\substack{k\neq 1\\ k\varepsilon e_i}} P_{kt}\pi_{ik})$ consumer i will buy $w_i n_i$ units of B_1 in period t yielding M_P per unit to the manufacturer of B_1. For the next n_i-1 periods consumer i will be out of the market therefore yielding \$0 to the manufacturer of B_1 during those periods.

If B_1 is on promotion in period t but consumer i is not reacting to promotions ($1-\gamma_i$) then with probability π_{i1} consumer i will buy w_i units of B_1 yielding M_P per unit to the manufacturer of B_1 in period t. We don't know what will happen in the subsequent n_i-1 periods. B_1 may or may not be on promotion. Consumer i may or may not react to promotions. Our best guess of the profit that the manufacturer of B_1 can expect to receive from consumer i in those periods is $G_{i\bullet}$, that quantity for which we are trying to solve. Hence we develop a recursive relationship in equation (3).

Consider now the case in which B_1 is not on promotion in period t. If consumer i is reacting to promotions in period t and if any brand acceptable to consumer i is on promotion during period t then consumer i will buy n_i units of that other brand yielding \$0 to the manufacturer of B_1 for all n_i periods. With probability $\prod_{\substack{k\neq 1\\ k\in e_i}} (1-P_{kt})$ consumer i will find no acceptable brand on promotion and will therefore choose among the brands she finds acceptable with probabilities proportional to her preferences for those brands. With probability π_{i1} she will buy w_i units of B_1 yielding M_N per unit to B_1's manufacturer. In each of the subsequent (n_i-1) periods, B_1's manufacturer can expect to make $G_{i\bullet}$ from consumer i.

If B_1 is not on promotion in period t and if consumer i is not restricting her choice to promoted brands in period t then consumer i is expected to buy w_i units of B_1 in period t with probability π_{i1} yielding M_N to B_1's manufacturer. In each of the subsequent n_i-1 periods, B_1's manufacturer expects to make $G_{i\bullet}$ from consumer i.

To solve for $G_{i\bullet}$, the profit that B_1's manufacturer expects from consumer i during any given purchase cycle, we take the expectation of equation (3) across time.

$$E_t\left[\int_{\tau=t}^{t+n_i-1} G_{it}\right] = n_i G_{i\bullet} = w_i\pi_{i1}\{\alpha_1[\gamma_i n_i k_{i1}+(1-\gamma_i)]M_P$$

$$+ (1-\alpha_1)[\gamma_i\beta_{i1}+(1-\gamma_i)]M_N\}$$

$$+ (n_i-1)G_{i\bullet}[(1-\gamma_i)+(1-\alpha_i)\beta_{i1}\gamma_i]$$

$$G_{i\bullet} = \frac{w_i\,\pi_{i1}}{1+(n_i-1)\gamma_i(1-\beta_{i1}(1-\alpha_1))}\{\alpha_1[\gamma_i n_i k_{i1}+(1-\gamma_i)]M_P$$

$$+ (1-\alpha_1)[\gamma_i\beta_{i1}+(1-\gamma_i)]M_N\} \qquad (4)$$

where k_{il} is defined as before and

$$\beta_{il} = E_t \left[\prod_{\substack{k \neq l \\ k \in e_i}} (1-P_{kt}) \right]$$

assuming P_{kt} independent across k

$$\beta_{il} = \prod_{\substack{k \neq l \\ k \in e_i}} (1-\alpha_k) \quad .$$

Equation (4) can be interpreted as follows. During any arbitrary purchase cycle, we assign probability $1/(1+(n_i-1)\gamma_i(1-\beta_{il}(1-\alpha_i)))$ to consumer i being in the market[4] (i.e., that she will not be forgoing purchase because she has a stockpile at home). Given that consumer i is in the market, she will see B_l on promotion with probability α_l. If she reacts to promotions, she will choose B_l with probability $\pi_{il}k_{il}$ and buy $w_i n_i$ units yielding M_P per unit to B_l's manufacturer. If she is not reacting to promotions, she will choose w_i units of B_l with probability π_{il} yielding M_P per unit to B_l's manufacturer. With proability $(1-\alpha_l)$ consumer i will not see B_l on promotion. If she wants to react to a promotion but none of the other acceptable brands is on promotion $(\gamma_i\beta_{il})$ or if she does not choose to react to promotion $(1-\gamma_i)$ she will choose w_i units of B_l with probability π_{il} yielding M_N per unit to B_l's manufacturer.

Embedded Purchase Incidence and Brand Choice Models. From equation (4) one can extract two probabilistic models. The probability $1/(1+(n_i-1)\gamma_i(1-\beta_{il}(1-\alpha_l)))$ can be viewed as a purchase incidence model. Consumer i who stockpiles (has $n_i>1$) will be expected to make a purchase during any arbitrarily selected purchase cycle with this probability. Note that if consumer i is not a stockpiler (has $n_i=1$) we expect the consumer to make a purchase during every purchase cycle.

We can also extract a brand choice model from equation (4). The probability that we assign to consumer i choosing B_l is

$$\gamma_i[\alpha_l \pi_{il} k_{il}] + \gamma_i(1-\alpha_l)\beta_{il}\pi_{il} + (1-\gamma_i)\pi_{il}.$$

Referring back to equation (3) we can infer the probability that consumer i will choose B_l at time t is

$$\pi_i^t[B_l] = \gamma_i \frac{\pi_{il} P_{lt}}{\sum_{k \in e_i} \pi_{ik} P_{kt}} + \gamma_i [\prod_{\substack{k \neq l \\ k \in e_i}} (1-P_{kt})] \pi_{il} + (1-\gamma_i)\pi_{il} \quad (5)$$

MANAGERIAL IMPLICATIONS

Impact of Promotions on Long Run Market Share: Small Preference Brand Advantage

From equations (1) and (5) we can see that if no brand ever promoted (i.e., if $P_{jt}=0$ for all j and all t), then the long run market share for B_j (denoted M_j) would be expected to equal preference share among regular consumers of the product class ($\pi_{\bullet j}$), where

$$\pi_{\bullet j} = (\sum_{i \in I} w_i \pi_{ij}) / \sum_{i \in I} w_i$$

However, if consumers are promotion sensitive (some γ_i's>0) and if some brands promote much more frequently than others, we would expect (from equations (1) and (5)) that those brands that promote much more frequently will have long run market shares that exceed their preference shares. Conversely, we would expect those brands that promote much less frequently to have long run market shares that fall below their preference shares. In this way a brand's own promotion schedule and its competitors' promotion schedules come together to determine, in part, which brands gain share and which lose share due to promotion activity.

Promotion driven share gains and losses might result from promotion effectiveness as well as from relative promotion frequency. A promotional price

cut of \$.40 on a \$1.00 item would probably have a larger impact on share shifts than would a cut of \$.20. A promotional price cut that received a great deal of retailer support (feature, display, etc.) would probably have a larger impact on share shifts than would an unsupported price cut. One might also expect intrinsic properties of a brand (level of national advertising support, market share, etc.) to temper promotion effectiveness. From the models in equations (1) and (5) we can see that one such intrinsic quality, preference share (π_{ij}) does influence promotion effectiveness. Among acceptable brands, smaller preference brands get "more bang for their promotion buck" than do larger preference brands.

To see this consider the factors by which two brands (B_1 and B_2 , $\pi_{i1}>\pi_{i2}>0$) can expect to inflate, through promotion, the probability with which consumer i will choose them, given the same level of competitive promotional activity.

$$\text{Inflation factor for } B_1 = \frac{1}{\pi_{i1} + \sum\limits_{\substack{k\neq 1,2 \\ k\in e_i}} P_{kt}\pi_{ik}}$$

$$\text{Inflation factor for } B_2 = \frac{1}{\pi_{i1} + \sum\limits_{\substack{k\neq 1,2 \\ k\in e_i}} P_{kt}\pi_{ik}} \quad .$$

Since $\pi_{i1} > \pi_{i2}$, the inflation factor for B_2 is greater than that for B_1. B_2 can, therefore, get a greater percentage increase in sales than B_1 for the same promotional effort.

Impact of Promotion on Sales Patterns

From equations (2) and (4) we can infer that B_1, when not on promotion, expects "baseline" sales of:

$$\sum_{i\in I} \frac{w_i \pi_{i1}}{1+(n_i-1)\gamma_i(1-\beta_{i1}(1-\alpha_1))} \left[\gamma_i\beta_{i1} + (1-\gamma_i)\right]$$

When promoted, B_1 expects a promotional sales peak of:

$$\sum_{i \in I} \frac{w_i \pi_{i1}}{1+(n_i-1)\gamma_i(1-\beta_{i1}(1-\alpha_1))} [\gamma_i n_i k_{i1} + (1-\gamma_i)] + \sum_{i \in I'} w_i' k_{i1} \pi_{i1}$$

Figure 1 illustrates these levels of expected baseline and promoted sales.

[Figure 1 about here]

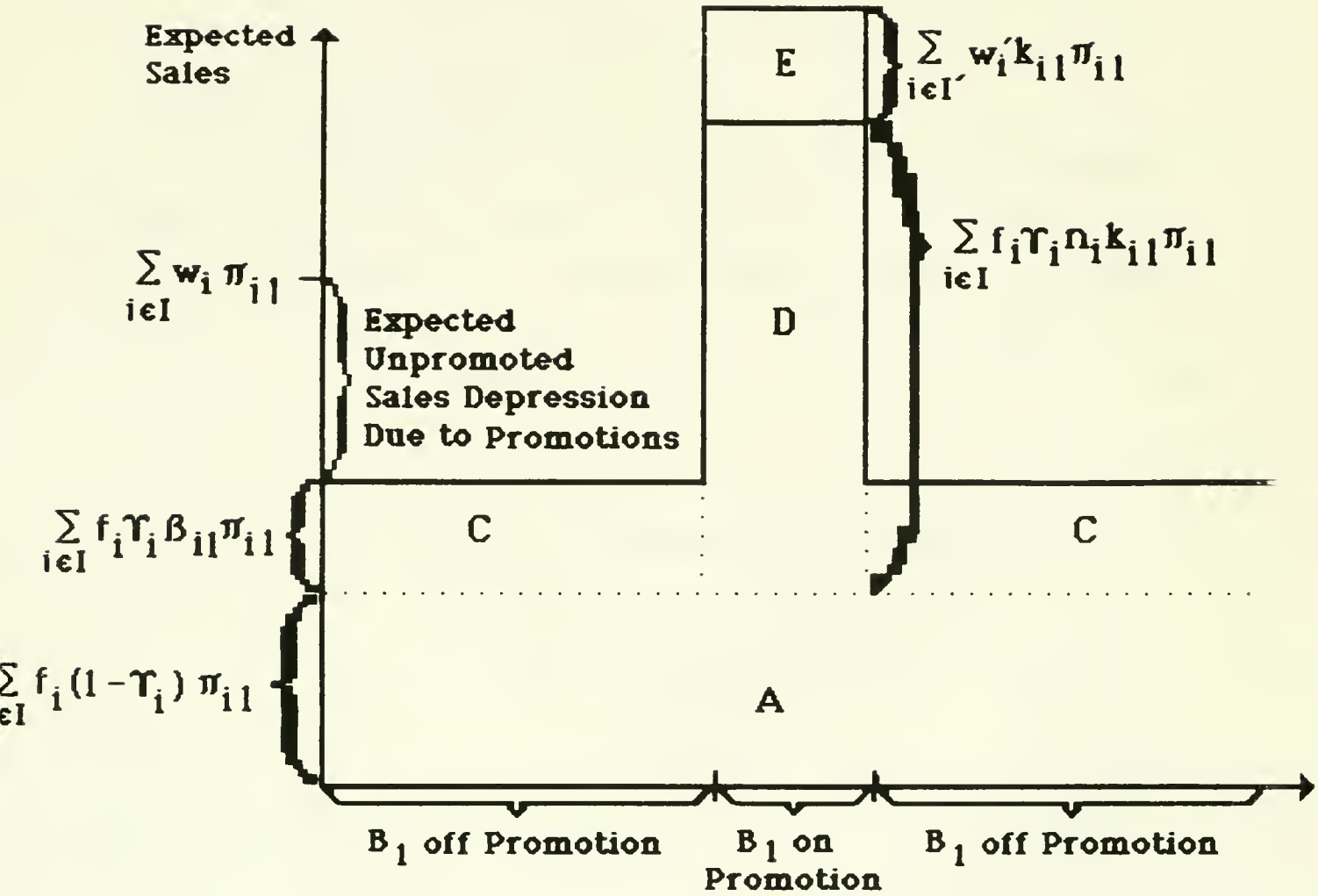
The point on the expected sales axis marked $\sum_{i \in I} w_i \pi_{i1}$ represents the level of sales that B_1 would expect if neither B_1 nor any other brand ever promoted. Region E represents sales to category expansion consumers while regions A, C and D represent sales to regular consumers of the product class. The height of region A is proportional to expected sales to regular consumers who are not responding to promotions. The height of region C is proportional to expected sales to regular consumers who would like to respond to promotions but find no acceptable brand on promotion. The height of region D is proportional to expected sales to regular consumers who respond to B_1's promotions.

It is interesting to consider the impact of differing promotional responses on the "baseline" (region A + region C) and on the height of the promotional sales peak (region A + region D + region E). If regular consumers in the product class stockpiled but did not switch brands in response to promotions, then the B_1's expected baseline and expected promotional sales peak (functions of α when n_i is greater than 1) would be driven down by B_1's own promotions and uneffected by competitive brands' promotions.

If regular consumers of the product class switched brands but did not stockpile in response to promotions, then the B_1's expected baseline (a function of β_{i1}) and expected promotional sales peak (a function of k_{i1}) would be driven down by competitive brand's promotions and uneffected by B_1's own promotions.

If regular consumers stockpile and switch brands in response to promotions then B_1's baseline and expected promotional sales peak are depressed by both its own and competitive brands' promotional activity.

FIGURE 1: Expected Sales to B_1



$$f_i = \frac{w_i}{1+(n_i)\Upsilon_i(1-\beta_{i1}(1-\alpha_1))}$$

Impact of Promotions on Profit

From equations (2) and (4) we can develop an expression for the total profit that the manufacturer of B_1 expects to make.

$$G_{\bullet\bullet} = E_i[G_{i\bullet}] = \sum_{i\varepsilon I} G_{i\bullet} + \sum_{i\varepsilon I'} G'_{i\bullet}$$

To establish the attractiveness of promoting to this collection of consumers we consider the derivative of the expected profit function, $G_{\bullet\bullet}$, with respect to α_1, the fraction of time that B_1 is on promotion. If that derivative is positive then gross profit to B_1 increases as the promotion of B_1 increases. More promotion is better. If that derivative is negative then gross profit to B_1 decreases as the promotion of B_1 increases. Less promotion is better.

$$\frac{\partial G_{\bullet\bullet}}{\partial \alpha_1} = \sum_{i\varepsilon I} \frac{\partial G_{i\bullet}}{\partial \alpha_1} + \sum_{i\varepsilon I'} \frac{\partial G'_{i\bullet}}{\partial \alpha_1}$$

where:

$$\frac{\partial G_{\bullet i}}{\partial \alpha_1} = \frac{w_i \quad \pi_{i1}}{[(1+(n_i-1)\gamma_i(1-\beta_{i1}(1-\alpha_1))]^2}$$

$$\{[1+\gamma_i(n_i-1)(1-\beta_{i1})][\gamma_i n_i k_{i1}+(1-\gamma_i)]M_P$$

$$-[1+\gamma_i(n_i-1)][\gamma_i\beta_{i1}+(1-\gamma_i)]M_N\} \tag{6}$$

and

$$\frac{\partial G'_{\bullet i}}{\partial \alpha_1} = \pi_{i1}k_{i1}w_i M_P \quad . \tag{7}$$

From (7) we observe that $\partial G'_{\bullet i}/\partial\alpha_1$ is always positive. The manufacturer of B_1 is always made more profitable by promoting to those consumers for whom extra consumption can be induced by promoting.

From (6) we observe that $\partial G_{\bullet i}/\partial\alpha_1 > 0$ if

$$[1+\gamma_i(n_i-1)(1-\beta_{i1})[\gamma_i n_i k_{i1}+1-\gamma_i]M_P >$$

$$[1+\gamma_i(n_i-1)][\gamma_i\beta_{i1}+1-\gamma_i]M_N \tag{8}$$

Inequality (8) will hold for some consumers and not for others. We next consider profitability of different patterns of consumer response to promotions.

Consider first those consumers who do not respond to promotions ($\gamma_i = 0$). For these consumers inequality (8) reduces to $M_P > M_N$ and, by definition, this cannot hold (promoted margin, M_P, is defined as being smaller than unpromoted margin, M_N). It is, unsurprisingly, not profitable to promote to consumers who do not respond to promotions.

Consumers might respond to promotions by stockpiling but not switching brands. ($\pi_{il} = 1$, $n_i > 1$, $k_{il} = 1$, $\beta_{il} = 1$). In this case, too, inequality (8) reduces to $M_P > M_N$. Promotion to these consumers is unprofitable because they take advantage of the promotion to buy, at a reduced price, $w_i n_i$ units of the brand which they would have bought anyway and then forego purchase of that brand in the next $n_i - 1$ periods.

Other consumers might be willing to switch brands for a promotion but not stockpile ($k_{il} > 1$, $\beta_{il} < 1, n_i = 1$). Promotion to these consumers will be profitable if

$$\sum_{i \text{ a switcher}} \pi_{il}(\gamma_i k_{il} + 1 - \gamma_i) M_P > \sum_{i \text{ a switcher}} \pi_{il}(\gamma_i \beta_{il} + 1 - \gamma_i) M_N \quad .$$

The logic behind this condition is illustrated in Figure 1. If B_1 promotes it expects sales proportional to the height of region D + region A ($\sum w_i \pi_{il} (\gamma_i k_{il} + 1 - \gamma_i)$) at margin M_P. If B_1 does not promote it expects sales proportional to the height of region C + region A ($\sum w_i \pi_{il} (\gamma_i \beta_{il} + 1 - \gamma_i)$) at margin M_N. If the promotional sales peak times the smaller margin is greater than the base line times the larger margin (i.e., if the promotional sales "bump" is "big enough") then promoting to these consumers is profitable.

If consumers respond to promotions by switching and stockpiling, there is no simple rule of thumb for evaluating promotion profitability. It is not appropriate to simply "measure the bump" since a brand's own promotions are lowering its

baseline. Inequality (8) asks whether profit from the promotional sales peak at M_P per unit is greater than baseline sales at M_N per unit inflated by the factor $[1+\gamma_i(n_i-1)]/[1+\gamma_i(n_i-1)(1-\beta_{i1})]$ to account for future unpromoted sales that will be lost because of stockpiling.

APPLICATION

Data

The data used to illustrate the procedure just described is the same as was used by Guadagni and Little (1983). The purchase hiatories include competitive promotional environment at the time of each purchase for a SAMI panel of 200 consumers, each making more than 90% of their purchases in one of four stores in Kansas City over a period of 78 weeks from September 14, 1978 to March 12, 1980. Because competitive promotional environment data did not become available until December 20, 1978, our analysis is restricted to the 65 weeks between December 20, 1978 and March 12, 1980.

We will initially, use the 2223 purchases from the first 44 weeks to estimate models for 100 of the consumers. The predictive ability of these models is tested against the 747 purchases made during the next 20 weeks. We then reestimate the models using 65 weeks[5] of data and use these reestimated parameters to develop managerial guidelines.

The brands among which consumers chose are Butternut 1 lb. (BUT.S), Butternut 3 lb. (BUT.L), Folgers 1 lb. (FOL.S), Folgers Flake 1 lb. (FOL.F.S.), Folgers 3 lb. (FOL.L), Maxwell House 1 lb. (MH.S), Maxwell House 3 lb. (MH.L), Mellow Roast 1 lb. (MEL.S).

Category Expansion Consumers

Given the nature of coffee consumption, one would not expect to find a preponderance of consumers whose consumption rate would be effected by promotion. (Such behavior would probably be more evident in snack food categories). In fact,

we find very little evidence of such altered consumption rates in this data. Category expansion consumers should either:

a) Make all purchases on promotion, or

b) Buy more units on promoted purchase occasions than on unpromoted purchase occasions without effecting interpurchase times.

Among the 200 members of the SAMI panel we find only 5 who make every purchase on promotion. One of these consumers makes more than twice as many purchases as does the average panel member (48 for this consumer versus 21 for the average consumer). This consumer also buys six of the eight brands offered. This suggests that this consumer might be a regular consumer of the product class who is highly promotion sensitive and willing to switch brands to take advantage of promotions. The other four consumers purchase only infrequently, making a total of 33 purchases (less than 1% of all purchases).

We also found very little evidence of increased consumption by regular consumers of the product class. The purchase of multiple packages of coffee on a single shopping trip was rare. Only 68 of the 200 consumers in the sample ever purchased multiple packages of coffee on a single shopping trip. Nine of those 68 consumers accounted for 60% of the shopping trips in which multiple packages of coffee were purchased. (Examining these nine consumers' purchase histories reveals that these consumers' regular purchase quantity of coffee included multiple packages.) This implies that the other 59 consumers who ever purchased multiple packages of coffee on a shopping trip did so an average of 1.75 times out of an average 21.1 shopping trips.

It is also important to note that the multiple package purchases were not especially associated with promotional offers. Among all 4,216 choices made by all consumers in the panel, 51% were made on promotion. Among the 254 shopping trips that involved multi-package purchases, 45% were made on promotion. Among those 151

multiple package shopping trips made by the nine consumers who regularly purchase multiple packages, 50% of the multiple purchases were on promotion. Hence, it appears that some force other than promotion drives multiple package purchases. The very infrequent multiple package purchases (1.75 out of 21.1) is consistent with consumers having an occasional need to purchase extra coffee for entertaining. Consistent with this we see that 24% of all multiple package purchases occurred around Thanksgiving, Christmas, and New Years.

Since there are so few consumers in this database who might be category expansion consumers and since those consumers' behavior is not inconsistent with the model of regular consumers of the product class, we opt to not treat them separately.

Estimation: Purchase Incidence Model

Estimates of α_j and β_{i1} can be drawn directly from the data: α_j by the faction of time that B_j is on promotion and β_{i1} by $\prod_{\substack{j \neq 1 \\ j \in e_i}} (1-\alpha_j)$. We will obtain an estimate of γ_i from the brand choice model. To estimate n_i, we again turn to the data.

Stockpiling might manifest itself in at least two different ways. A consumer who purchases at regular intervals might purchase $w_i n_i$ units on a promoted purchase occasion and then skip purchasing for the next n_i-1 purchase cycles. Alternatively, a consumer might manifest her stockpiling behavior by making an additional (promoted) purchase in the middle of a purchase cycle and then forego purchase at the expected purchase time in her purchase cycle. Such behavior could be accommodated in the proposed model by estimating n_i as the average number of units chosen during purchase cycles in which consumers accelerated purchase to take advantage of promotions.

As just noted, we found no evidence of multiple-package purchases being especially associated with promotion. We also found no effect of promotions on

purchase timing. If consumers accelerated their purchases for promotions, one would expect (following Blattberg, Eppen, and Lieberman 1981) the time between a nonpromoted and a promoted purchase (NP→P) to be shorter than the time between two nonpromoted purchases (NP→NP). In this data base, we found that the average value of the 727 occurrences of NP→P was 19.4 days, and the average value of the 1264 occurrences of NP→NP was 19.1 days. This pattern reverses that which one would expect if purchases were being accelerated due to promotions.

Given that promotions seemed to affect neither the number of packages purchased nor the timing of purchases for the consumers, we take $n_i = 1$ and the purchase incidence model loses importance in this application.

Estimation: Brand Choice Model

We use maximum likelihood to estimate the π_{ij}'s and γ_i for each consumer based on her purchase history and the promotional environments she faced. For each purchase occasion, we create a probability expression using equation (5). The expression shows the probability of consumer i selecting the brand actually chosen at time t. The likelihood function made up by multiplying these probability expressions together is maximized subject to the constraint that $0 \leq \gamma_i \leq 1$ to obtain estimates of γ_i and the π_{ij}'s.

We began by estimating the proposed model using the first 44 of the 64 weeks of purchase histories of the 100 randomly chosen consumers on whom Guadagni and Little (1983) fit their model. This gave, on average, 14 purchase observations to estimate, on average, 4.5 parameters (3.5 π's and 1 γ) per consumer. Unsurprisingly, the model fit very well. The average probability assigned to the brand actually selected across all 1,417 purchases made by the 100 consumers during the 44 estimation weeks was 0.656. The average probability assigned to the brand actually selected during the 20 week holdout period was 0.539. The decline in average probability between the fit and prediction periods indicates a degree of overfitting. However, the predictions made by the proposed model are quite good.

When compared to predictions made by Guadagni and Little's (1983) model that used several other predictor variables (e.g., regular price, size of price cut, whether prior purchases were on promotion), the proposed model was shown to make statistically significantly better predictions (average predicted probability for Guadagni and Little = 0.477, t-statistic associated with the difference between predictions = 6.04, $p < 0.001$; Wilcoxon statistic = 173851.5, $p < 0.001$). Having thus gauged the predictive ability of the proposed model, we estimated the parameters for all 200 consumers using the entire 64 weeks of data. The average number of parameters estimated per consumer remains unchanged while the average number of choices available to estimate those parameters rises to 21.5. This increase in the ratio of observations to estimated parameters should ease the problem of overfitting.

We also used a Monte Carlo procedure like that proposed by Chapman and Staelin (1982) to test for possible bias in model parameters. The procedure (detailed in the Appendix) takes as input a set of "true" π^T_{ij} and γ^T_i. It then chooses a set of random promotional environments and generates a choice history. That history, along with the related promotional environments, are passed through the maximum likelihood procedure to get estimates, π^E_{ij} and γ^E_i. We are interested in the differences $\pi^T_{ij} - \pi^E_{ij}$ and $\gamma^T_i - \gamma^E_i$. Since the $\sum_j \pi^E_{ij} = 1$, it is meaningless to consider $\pi^T_{ij} - \pi^E_{ij}$ for all j. Instead, we choose a random brand for each individual. Gamma bias is measured by performing a two-sided t-test on $\gamma^T_i - \gamma^E_i$. Bias for the π_{ij}'s is measured analogously. The sample is made up of 100 randomly chosen individuals.

From Table 1 we see that the π_{ij}'s appear to be unaffected by bias[6], but when sample sizes become very small, gammas are biased downward. The reason for this bias is closely related to the issue of overfitting discussed earlier. When five or fewer observations are used to estimate about three parameters, at least

one parameter becomes useless. The π_{ij}'s alone explain most of the variance present in such small samples. When a consumer makes so few purchases, it is difficult to make strong conclusions about her promotional sensitivity. Fortunately, most members of our sample make enough purchases to avoid these small sample problems.

[TABLE 1 ABOUT HERE]

A discretized frequency distribution of estimated π_{ij}'s across all 200 consumers for each brand j is given in Figure 2. We see that each brand-size has a mass of consumers with values of π_{ij} between 0 and .05. This mass is largely made up of consumers who never buy the brand-size. The size of that group ranges from 53 consumers for Folgers 1 lb. to 184 consumers for Mellow Roast 1 lb. The bulk of the non-zero π_{ij}'s have values less than .5. Each brand-size has a few consumers with values of π_{ij} greater than .5, but in general the upper tails are thin. Folgers 1 lb. has the thickest upper tail which accounts for the relatively high value of $\pi_{\bullet FOL.S} = .330$.

[Figure 2 About Here]

Figure 3A displays a discretized frequency distribution of values of γ_i across the total sample. We see a spike of highly promotion sensitive consumers and then generally fewer consumers with lower levels of promotion sensitivity until we get to extreme promotion insensitivity where we see another, smaller spike. Figures 3B-3E show the distribution of values of γ_i in each of the four stores in this data base. Store 1, 2 and 3 are members of national chains. Store 4 is a warehouse store. The stores appear to have distinct consumer promotion sensitivity profiles. In particular only the warehouse store (Store 4) has a spike of promotion insensitive consumers and only Store 1 lacks a spike of promotion sensitive consumers. Each store has consumers that display a range of values of promotion sensitivities. On average, the level of promotion sensitivity in the chain stores is higher than in the warehouse store.

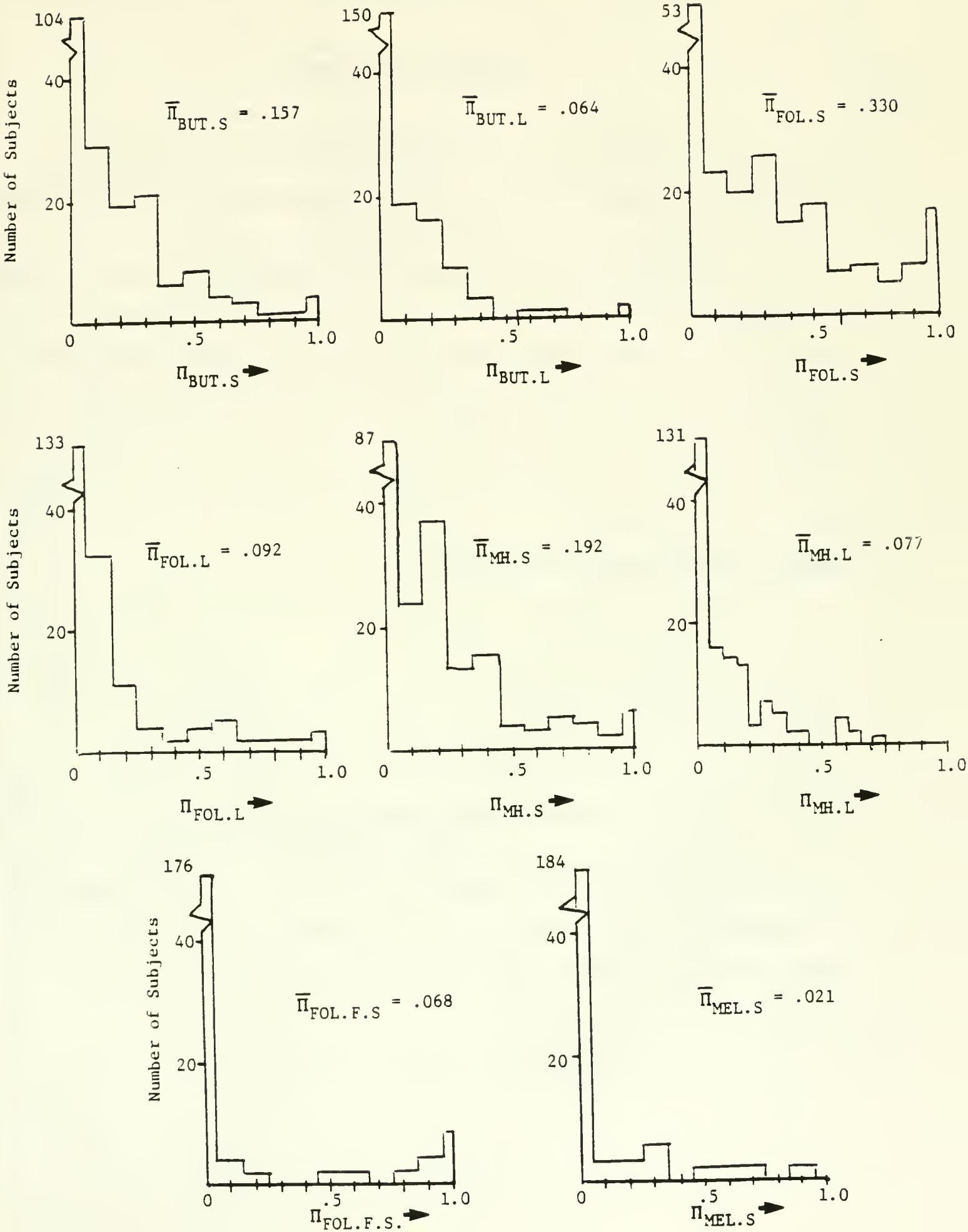
TABLE 1. AVERAGE VALUE OF BIAS IN MODEL PARAMETERS
Number of Simulated Choices

	5	8	10	20
Average $(\gamma^T - \gamma^E)$	-0.108*	-0.047	-0.003	0.002
Average $(\pi^T - \pi^E)$	-0.002	-0.001	-0.005	0.0002

* Significant at $p < 0.01$. All others significant at values of $p > .1$.

FIGURE 2 : FREQUENCY DISTRIBUTION OF VALUES OF Π_{ij}

ACROSS THE 200 SUBJECTS



[Figure 3 About Here]

MANAGERIAL IMPLICATIONS

Since these consumers do not display stockpiling behavior in response to promotions, we can estimate market level statistics by a simple weighted averaging.

[Table 2 About Here]

Having aggregated parameters to estimate market response we can now investigate a number of questions of interest to managers. We begin by considering the effect of promotion on a brand's long run share. We investigate several forces behind the resulting gain or loss in share: brand characteristics, competitive brands' promotional activity and retailer cooperation. We then consider the impact of promotion on expected sales patterns. Finally, we consider the impact of promotion on a brand's profibability.

Impact of Promotions on Long Run Share

The basic unit of analysis will be $f_{ij} - \pi_{ij}$, where f_{ij} is the share of consumer i's choices that go to brand j, and π_{ij} is the share of consumer i's preference that goes to brand j. If no brand ever promoted or if consumer i were insensitive to promotions, then f_{ij} would be expected to equal π_{ij}. If $f_{ij}-\pi_{ij} > 0$, then brand j's promotion calendar was effective on consumer i relative to competitive brands' promotion calendars. Consumer i was induced to buy brand j more frequently than she would have had there been no promotions by any brands. If $f_{ij} - \pi_{ij} < 0$, then brand j's promotion calendar was ineffective on consumer i relative to competitive brands' promotion calendars. Consumer i bought brand j less frequently than she would have had there been no promotions by any brands.

FIGURE 3: FREQUENCY DISTRIBUTION OF VALUES OF γ_i ACROSS 200 SUBJECTS AND WITHIN EACH OF THE FOUR STORES

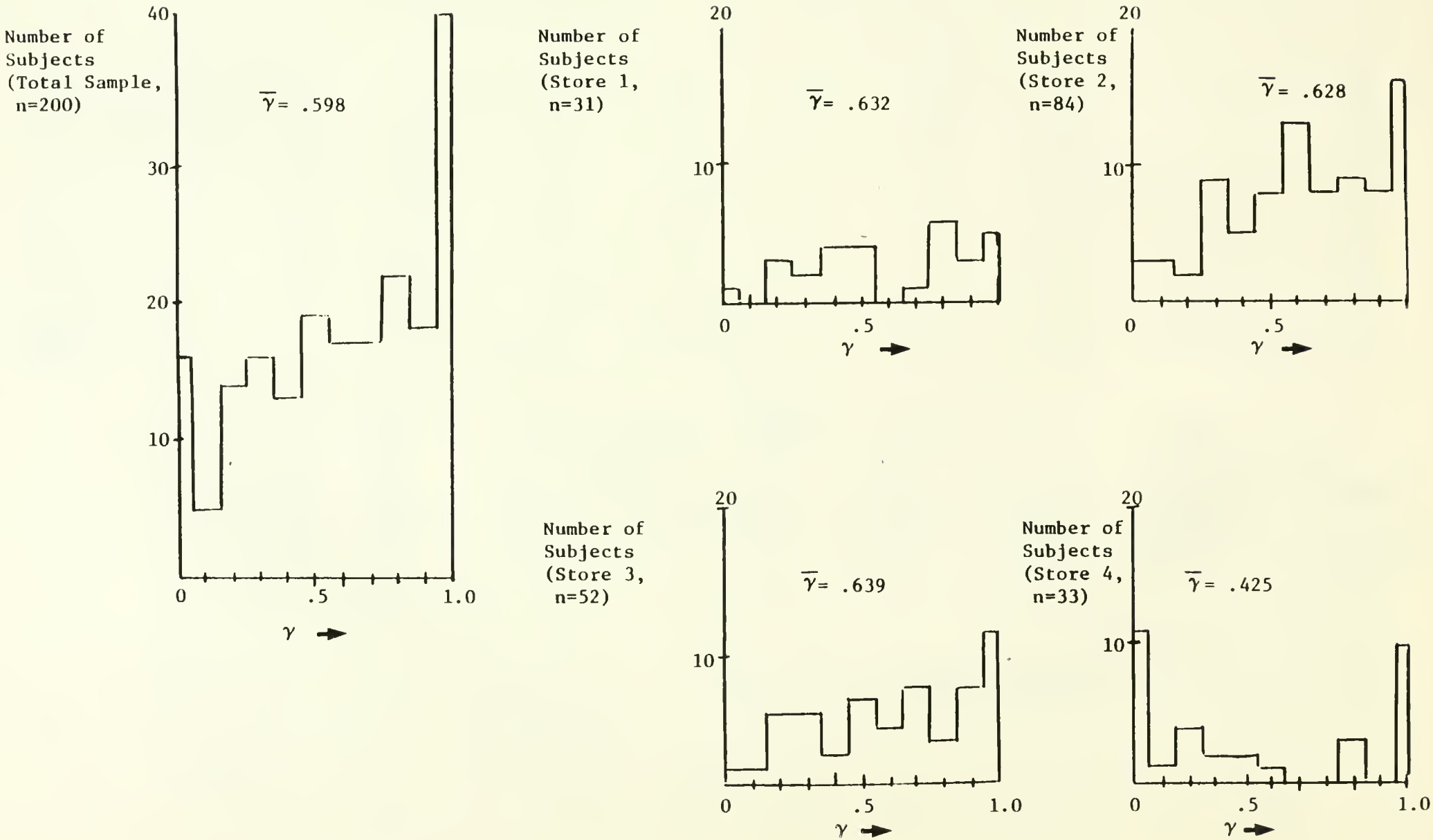


TABLE 2. MARKET RESPONSE PARAMETERS

Brand j	M_j = Market Share Among These 200 Customers	$\pi_{\bullet j}$ = Weighted Average Pref. Share Among Customers	$M_j - \pi_{\bullet j}$ = Weighted Average of $f_{ij} - \pi_{ij}$	α_j = Fraction of Time Brand j was on Promotion	$\bar{\gamma}_j$ = Average Value of γ_i Among Consumers Who Find Brand j Acceptable	$\overline{\gamma\pi_j k_j}$ = Weighted Average of $\left[\frac{\gamma_i \pi_{ij}}{\pi_{ij} + \sum \alpha_j \pi_{ij}}\right]$	$\overline{(1-\gamma)\pi_j}$ = Weighted Average of $[(1-\gamma_i)\pi_{ij}]$	$\overline{\gamma\pi_j \beta_j}$ = Weighted Average of $[\gamma_i \pi_i \Pi(1-\alpha_j)]$ $j \neq 1$ $j \varepsilon e_i$	$L_j = \frac{\overline{\gamma\pi_j k_j} + \overline{(1-\gamma)\pi_j}}{\overline{\gamma\pi_j \beta_j} + \overline{(1-\gamma)\pi_j}}$
Butternut 1 lb.	.171	.157	.014	.254	.64	.186	.063	.050	2.204
Butternut 3 lb.	.098	.064	.034	.223	.71	.100	.016	.018	3.412
Folgers 1 lb.	.284	.330	-.046	.189	.63	.327	.143	.111	1.850
Folgers 3 lb.	.155	.092	.063	.166	.62	.114	.044	.032	2.079
Maxwell House 1 lb.	.140	.192	-.052	.192	.67	.250	.057	.072	2.380
Maxwell House 3 lb.	.106	.077	.029	.176	.71	.118	.019	.021	3.425
Folgers Flake 1 lb.	.030	.068	-.038	.077	.50	.041	.044	.019	1.349
Mellow Roast 1 lb.	.016	.021	-.005	.023	.50	.024	.015	.006	1.857

The third column of Table 2 reports $M_j - \pi_{\cdot j}$, the weighted average of $f_{ij} - \pi_{ij}$ across consumers for each brand j. Folgers 1 lb., Folgers Flake 1 lb., Maxwell House 1 lb., and Mellow Roast 1 lb. are shown to have lost share while Butternut 1 lb. and 3 lb., Folgers 3 lb., and Maxwell House 3 lb. all gained share.[7] From the fourth column of Table 2, we see that Folgers Flake 1 lb. and Mellow Roast 1 lb. promoted much less frequently than did other brands. Given this, it is not surprising that the net effect of all brands' promotions was to lower Folgers Flake 1 lb.'s share and Mellow Roast 1 lb.'s share. Folgers 1 lb. and Maxwell House 1 lb., on the other hand, are among the heaviest promoters and yet they too lost share. This effect seems not to be driven by consumer preferences among manufacturers. Folgers 3 lb. and Maxwell House 3 lb. both gain share despite the fact that they promote less frequently than their 1 lb. counterparts. The effect seems also not to arise from a differential sensitivity of Folgers 1 lb. and Maxwell House 1 lb. consumers to promotions. As reported in the fifth column of Table 2, the average values of γ_i for consumers who chose Folgers 1 lb. and for consumers who chose Maxwell House 1 lb. are in the middle of the range of values that that statistic takes on.

Small Preference Brand Advantage. The following regression sheds some light on the reasons behind Folgers 1 lb.'s and Maxwell House 1 lb.'s share losses. The dependent variable in this regression is $f_{ij} - \pi_{ij}$. With one observation for each brand in each consumer's acceptable set, we have 723 observations. The independent variables are $PROM_{s_i j}$, the standardized frequency[8] of brand j's promotions in store s_i to which consumer i is loyal ; π_{ij}, consumer i's preference for brand j, and dummy variables BUT, FOL and MH that indicate the brand's manufacturer. Note that Mellow Roast has no manufacturer dummy and therefore the coefficients of BUT, FOL and MH should be interpreted as the advantage or disadvantage to those

manufacturers' brands relative to Mellow Roast. The regression[9] is:

$$f_{ij}-\pi_{ij} = \underset{(t=1.31)}{.038} + \underset{(t=2.98)}{.025\ PROM_{s_i j}} - \underset{(t=-18.88)}{.261\ \pi_{ij}}$$

$$+ \underset{(t=0.47)}{.016\ BUT} + \underset{(t=1.36)}{.040\ FOL} + \underset{(t=0.39)}{.012\ MH} \qquad (9)$$

$$\bar{R}^2 = .344$$

$$n = 723$$

Here we see that more frequent promotion leads to higher values of $f_{ij}-\pi_{ij}$, and that Folgers, a brand manufacturered in the Kansas City area, appears to have a slight advantage over other manufacturers' brands. The most important predictor of $f_{ij}-\pi_{ij}$, however, is π_{ij}. We see that larger values of π_{ij} result in smaller values of $f_{ij}-\pi_{ij}$.[10] This regression suggests that Folgers 1 lb. and Maxwell House 1 lb. lost share because they are both relatively high preference brands. As was pointed out earler in this paper, widely accepted, smaller preference brands have an advantage in promoting.

Retailer Favoritism. The value of $\bar{R}^2$ in the regression reported in equation (9) reflects in part, the differences in how different manufacturers' brands are treated in different retail stores. We explore this retailer heterogenity by running the regressions within stores. If a retailer favors one manufacturer's brands over another's (e.g., gives deeper price cuts or better display to one of the manufacturer's brands), this favoritism should show up as a significant coefficient on the dummy variable(s) corresponding to the favored manufacturer(s). The results of those regressions[11] are:

STORE	n	$\bar{R}^2$	CONSTANT	$PROM_{s_i j}$	π_{ij}	BUT	FOL	MH
1	110	.44	-.050	.021	-.297	.084	.141	.157
			(t=-.53)	(t=.62)	(t=-8.07)	(t=.68)	(t=1.44)	(t=1.53)
2	362	.35	.103	.031	-.263	-.061	-.042	-.066
			(t=2.50)	(t=3.21)	(t=-13.20)	(t=-1.29)	(t=-1.02)	(t=-1.55)
3	165	.45	.100	.047	-.343	-.022	.020	-.035
			(t=1.17)	(t=1.51)	(t=-10.93)	(t=-.21)	(t=.23)	(t=.34)
4	86	.22	-.060	.007	-.096	.124	.107	.046
			(t=-1.40)	(t=.39)	(t=-3.41)	(t=2.40)	(t=2.44)	(t=.92)

From these results we see that the negative coefficient for π_{ij} shows itself as the strongest effect within each store. The results also suggest that Store 2 treats all manufacturers' promotions equally, Store 3 favors Folgers, Store 1 favors Folgers and Maxwell House and Store 4 favors Folgers and Butternut.

Such results should be used only as indications of possible retailer bias. Discussions with the sales force could help corroborate these indications and might lead the sales force to discover and hopefully remedy problems of which they might have been unaware.

Impact of Promotion on Sales Patterns

The heavy lines in Figure 4A-4H represent the expected levels of promoted and unpromoted purchase share [12] for the eight brand-sizes in this study. The lower level of the heavy line represents the expected level of the brand-size's baseline purchase share when that brand-size is not being promoted. A peak represents the expected level of the brand-size's purchase share when that brand-size is being promoted. (For example, in Figure 4A we see that Butternut 1 lb. expects a

purchase share of 0.11 when unpromoted and a purchase share of 0.25 when promoted.) The width of the expected promotional purchase share peak reflects the relative frequency with which the brand-size was promoted. (For example, Butternut 3 lb. was promoted three times as frequently as Folgers Flake 1 lb. Consequently, the expected purchase share peak for Butternut 3 lb. is three times as wide as the expected peak for Folgers Flake 1 lb.)

[Figure 4 About Here]

Impact of Promotion on Profitability

L_j, the coefficient of promotional leverage for brand j, is reported in the upper right-hand corners of Figure 4A-4H. (These values are also reported in the last column of Table 2.) L_j is the ratio of the expected promoted share to expected unpromoted share for brand j. Since consumers aren't stockpiling, $L_j M_P > M_N$, implies that B_j can expect to be made more profitable by promoting than by not promoting. If all brands have the same values of M_P and M_N, then Maxwell House 3 lb. and Butternut 3 lb. should expect to find promotion profitable if any brand-size does, since $L_{MH.L}$ and $L_{BUT.L}$ take the largest values. Similarly, Folgers Flake 1 lb., Mellow Roast 1 lb., and Folgers 1 lb. should expect to find promotion profitable only if all other brand-sizes find promotion profitable, since $L_{MEL.S}$, $L_{FOL.F.S}$, and $L_{FOL.S}$ take the smallest values.

Maxwell House 3 lb. and Butternut 3 lb. owe their large values of L_j to the fact that those consumers who choose Maxwell House 3 lb. and Butternut 3 lb. tend to be more promotion sensitive than average. (The fifth column of Table 2 reveals that the average value of γ_i for consumers of these two brands is 0.71, the largest such value in the column.) Mellow Roast 1 lb. and Folgers Flake 1 lb. owe their small values of L_j to the fact that consumers who choose Mellow Roast 1 lb. and Folgers Flake 1 lb. tend to be less promotion sensitive than average (average value of γ_i for consumers of MEL.S and FOL.F.S = 0.50, the smallest value in the fifth column of Table 2.)

FIGURE 4A: EXPECTED PURCHASE SHARE FOR BUTTERNUT 1 LB.

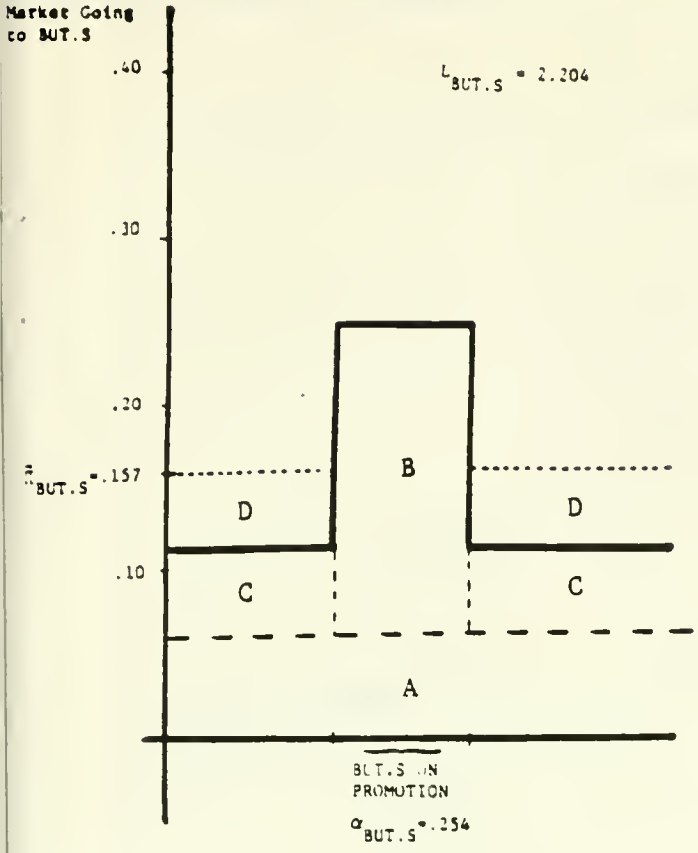


FIGURE 4B: EXPECTED PURCHASE SHARE PATTERN FOR BUTTERNUT 3 LB

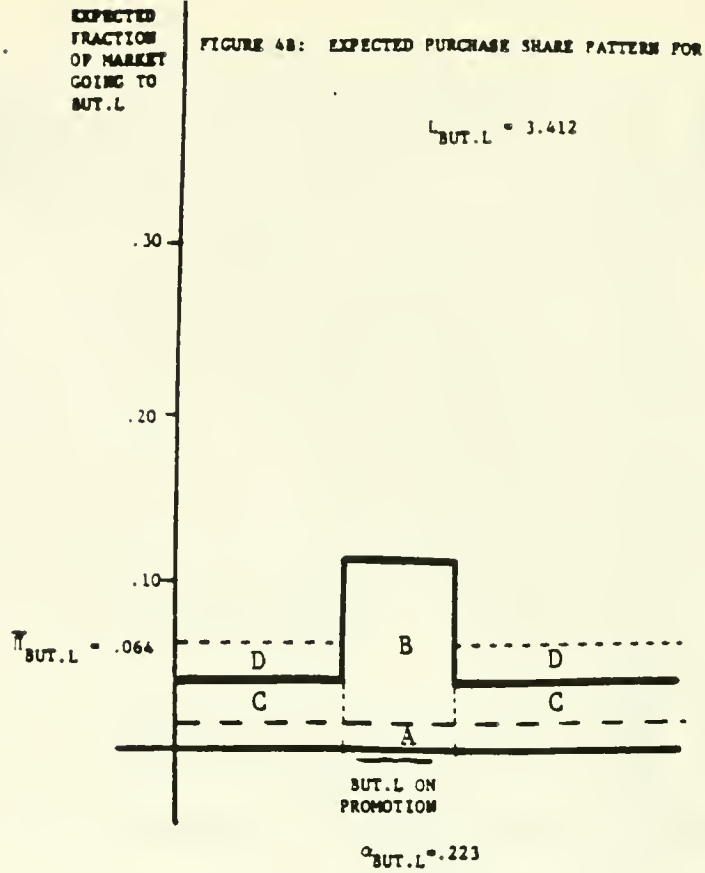


FIGURE 4C: EXPECTED PURCHASE SHARE PATTERN FOR FOLGERS 1 LB.

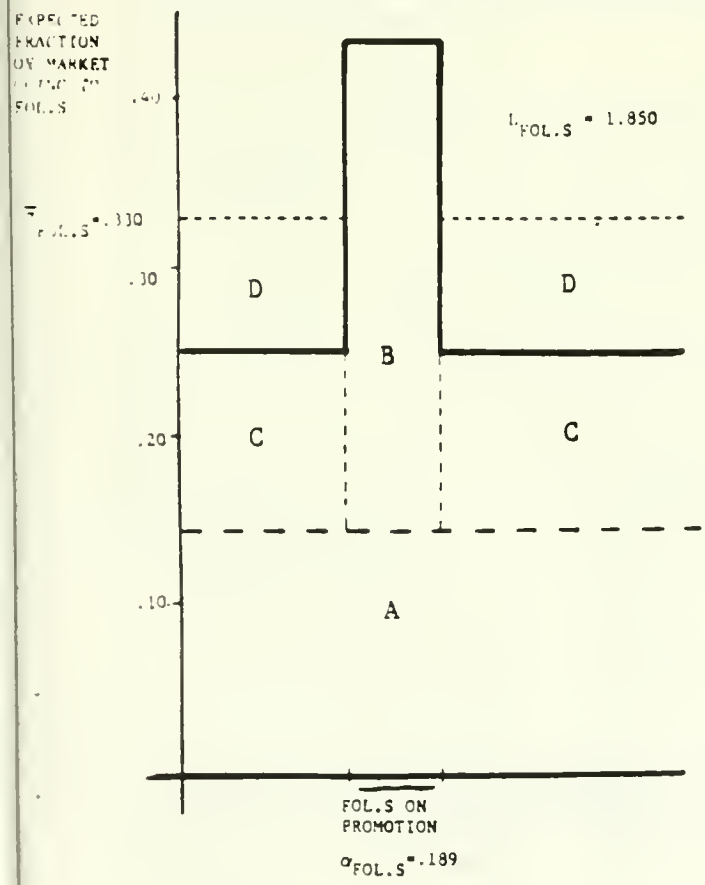


FIGURE 4D: EXPECTED PURCHASE SHARE PATTERN FOR FOLGERS 3 LB.

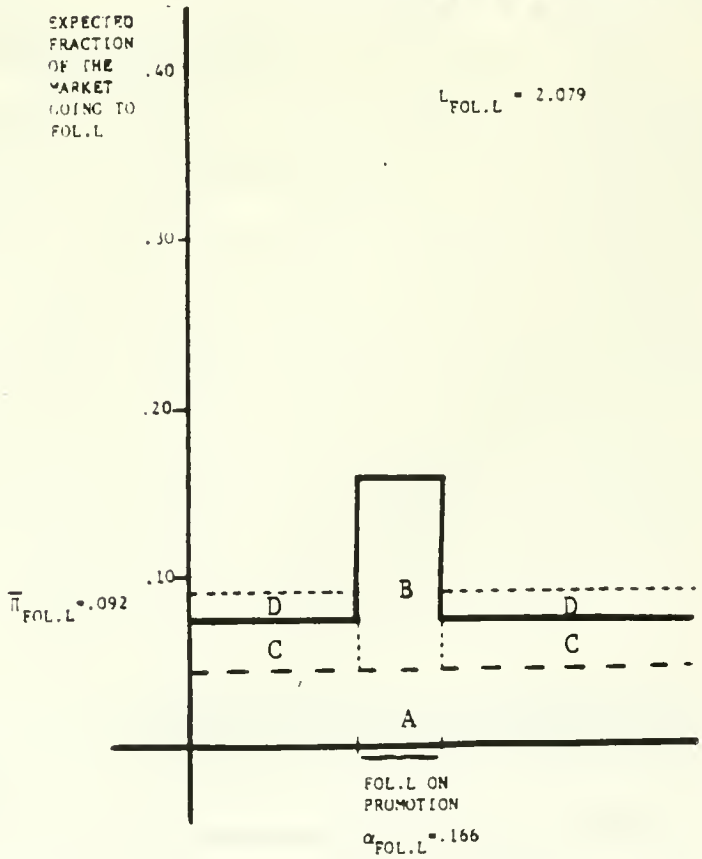


FIGURE 4E: EXPECTED PURCHASE SHARE PATTERN FOR MAXWELL HOUSE 1 LB.

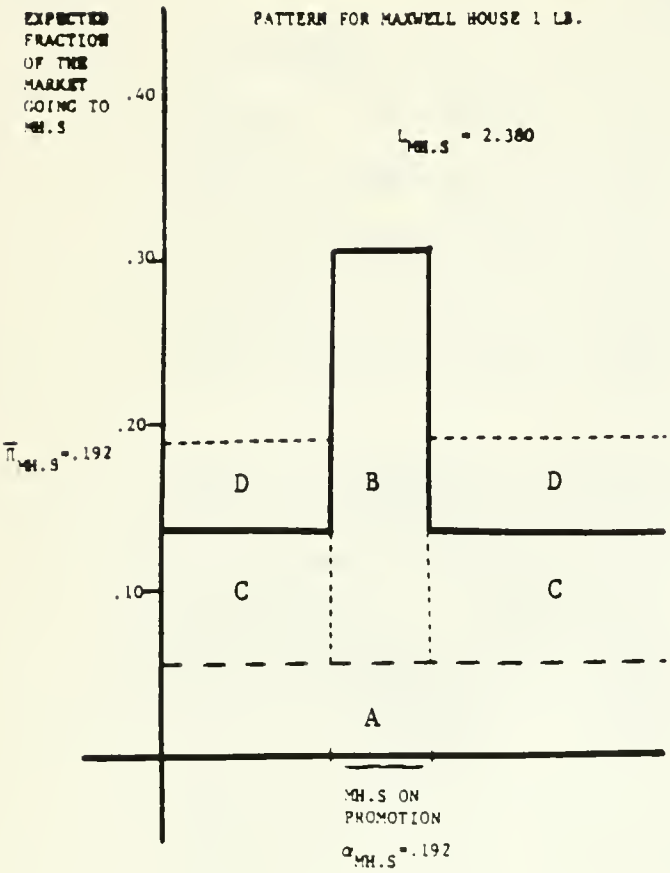


FIGURE 4F: EXPECTED PURCHASE SHARE PATTERN FOR MAXWELL HOUSE 3

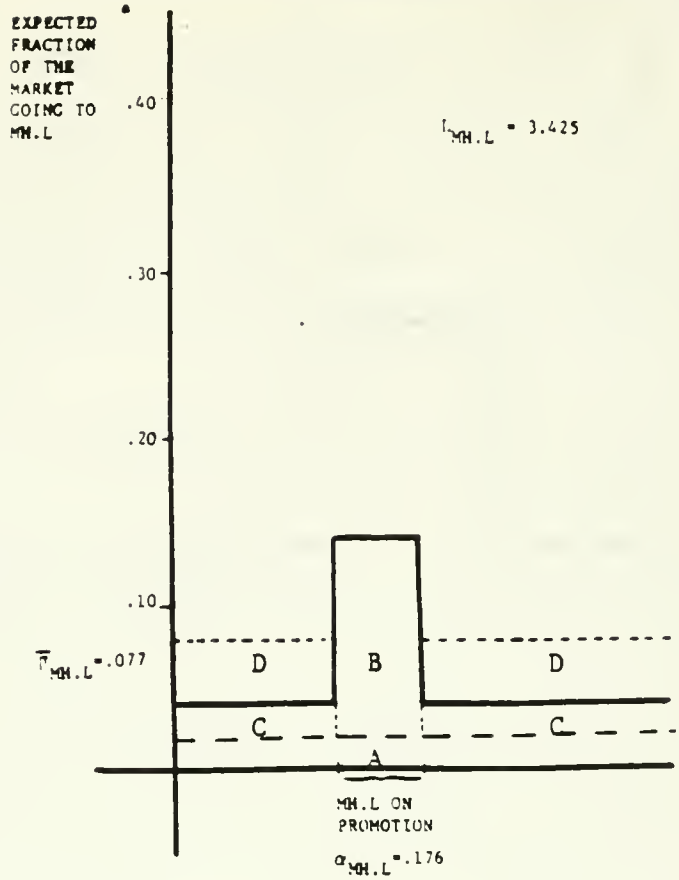


FIGURE 4G: EXPECTED PURCHASE SHARE PATTERN FOR FOLGERS FLAKES 1 LB.

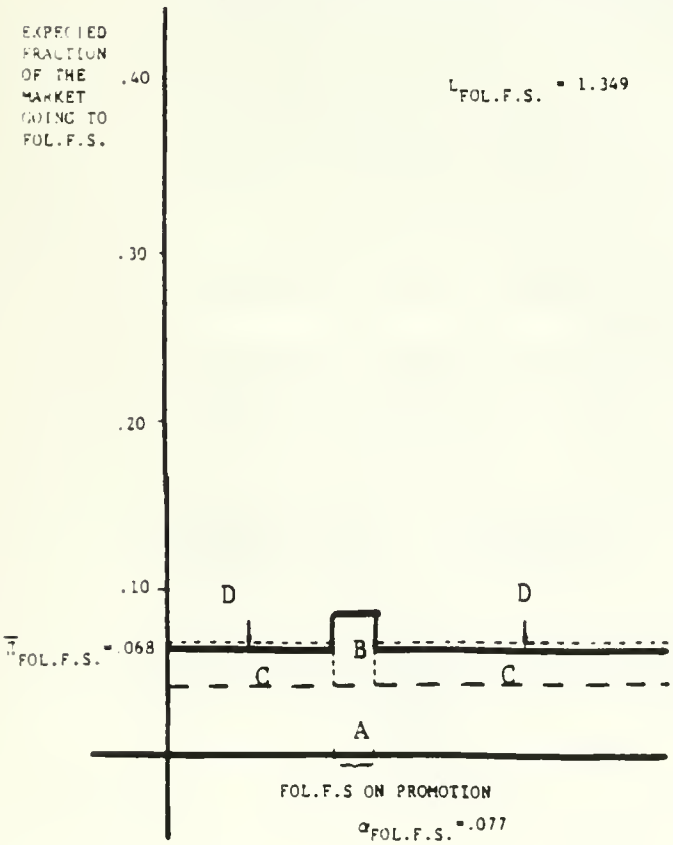
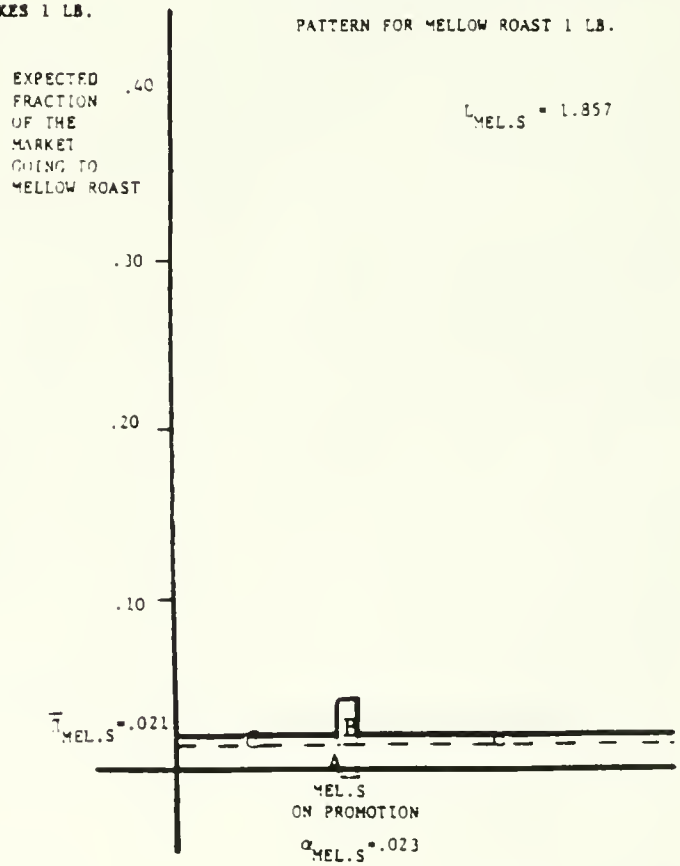


FIGURE 4H: EXPECTED PURCHASE SHARE PATTERN FOR MELLOW ROAST 1 LB.



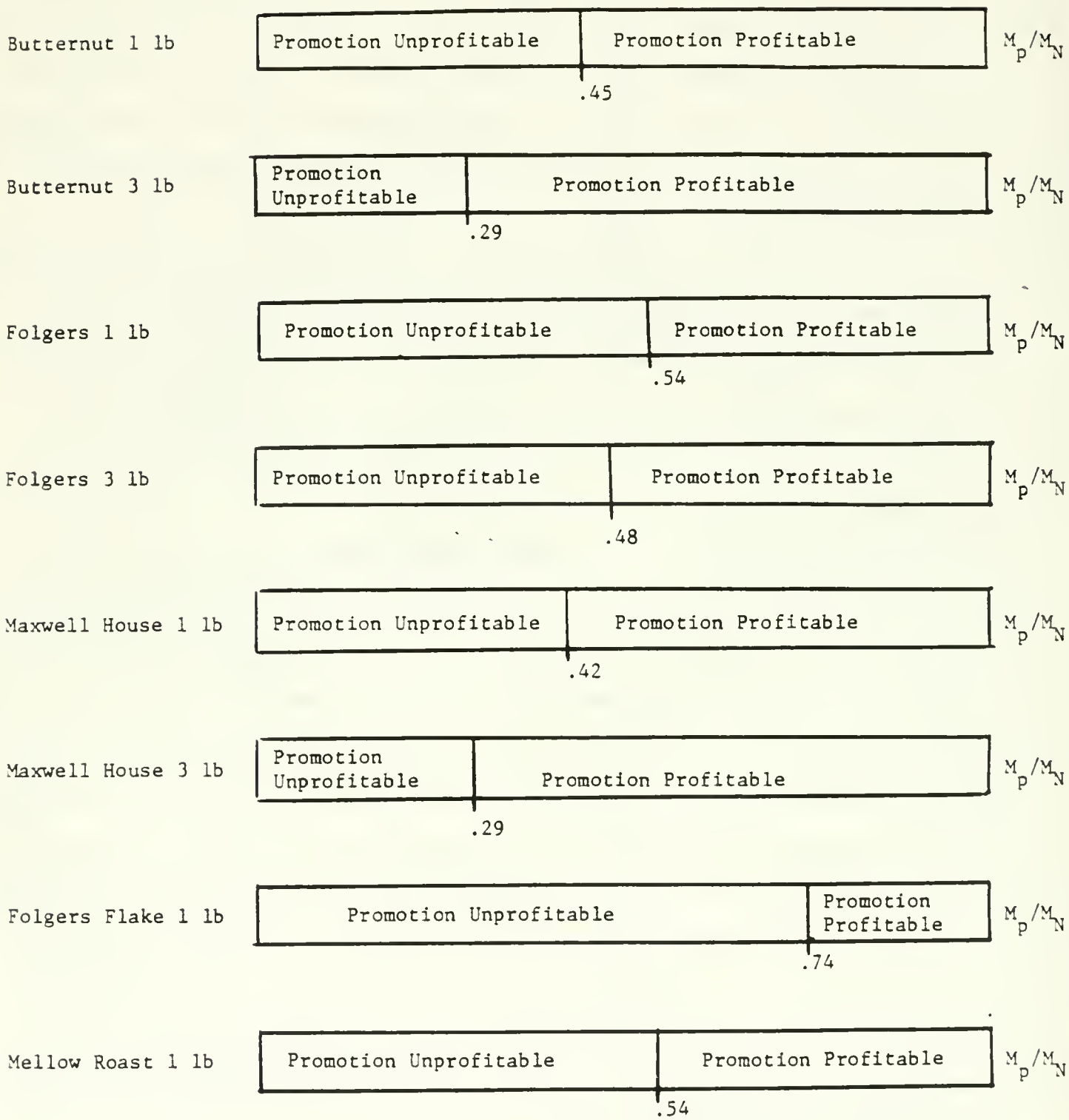
That Folgers 1 lb. has a relatively small value of $L_{FOL.S}$ cannot be completely explained by the promotion sensitivity of Folgers 1 lb. consumers since that value is in the same range as values of average γ_i for brands with higher values of L_j. The driving force here is another manifestation of the "small preference brand effect" noted earlier. L_j is, essentially, the percent increase in share that B_j expects when it promotes. Since the expected unpromoted level of Folgers 1 lb. share is so high, it would require a much larger share increase than the other brand-sizes to expect a similar <u>percentage</u> increase in share as those brands expect.

It is reasonable to expect that promoted profit margin per unit and unpromoted profit margin per unit will differ across brand-sizes. Letting M_{Pj} and M_{Nj} be the promoted and unpromoted profit margin per unit, respectively, for B_j, then B_j will find promotion profitable is $M_{Pj}/M_{Nj} > 1/L_j$. Figure 5 graphs the optimal promotion policy for each brand-size as a function of the ratio of its unpromoted to promoted margin, M_{Pj}/M_{Nj}:

[FIGURE 5 ABOUT HERE]

If a brand-size must give up almost its entire profit margin in order to be promoted, then M_{Pj}/M_{Nj} will be "small" (in this case, $M_{Pj}/M_{Nj} < 0.29$ is "small") and any of the eight brand-sizes in this study will make less profit promoting than by not promoting. For values of $M_{P,BUT.L}/M_{N,BUT.L}$ and $M_{P,MH.L}/M_{N,MH.L}$ greater than 0.29, Butternut 3 lb. and Maxwell House 3 lb. make more profit by promoting than by not promoting. Similarly, for $M_{P,MH.S}/M_{N,MH.S} > 0.42$, $M_{P,BUT.S}/M_{N,BUT.S} > 0.45$, $M_{P,FOL.S}/M_{N,FOL.S} > 0.54$, $M_{P,MEL.S}/M_{N,MEL.S} > 0.54$, $M_{P,FOL.F.S}/M_{N,FOL.F.S} > 0.74$, Maxwell House 1 lb., Butternut 1 lb., Folgers 1 lb., Mellow Roast 1 lb., and Folgers Flake 1 lb., respectively, make more profit by promoting than by not promoting. If it costs a manufacturer very little to promote, then M_{Pj}/M_{Nj} will be "large" (in this case $M_{Pj}/M_{Nj} > 0.74$ is "large"), and it will be more profitable for any of these eight brand-sizes to promote than to not promote.

FIGURE 5: BRAND-SIZE SPECIFIC OPTIMAL PROMOTION POLICIES AS A FUNCTION OF M_p/M_N



SUMMARY AND CONCLUSIONS

Market response to promotion was shown to be a function of competitive promotional activity and heterogeneous' consumers tastes and promotional responses. Smaller preference brands (rather than larger preference brands as suggested by Blattberg, Eppen and Lieberman 1981 and Fraser 1983) were shown to "get more bang for their promotion buck". Further, we found that a brand's expected baseline level of unpromoted sales and its expected promotional sales peak are depressed by its own promotions if consumers react to promotions by stockpiling. Expected sales levels are depressed by competitor's promotions if consumers react to promotions by increasing the probability of choosing the brand on promotion. We also showed that promotion is unprofitable if consumers are not promotion sensitive or if they respond to promotions by stockpiling the brand they would have bought anyway. Promotion becomes profitable if the number of consumers who can be persuaded to switch to the promoted brand is sufficient to make up for the profit foregone by offering the lower, promoted price to those consumers who would have bought the brand anyway.

Using data from 200 store loyal households in the 1978-1980 SAMI Kansas City scanner panel we estimated individual level models of consumer response to promotion. The models were shown to have predictive validity and the parameter estimates were shown to be expected to be unbiased.

Investigation of response parameters showed that brands are more likely to gain share due to promotions if they promote more frequently and if they are widely accepted but smaller preference brands. Analyses at the level of the retail stores showed that different stores appear to favor different manufacturers and that favoritism also affects promotion effectiveness.

We aggregated individual level response parameters to estimate market level promotion response. The ratio of a brand's expected promoted share to its expected

unpromoted share defines its coefficient of promotional leverage. If this coefficient is larger than the ratio of the brand's promoted margin to unpromoted margin (M_P/M_N) it is more profitable for that brand to promote than to not promote. Among the widely accepted brands, that coefficient was larger for smaller preference brands, once again consistent with the small preference brand advantage.

It is interesting to note that the effect of promotion on long run market share is independent of the effect of promotion on profitability. If $M_P/M_N = .44$ for these brands, Maxwell House 1 lb. would have found promotion profitabile despite the fact that it lost long run share due to promotion. Butternut 1 lb., on the other hand, would have found promotion unprofitable despite the fact that it gained long run share due to promotion.

This modeling effort should be extended in several ways. The model should accommodate increasing levels of market response for increasing promotional offers. The model form should be adapted to account for differing responses to differing promotional instruments (e.g., price discount, manufacturer coupon, display). The resulting promotional response profiles could then be correlated with demographic data. It would also be useful to estimate the model in different product classes to develop intuition concerning the product class determinants of promotion response. Finally, the interaction between promotion and advertising in stimulating consumer response should be investigated.

APPENDIX

The Bias Test Procedure

(1) Choose a γ_i and set of π_{ij}'s by drawing a random consumer from the panel of 200. Estimate the proposed model using all 65 weeks. Call the resulting γ_i and π_{ij}'s the "true parameters" γ_i^T and π_{ij}^T (j=1 through 8).

(2) Randomly choose a specific number of store environments from the 260 different environments (4 stores x 65 weeks) present in the database. The number of environments used, NENV, will be set to different values, ranging from 5 to 20.

(3) For each of the NENV purchase occasions, calculate choice probabilities for all eight brands by applying equation (1) to the parameters from step 1 and the promotional environments from step 2.

(4) Simulate a brand choice decision by using the choice probabilitaies from step 3 and choosing a random number.

(5) After steps 3-4 have been performed for each of the NENV synthetic purchase occasions, we have a full purchase history. There is now sufficient data to run the MLE procedure. The end result is a γ_i^E and a set of π_{ij}^E's. When there is no bias, $\gamma_i^E = \gamma_i^T$ and $\pi_{ij}^E = \pi_{ij}^T$ for all j.

FOOTNOTES

1 "Car-Rental Firms Sling it Out with Golf Balls and Tote Bags", Wall Street Journal, December 15, 1982, p. 29.

2 From Robert L. Simison's article "Why are Auto Sales Strictly for the Birds? Just Ask Any Pigeon", Wall Street Journal, December 15, 1982, page 1.

3 Other studies have attempted to characterize promotion sensitive consumers with demographic and psychographic variables (Webster 1965, Massy, Frank and Lodahl 1968, Montgomery 1971, Blattberg, Buesing, Peacock and Sen 1978, Narisimhan 1984). In general, these studies show that education, income and other household resource variables do effect promotion sensitivity, though often in complicated ways.

4 To see this let V_{it} = 1 if consumer i is "in the market" at time t and = 0 if consumer i is not "in the market" at time t (i.e., is consuming stockpiled product rather than buying more units at time t). Then

$$V_{i,t+1} = V_{it}\,(\gamma_i \beta_{i1}(1-\alpha_1)+(1-\gamma_i))+(1-V_{it})(1/(n_i-1))$$

That is, if consumer i is "in the market" at time t (V_{it}=1) then she will only be "in the market" at time t+1 if she wants to restrict her choice at time t to promoted brands brands but finds no brand on promotion ($\gamma_i \beta_{1t}(1-\alpha_1)$) or if she is not reacting to promotions at time t ($1-\gamma_i$). If consumer i is not "in the market" at time t (V_{it} = 0, therefore $1-V_{it}$ = 1) then there is a $1/(n_i-1)$ chance that she will exhaust her stockpile in period t and return to the market at time t+1. If we solve the above equation for an equilibrium value of V_i, we get

$$V_i = V_i(\gamma_i \beta_{i1}(1-\alpha_1)+(1-\gamma_i))+(1-V_i)(1/(n_i-1))$$

$$\text{or } V_i = \frac{1}{1+(n_i-1)\gamma_i(1-\beta_{i1}(1-\alpha_1))}\ .$$

5 The period December 29, 1978 to March 12, 1980 is made up of 65 weeks. We ignore the last week of this data in testing the predictive ability of the model in order to be consistent with the data usage pattern in Guadagni and Little (1983).

6 The lack of bias in the estimates of π_{ij}'s, even for small sample sizes probably results from the choice of starting values for the maximum liklihood procedure. The initial guess for π_{ij} that is passed to the algorithm is f_{ij}, the frequency with which consumer i chooses brand j.

7 Relevant n's, Wilcoxon statistics and p values associated with the differences are:

Brand	test n	Wilcoxan Statistic for $\overline{f_{ij} - \pi_{ij}}$	p
Butternut 1 lb.	79	2453.0	.000
Butternut 3 lb.	40	438.0	.712
Folgers 1 lb.	108	2394.0	.093
Folgers 3 lb.	60	1145.0	.091
Maxwell House 1 lb.	93	2304.0	.650
Maxwell House 3 lb.	57	1066.0	.058
Folgers Flake 1 lb.	23	72.5	.048
Mellow Roast 1 lb.	10	3.0	.014

8 Letting F_{sj} = fraction of time brand j is on promotion in store s, $\bar{F}_s$ = the average length of time any brand is on promotion in store s, and σ_{sF} = the standard deviation of the fractions of time any brand is on promotion in store s we have $PROM_{sj} = (F_{sj} - \bar{F}_s)/\sigma_{sF}$

9 Since $\sum_{i,j} f_{ij} - \pi_{ij} = 0$, $\sum_{i,j} PROM_{s_i j} = 292$, $\sum_{i,j} \pi_{ij} = 200$, $\sum_{i,j} BUT = 193$, $\sum_{i,j} FOL = 295$, $\sum_{i,j} MH = 219$, we must impose constraints on the model's coefficients to guarantee logical consistency (McGuire and Weiss 1976).

9 (cont.)

Imposition of these constraints requires suppressing the constant and replacing predictors π_{ij}, $PROM_{s_i j}$, BUT, FOL, and MH with (π_{ij} - 200/723), ($PROM_{s_i j}$ - 292/723), (BUT - 193/723), (FOL - 295/723), (MH - 219/723). We then get

$$f_{ij} - \pi_{ij} = \underset{(t=2.98)}{.025\ PROM_{s_i j}} - \underset{(t=-18.89)}{.261\ \pi_{ij}}$$

$$+ \underset{(t=.47)}{.016\ BUT} + \underset{(t=1.37)}{.040\ FOL} + \underset{(t=.39)}{.012\ MH}$$

Since the constant has been suppressed, we cannot report an $\bar{R}^2$ value. Notice that the magnitudes and signs of the coefficients are unchanged.

10 One might think that the negative coefficient of π_{ij} in the regression reported in equation (9) is driven by the fact that π_{ij} is subtracted from f_{ij} to obtain the dependent variable. This is not, however, the driving force behind the sign of that coefficient. We can rerun regression (9) substituting f_{ij} for π_{ij} as a predictor and we get:

$$f_{ij} - \pi_{ij} = \underset{(t=.93)}{.008} + \underset{(t=2.15)}{.009\ PROM_{s_i j}} - \underset{(t=-5.08)}{.054\ f_{ij}}$$

$$+ \underset{(t=.04)}{.001\ BUT} - \underset{(t=-.27)}{.002\ FOL} - \underset{(t=-.46)}{.005\ MH}$$

$\bar{R}^2 = .02$

$n = 723$

Here we see that the coefficient of relative promotion frequency is still positive and that the coefficient of f_{ij} (a surrogate for π_{ij}) is

10 (cont.)

negative. This despite the fact that f_{ij} is added to form the dependent variable. $\bar{R}^2$ drops dramatically indicating that f_{ij} is a poor surrogate for π_{ij}. The implication is that small preference brands have an advantage in promoting and that f_{ij} tends to be smaller when π_{ij} is smaller and vice-versa.

11 As before, constraints can be imposed to insure logical consistency. In store k we will have

$$\sum_{i,j} f_{ij}\pi_{ij} = 0, \quad \sum_{i,j} PROM_{s_i j} = S_{PROM,k},$$

$$\sum_{i,j} \pi_{ij} = S_{\pi,k}, \quad \sum_{i,j} BUT = S_{BUT,k}, \quad \sum_{i,j} FOL = S_{FOL,k},$$

$$\sum_{i,j} MH = S_{MH,k} \text{ where:}$$

Store k	n_k = Number of Observations in Store k	$S_{PROM,k}$	$S_{\pi,k}$	$S_{BUT,k}$	$S_{FOL,k}$	$S_{MH,k}$
1	110	44	31	32	42	33
2	362	146	84	98	138	121
3	165	57	52	45	68	48
4	86	45	33	18	47	17

The coefficients and t-statistics that result when the logically consistent regressions are run are summarized below.

Footnotes 11 continued

Store	$PROM_{kj} - (S_{PROM,k}/n_k)$	$\pi_{ij} - (S_{\pi,k}/n_k)$	$BUT - (S_{BUT,k}/n_k)$	$FOL - (S_{FOL,k}/n_k)$	$MH - (S_{MH,k}/n_k)$
1	.021	-.297	.084	.141	.158
	(t=.62)	(t=-8.11)	(t=.68)	(t=1.45)	(t=1.54)
2	.031	-.264	-.061	-.042	-.066
	(t=3.21)	(t=-13.22)	(t=-1.29)	(t=-1.02)	(t=-1.55)
3	.047	-.343	-.022	.020	-.035
	(t=1.52)	(t=-10.96)	(t=-.21)	(t=.23)	(t=-.34)
4	.007	-.096	.124	.107	.046
	(t=.39)	(t=-3.43)	(t=2.48)	(t=2.46)	(t=.92)

Once again we see that the coefficients remain fairly stable when the contraint is imposed.

12 We present expected levels of promoted and unpromoted purchase share rather than expected levels of promoted and unpromoted sales to avoid distortion due to seasonality.

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