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A TWO-STATE MODEL OF PURCHASE INCIDENCE AND BRAND CHOICE

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The authors develop and test a probabilistic model of purchase incidence and brand choice for frequently purchased consumer products. The model incorporates two ways of shopping in a category. Shoppers who have planned their purchasing (made a decision before entering the store) do not process in-store information and show no response to point-of-purchase promotions. Consumers who have not planned their purchasing in a category (deciding at the point of purchase) may process in-store information and may be strongly influenced by promotions. The two modes of information processing are called decision states and are labelled *planned* and *opportunistic*, respectively. The two-state model is calibrated on IRI scanner purchase records for saltine crackers. The model yields a significantly better fit than a one-state nested logit model and provides new insights into the relationship between shopping behavior and consumer purchase response.
(Brand Choice; Purchase Incidence; Nested Logit; Promotion; Shopping Behavior)

1. Introduction

One long-standing rationale for manufacturers' growing spending on trade promotions is the opportunity to influence consumers at the point of purchase. For products sold in supermarkets, point-of-purchase promotion is particularly attractive given the large proportion of grocery purchase decisions made after entering the store. A recent study by the Point-of-Purchase Advertising Institute (POPAI) found that two-thirds of supermarket purchases are the result of an in-store decision (Agnew 1987). This is consistent with previous industry studies and with research conducted by marketing academics which found that approximately 50 percent of grocery purchases can be classified as "unplanned" (POPAI Special Report 1978; Kollat and Willet, 1967; Park, Iyer, and Smith 1989).

The goal of this research is to improve our understanding and prediction of consumer response to in-store promotions by addressing some of the differences between planned and unplanned purchasing. We develop and test a probabilistic model of purchase incidence and brand choice that incorporates these two distinct modes of consumer shopping behavior. We argue that consumers who have planned their purchasing before entering the store will have no need to process in-store information. Having, in effect, already made up their minds, their purchase decisions are unlikely to be influenced by in-store promotions. Consumers who have not planned their purchasing, however, are likely to process in-store information. Thus, they may be strongly influenced by promotions since their purchases, as unplanned, typically occur as the result of a bargain opportunity or

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the chance to fill a forgotten need. We refer to the two modes of shopping behavior as consumer decision states, and label them *planned* and *opportunistic*, respectively.

Our "two-state" model holds that the factors influencing brand choice and purchase incidence decisions will differ depending upon whether the consumer's shopping takes place in the planned or opportunistic state. We model brand choice probabilities in the opportunistic state as a function of prevailing marketing activity (e.g., feature, display, and price) and the consumer's established preferences for the brands in the category. Brand choice in the planned state, however, is determined entirely by established preferences and price and promotion have no impact. We model the probability of purchase incidence in the opportunistic state as a function of household inventory, usage rate, and the current value of a category purchase (itself a function of prevailing marketing activity and established brand preferences). Purchase incidence in the planned state also depends on inventory and usage rate, but current in-store marketing activity carries no influence.

The two-state model extends recent research aimed at achieving a better understanding of consumer purchase behavior. By explicitly taking into account that some consumers on some choice occasions are not directly influenced by point-of-purchase marketing activity, we hope to improve upon the ability of existing models (e.g., Guadagni and Little 1983, Gupta 1988) to fit consumer purchase behavior. Our approach also differs from other recent models suggesting that brand choice may be the result of a two-stage (Landwehr 1986) or phased (Fader and McAlister 1990) decision strategy. The two-state model integrates brand choice *and* purchase incidence, allows for behavioral differences not only across *individuals* but also over *time*, and does not require *a priori* classification of choice occasions in order to be estimated.

We calibrate and test the two-state model with data from a UPC scanner panel of households in the saltine cracker category. With the limitations of secondary data in mind, we identify trait and situational variables influencing the probability that a household is shopping in the planned or opportunistic state. We use three variables, constructed from scanner purchase records, to determine decision state at a shopping occasion: (1) familiarity with the shopping environment, as measured by store loyalty, (2) historical tendency for purchases to be influenced by in-store stimuli, as measured by deal loyalty, and (3) the household's current need to purchase in the category, as measured by household inventory. We calibrate the model cross-sectionally much like Guadagni and Little (1983, 1987). The model parameters are estimated simultaneously by maximum likelihood.

Our results lend strong support to the two-state model formulation. We also find empirical support for behavioral theories relating store loyalty and other factors to shopping behavior and show that these results hold up to cross-validation. Due to the special structure of the two-state model, we also offer insights into the relationship between shopping behavior and purchase response not available from existing models (e.g., the nested logit).

The balance of the paper follows in several sections. §2 develops the conceptual background for the two-state model. §3 presents the model's mathematical specification and describes the measurement of independent variables. §4 describes the data and the results of model calibration and validation. §5 discusses some implications of the two-state model and §6 concludes the paper.

2. Conceptual Development

The behavioral rationale for the two-state model is grounded in consumer information processing. Our core hypothesis is that a consumer who has planned his/her shopping before entering the store is much less likely to undertake external search once inside the store than a consumer who has not planned his/her shopping. The differing propensities for external search translate into differing propensities to process the information available inside the store. Thus, the planned shopper is unlikely to be as influenced by in-store stimuli as the unplanned shopper. This implies differing inputs into the consumer's purchase incidence and brand choice decisions depending upon whether or not the consumer is shopping in the planned or opportunistic state with respect to a given product category.

Bettman (1979) points out that "individuals may use the external memory provided by in-store displays to different extents, and differ in the amount of prior planning done before entering the store" (p. 127). He also notes the differences between decisions made in-store versus out-of-store: "In some cases, processing of alternatives may be carried out prior to arrival in the store environment. . . . The *in-store* method refers to cases where the consumer waits until actually in the store to make the choice. . . . [S]ituational influences may be of different types under the two methods" (p. 186).

Our formal definitions of the planned and opportunistic shopping decision states are:

PLANNED STATE: *A consumer is in the planned decision state with respect to a given product category and shopping occasion if, before entering the store, he or she has* (1) *considered a purchase, and* (2) *made a decision to buy a given brand or not to buy at all.*

OPPORTUNISTIC STATE: *A consumer is in the opportunistic state with respect to a given product category and shopping occasion if, before entering the store, he or she has not considered a purchase or, having considered a purchase, has not decided whether or what to buy.*

Note that our definitions of decision state are specific to a particular shopping occasion and product category. For most frequently purchased consumer products, a visit to a grocery store constitutes a shopping occasion. On a given occasion, a consumer may have planned purchases in some categories, but not in others. This is consistent with the empirical findings of Kollat and Willet (1967) and Park, Iyer, and Smith (1989). Rarely, they find, does any shopper plan *all* of his/her grocery purchases at a given shopping occasion.

In our framework, different factors influence brand choice depending upon the decision state of the consumer. In the opportunistic state, consumers obtain information about the brands in a category not only from internal searches but also from external searches conducted at the point of purchase. External information includes prevailing marketing activity in the category while internal information bears on the consumer's established needs and preferences. In the planned state, consumers access internal information on established needs and preferences and possibly external information outside the store environment, such as recent consumption behavior. We therefore expect their brand choice decisions to be based on established preferences and recent consumption and their purchase incidence decisions to be based on usage rate and level of inventory.

We contend that decision state will vary across households (according to certain household traits) and within households over time (depending upon the situation). At the trait level, some consumers simply plan more of their shopping than others due to a wide variety of demographic (economic necessity, family size, etc.) and/or psychographic reasons. At the situational level, consumers appear more likely to plan their purchasing when shopping in a familiar environment (e.g., Park, Iyer, and Smith 1989) or when facing urgent household needs. Accordingly, and mindful of the limitations of secondary data, we propose to measure and test three factors indicative of decision state:

Familiarity with the shopping environment. We use an index of store loyalty to measure a consumer's familiarity with a store. Following Park, Iyer, and Smith (1989), we expect that consumers shopping in a relatively familiar environment will be more likely to have planned their purchases in advance. With the store-loyalty measure, we seek to explain variation in decision state across consumers (since households have different patterns of store loyalty) as well as over time (since a household may shop in both familiar and unfamiliar stores).

Category deal loyalty. Consumers who make a large proportion of their category purchases on deal are also likely to be the consumers who have postponed their decisions until after entering the store. By our definition, these are opportunistic shoppers. While some planned purchases may be coincident with discounts, it is unlikely that such coincidences would occur all or even most of the time. Thus, we believe that deal-loyal, or deal-prone (e.g., Webster 1965), consumers are more likely to be those who either "plan" to shop opportunistically (on the look-out for a discount) or those who rely on in-store stimuli as reminders. To capture this variation in decision state, we use an index of each household's category deal loyalty.

Household inventory level. With each purchase from a given category, the household replenishes its inventory of the product. If the supply on hand is still sufficient before the next shopping trip, the consumer is likely to plan *not* to purchase from the category (since the pantry is full and need for the product is low). Hence, immediately following a category purchase the probability that the consumer is in the planned state is relatively high. As time passes, the household draws down its inventory. With a lower supply on hand, the household has room to take on additional inventory, but may do so only if there is a special purchase opportunity (e.g., a price promotion) to provide the incentive. Thus, as the home inventory of the product decreases, the consumer is more likely to approach the category in the opportunistic state. We therefore expect to see a positive relationship between inventory and planned purchase behavior.[1]

3. The Two-State Model

The two-state model is a disaggregate probabilistic choice model for a given product category that is conditional upon a shopping occasion. We define a shopping occasion to be a visit to any grocery store in the market area. Given a shopping occasion at time t, the model represents the probability that household h purchases brand i.

In the planned state, which occurs with probability $P_t^h(\text{plan})$, a shopper will purchase from the category with probability $P_t^h(\text{inc}\,|\,\text{plan})$ and choose brand i with probability $P_t^h(i\,|\,\text{inc \& plan})$. In the opportunistic state, which occurs with probability $P_t^h(\text{opp}) = 1 - P_t^h(\text{plan})$, a shopper will purchase from the category with probability $P_t^h(\text{inc}\,|\,\text{opp})$ and choose brand i with probability $P_t^h(i\,|\,\text{inc \& opp})$. The overall probability that household h purchases brand i at a given store visit is

$$P_t^h(i) = P_t^h(\text{plan})P_t^h(\text{inc}\,|\,\text{plan})P_t^h(i\,|\,\text{inc \& plan}) + P_t^h(\text{opp})P_t^h(\text{inc}\,|\,\text{opp})P_t^h(i\,|\,\text{inc \& opp}). \quad (1)$$

In each decision state, we model the probabilities of brand choice and purchase incidence as a nested logit[2] (e.g., McFadden 1981, Guadagni and Little 1987), where the probability of purchase incidence is a function of the expected maximum utility of the brand choice outcome.

[1] At very low levels of inventory, the probability of planned purchase may increase, as the consumer decides in advance to go out and buy the product. However, this type of planned purchase will occur only after two conditions are met: (1) the household exhausts its inventory, and (2) an occasion arises in which the household has a need for the product. Unfortunately, our model of household inventory is too rough to accurately predict the occurrence of condition (1) and we have no information with which to pinpoint the occurrence of condition (2). We are therefore best able to track the shifts in decision state at higher levels of inventory where our measurements are more reliable.

[2] We have not attempted to model purchase quantity in the two-state model. Thus, our approach should not be used to predict category volume unless the frequency of multi-item purchases is low.

We now outline the mathematical specification and measurement of variables for each of the six probability terms given in the right-hand side of equation (1).

Planned vs. Opportunistic State

We model the probability that a household is in the planned decision state for a shopping occasion as a binomial logit function of deal loyalty, store loyalty, and inventory. The planned and opportunistic state probabilities are

$$P_t^h(\text{plan}) = \frac{\exp(W)}{1 + \exp(W)}, \qquad \text{and} \tag{2}$$

$$P_t^h(\text{opp}) = 1 - P_t^h(\text{plan}) \tag{3}$$

where

$W = \delta_0 + \delta_1 \mathrm{DL}^h + \delta_2 \mathrm{SL}_t^h + \delta_3 \mathrm{INV}_t^h$,
DL^h = deal loyalty of household h,
SL_t^h = loyalty of household h to the store visited at time t,
INV_t^h = index of inventory for household h at time t, and
$\delta_0, \delta_1, \delta_2, \delta_3$ = parameters to be estimated.

From the discussion above, we hypothesize that $P_t^h(\text{plan})$ will be negatively related to DL^h, positively related to SL_t^h, and positively related to INV_t^h. Thus, we expect $\delta_1 < 0$, $\delta_2 > 0$, and $\delta_3 > 0$. Unlike the elimination by aspects model proposed by Fader and McAlister (1990), our model accounts for variation in decision state not only across households but also over time.

Brand Choice

We model the conditional probability that a household chooses brand i using a multinomial logit model. In the planned state, brand choice probabilities depend on established brand preferences and recent choice behavior, which we model using brand loyalty and last brand purchased, respectively. The probability of choosing brand i given a purchase in the planned decision state is

$$P_t^h(i \mid \text{inc \& plan}) = \frac{\exp(U_{i|\text{plan}})}{\sum_k \exp(U_{k|\text{plan}})}, \tag{4}$$

where

$U_{i|\text{plan}} = \alpha_i + \beta_1 \mathrm{LOY}_i^h + \beta_2 \mathrm{LP}_{it}^h$,
LOY_i^h = loyalty of household h to brand i,
LP_{it}^h = indicator of whether brand i last purchased by h, and
$\alpha_i, \beta_1, \beta_2$ = parameters to be estimated.

In the opportunistic state, brand choice probabilities depend on brand preferences and prevailing marketing activity, which we capture with brand loyalty, price, and promotion. The probability of choosing brand i given a purchase in the opportunistic state is

$$P_t^h(i \mid \text{inc \& opp}) = \frac{\exp(U_{i|\text{opp}})}{\sum_k \exp(U_{k|\text{opp}})}, \tag{5}$$

where

$$U_{i|\text{opp}} = \gamma_i + \beta_1 \mathrm{LOY}_i^h + \beta_3 \mathrm{PRICE}_{it} + \beta_4 \mathrm{PROMO}_{it} + \beta_5(\mathrm{PRICE}_{it} \times \mathrm{PROMO}_{it}),$$

PRICE_{it} = shelf price of brand i (including discounts) for occasion t,

PROMO_{it} = 1 if brand i is featured or displayed on occasion t and 0 otherwise, and

$\gamma_i, \beta_1, \beta_3, \beta_4, \beta_5$ = parameters to be estimated.

We include the term LOY_i^h in the utility functions $U_{i|\text{plan}}$ and $U_{i|\text{opp}}$ to account for the differences in established brand preferences across households.[3] We expect $\beta_1 > 0$. In the planned state (and in the absence of strong variety seeking behavior), the influence of recent choice and consumption experience with a brand should be reinforcing and we expect $\beta_2 > 0$. In capturing prevailing marketing activity, we expect price to have a negative effect ($\beta_3 < 0$) and promotion to have a positive effect over the entire range of price ($\beta_4 > 0$). We also include an interaction term between price and promotion to capture differences between promoted price changes and regular price changes. If, for example, the presence of promotion mitigates the negative effect of price on utility, then we expect to see $\beta_5 > 0$ (see also Lattin and Bucklin 1989).

Purchase Incidence

In the nested logit framework, the probability of category purchase incidence depends upon the expected maximum utility from the brand choice decision. This expected maximum utility reflects the category value, CV, to household h at time t. Ben-Akiva and Lerman (1985) show that CV is given by the log of the denominator of the brand choice probability. In the planned state $\text{CV}_{\text{plan}} = \ln\left(\sum_k \exp(U_{k|\text{plan}})\right)$, which reflects only the established brand preferences and recent purchase activity by the household. In the opportunistic state, $\text{CV}_{\text{opp}} = \ln\left(\sum_k \exp(U_{k|\text{opp}})\right)$, which reflects not only established brand preferences but also the marketing activity in the category at purchase occasion t.

For planned shopping behavior, the probability of purchase incidence is a binomial logit function of household consumption rate, inventory, and category value:

$$P_t^h(\text{inc}\,|\,\text{plan}) = \frac{\exp(V_{\text{plan}})}{1 + \exp(V_{\text{plan}})} \tag{6}$$

where

$V_{\text{plan}} = \theta_0 + \theta_1 \text{CR}^h + \theta_2 \text{INV}_t^h + \theta_3 \text{CV}_{\text{plan}}$,

CR^h = category consumption rate for household h,

INV_t^h = inventory of household h, on occasion t, and

$\theta_0, \theta_1, \theta_2, \theta_3$ = parameters to be estimated.

For opportunistic shopping behavior, we use a similar expression:

$$P_t^h(\text{inc}\,|\,\text{opp}) = \frac{\exp(V_{\text{opp}})}{1 + \exp(V_{\text{opp}})} \tag{7}$$

where

$V_{\text{opp}} = \theta_4 + \theta_1 \text{CR}^h + \theta_2 \text{INV}_t^h + \theta_5 \text{CV}_{\text{opp}}$, and

$\theta_4, \theta_1, \theta_2, \theta_5$ = parameters to be estimated.

Because probability of purchase should be positively related to household consumption rate, we expect $\theta_1 > 0$. When inventories are high (after a product purchase, for example), a household should be less likely to buy in the category, so we expect $\theta_2 < 0$. Finally,

[3] Because we expect the source of variation due to preference to be the same in both the planned and opportunistic states, we have constrained the parameter β_1 to be the same in both $U_{i|\text{plan}}$ and $U_{i|\text{opp}}$. Doing so enhances the stability of the model structure (i.e., improves convergence and avoids capitalization on chance variation) and preserves an additional degree of freedom.

purchase incidence should be positively related to category value; hence, we expect $\theta_3 > 0$ and $\theta_5 > 0$.[4]

Substituting equations (2)–(7) into equation (1) yields the expression for the probability that household h purchases brand i at shopping occasion t. The two-state model is diagrammed in Figure 1.

Measures

The two-state model requires the construction of several variables. For the brand choice component, we create LOY_i^h and LP_{it}^h:

$$\mathrm{LOY}_i^h = \frac{(1/n + \text{number of purchases of } i \text{ by } h)}{(1 + \text{number of purchases of all brands by } h)}, \quad \text{and}$$

$\mathrm{LP}_{it}^h = 1$ if brand i was last purchased by household h and 0 otherwise.

where n equals the number of brands.[5]

In the purchase incidence component, consumption rate, CR^h, is measured as the average weekly consumption of saltines in pounds by household h. This is computed as total number of pounds of saltines purchased by h in the initialization period divided by the number of weeks in the initialization period. In constructing our inventory measure, INV_t^h, we assume that households draw down their inventories linearly according to the estimated rate of consumption, CR^h. We initialize our inventory measure with a zero starting value and then compute inventory using the recursive equation[6]

$$\mathrm{INV}_t^h = \mathrm{INV}_{t-1}^h + Q_{t-1}^h - \mathrm{CR}^h \cdot I_{t-1,t} \tag{8}$$

where

Q_{t-1}^h = quantity of product bought on store visit $t-1$ by household h, and
$I_{t-1,t}$ = interval of time between store visit $t-1$ and t.

To make the measure purely longitudinal, we mean-centered INV_t^h by subtracting each household's *average* level of inventory during the calibration period. Thus, INV_t^h becomes a measure of *relative* inventory within a household. Lastly, we specify the measures for store loyalty (SL_t^h) and the deal loyalty (DL^h) as

SL_t^h = proportion of household h's *total* expenditures made in the initialization period in the store being visited on occasion t, and
DL^h = proportion of household h's purchases in the initialization period made when the brand purchased was being promoted.

[4] Note that the intercept (θ_4) and category value (θ_5) parameters are distinct from those in the planned incidence expression, but the consumption rate (θ_1) and inventory (θ_2) are the same. We do this for the same reasons that we fix the coefficient of LOY_i^h in the brand choice models. First, we expect the source of variation related to household consumption behavior to be the same across both decision states; second, it aids in simplifying and stabilizing the model.

[5] Our loyalty measure is designed to capture the heterogeneity in brand preference across households in this cross-sectional model. Because ours is a stationary measure (it is a Bayesian estimate based on equally likely priors with an equivalent sample size of one), it cannot track changes in preferences over time like a measure based on an exponential smoothing model (e.g., Guadagni and Little 1983).

[6] For some households, our measure of CR^h during the initialization period proved to be a poor reflection of actual consumption rate in the calibration period. To obtain a more robust measure of inventory, we recomputed INV_t^h and truncated the values at ± 3 (i.e., we never permitted the inventory measure to go above 3 lbs. or below -3 lbs.). This truncation affected fewer than 10 percent of the values in the original, nontruncated measure.

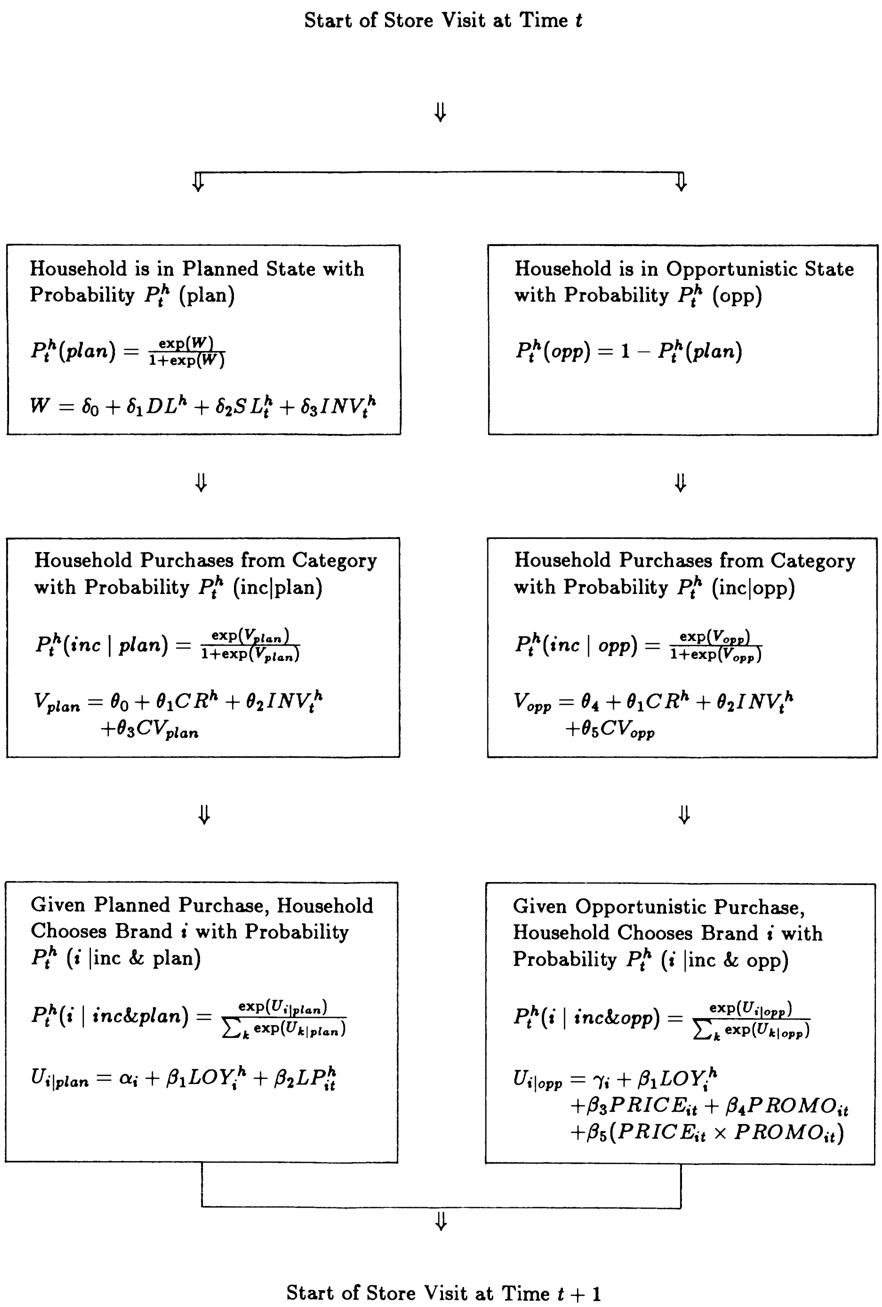

FIGURE 1. Diagram of the Two-State Model of Purchase Incidence and Brand Choice.

4. Data, Fit and Validation

In this section we describe the data set used to test the two-state model and present the results from the calibration and the hold-out validation.

Data

We calibrate the two-state model using a subset of the IRI scanner panel for saltine crackers. We begin by choosing the Williamsport, PA market. In this market there are

10 instrumented stores: regional chain A (stores 107–110), regional chain B (store 114), national chain C (stores 115–116), and independent chain D (stores 111–113).[7] To keep the data set to a manageable size, we selected the six top selling saltine brands (excluding unsalted) in the Williamsport market:

Brand	UPC Code	Name	Size	Share
1	06373 05077	SPL1	16 oz	6.8%
2	21662 01482	SPL2	16 oz	31.9%
3	24100 13067	Sunshine	16 oz	7.4%
4	30100 00133	Zesta	16 oz	6.9%
5	44000 00055	Premium1	16 oz	6.4%
6	44000 00057	Premium2	16 oz	26.0%

Brand 1 is a store private label, available only in store 114. Brand 2 is also a store private label, available in stores 107–110. Brands 3, 4, 5, and 6 are national brands available in all stores. Prices on the national brands range from \$0.70 to \$1.50 per one pound box. Prices on the private labels are lower, from \$0.60 to \$0.80. Brands were promoted, on average, about one week in eight.

Since our model is conditional upon a store visit, we use those households in the IRI panel with store trip information. Within this group, 456 households buy saltines. Of these, 252 households make at least two purchases of any of the six top brands in each of the two years in the IRI data set. (This screening potentially biases our results toward heavier users of saltine crackers.) We hold out 100 of these households for validation, leaving a calibration sample of 152. The 152 households make 943 purchases of saltines in 15,023 store visits. The 100 households in the validation sample make 612 saltine purchases in 9,999 store visits. More than 95 percent of these saltine purchase occasions involved the purchase of only one item. This indicates that the two-state model should closely approximate a model that also includes purchase quantity effects. Finally, we divide the 104 weeks of the data into a 52-week initialization period and a 52-week estimation period.

Calibration

We calibrate the two-state model cross-sectionally, maximizing the likelihood of the observed choice behavior across all store visits by the calibration sample households during the estimation period. Thus, we choose parameter values α_i, γ_i, $\beta_1 - \beta_5$, $\theta_0 - \theta_5$, and $\delta_0 - \delta_3$ to maximize the following log likelihood function:

$$\mathrm{LL} = \sum_h \sum_t \left[\sum_i y_{it}^h \ln \left(P_t^h(i)\right) + \left(1 - \sum_i y_{it}^h\right) \ln \left(1 - \sum_i P_t^h(i)\right)\right] \tag{9}$$

where y_{it}^h equals 1 if household h purchased brand i at shopping time t and 0 otherwise. By maximizing (9), we are able to calibrate the entire two-state model. Unlike the model proposed by Landwehr (1986), we are able to estimate the likelihood of planned and opportunistic shopping behavior without any *a priori* classification of store visits.

We used established gradient search routines to obtain parameter estimates, likelihood function values, and asymptotic standard errors. All parameter estimates (other than some of the brand-specific constants) were significant. Table 1 reports the parameter estimates and asymptotic t-statistics for the 25 parameters of the two-state model. We now consider results for each of the model components.

[7] Part way through the period, stores 112 and 113 closed and reopened as chain E. However, pricing and promotional activity changed little. We assumed that household store loyalty was based primarily on physical location rather than chain name.

In the planned state we have assumed brand choice is determined entirely by established preferences and recent choice behavior. The parameter estimates for both LOY_i^h and LP_{it}^h are positive and strongly significant ($\beta_1 = 3.27$, $t = 10.71$, $\beta_2 = 1.90$, $t = 11.04$).[8]

In the opportunistic state, shelf price is negative and significant ($\beta_3 = -17.02$, $t = -3.99$). The $PRICE_{it} \times PROMO_{it}$ interaction term is positive ($\beta_5 = 11.20$, $t = 3.00$) which suggests that the effect of price is less substantial in the presence of feature or display. Although β_4 is negatively signed ($\beta_4 = -6.86$, $t = -2.68$), this corresponds to

TABLE 1

Parameter Estimates for the Two-State Model

	Brand Choice			
	$P_t^h(i \mid \text{inc\&plan})$		$P_t^h(i \mid \text{inc\&opp})$	
Store Private Label 1	α_1	−2.124 (−2.67)[a]	γ_1	1.412 (3.08)
Store Private Label 2	α_2	−2.198 (−3.29)	γ_2	1.427 (4.24)
Sunshine	α_3	−0.549 (−1.28)	γ_3	−0.621 (−2.04)
Zesta	α_4	−0.260 (−0.55)	γ_4	0.455 (1.85)
Premium 1	α_5	−1.021 (−1.91)	γ_5	−0.394 (−1.35)
LOY_i^h (Loyalty)	β_1	3.268 (10.71)	β_1	3.268[b] (10.71)
LP_{it}^h (Last Purchase)	β_2	1.896 (11.04)	—	—
$PRICE_{it}$	—	—	β_3	−17.020 (−3.99)
$PROMO_{it}$	—	—	β_4	−6.859 (−2.68)
$PRICE_{it} \times PROMO_{it}$	—	—	β_5	11.204 (3.00)

Purchase Incidence						*Decision State*		
$P_t^h(\text{inc} \mid \text{plan})$			$P_t^h(\text{inc} \mid \text{opp})$			$P_t^h(\text{plan})$		
Intercept	θ_0	−3.968 (−13.30)	Intercept	θ_4	4.893 (2.77)	Intercept	δ_1	−0.750 (−2.12)
CR^h	θ_1	2.837 (9.14)	CR^h	θ_1	2.837[c] (9.14)	DL^h	δ_2	−1.813 (−3.63)
INV_t^h	θ_2	−0.516 (−11.01)	INV_t^h	θ_2	− 0.516[c] (−11.01)	SL_t^h	δ_3	2.463 (7.00)
CV_{plan}	θ_3	0.260 (4.22)	CV_{opp}	θ_5	0.689 (6.29)	INV_t^h	δ_4	0.361 (2.63)

(a) Asymptotic t-statistics in parentheses.
(b) Parameter β_1 in $P_t^h(i \mid \text{inc\&plan})$ is constrained to be equal to β_1 in $P_t^h(i \mid \text{inc\&opp})$.
(c) Parameters θ_1 and θ_2 in $P_t^h(\text{inc} \mid \text{plan})$ are constrained to be equal to θ_1 and θ_2 in $P_t^h(\text{inc} \mid \text{opp})$.

[8] One concern with our interpretation of $P_t^h(i \mid \text{inc \& plan})$ is that the lack of consumer response to marketing activity in the planned state is a result of the constraints we have imposed upon the parameters (i.e., β_3, β_4, and β_5 are set to zero) rather than the true pattern of consumer choice behavior. When we freed up these parameters and recalibrated the model, we found that none of the added parameters was significant at the 0.20 level (according to t-statistics based on asymptotic standard errors) and that the improvement in model fit was not significant at the 0.20 level (according to the likelihood ratio test).

the effect of promotion at zero price. Over the range of prices for the brands in the data set ($0.60 to $1.50), the impact of promotion is always positive.

In the model components for purchase incidence, all parameter estimates are correctly signed and significant. Consumption rate and inventory both have strong impacts on purchases incidence probabilities ($\theta_1 = 2.84$, $t = 9.14$, $\theta_2 = -0.52$, $t = -11.01$). There are large differences in the scaling of category value between the planned and opportunistic states; these are accommodated in the intercept terms θ_0 and θ_4. The impact of category value (which includes the swings induced by price and promotional changes among the brands) on purchase incidence in the opportunistic state is substantial ($\theta_5 = 0.69$, $t = 6.29$). Although there is less empirical variation in category value for the planned state, its coefficient also enters with a significant positive sign ($\theta_3 = 0.26$, $t = 4.22$). In both states, some variation in CV is due to the presence of important private label brands in the category which are not carried in all stores. Thus, households loyal to private labels from one chain who may be shopping in another chain will have substantially lower category value and hence a reduced probability of purchase incidence.

Each of the three hypothesized discriminants of decision state emerge correctly signed and statistically significant: deal loyalty ($\delta_2 = -1.81$, $t = -3.63$), store loyalty ($\delta_3 = 2.46$, $t = 7.00$), and inventory ($\delta_4 = 0.36$, $t = 2.63$). Examining the t-statistics, store loyalty appears to be the strongest discriminator of planned versus opportunistic state. This result corroborates experimental work by Park, Iyer, and Smith (1989) who find a positive effect of store knowledge on planned purchasing.

Model Validation

We assess the goodness of fit of the two-state model relative to a reference model that allows for only one state. If we assume that all consumers are always opportunistic in their choice behavior (i.e., $P_t^h(\text{plan}) = 0$ for all h and for all t), then the two-state model collapses to a "one-state" nested logit very similar to the model proposed by Guadagni and Little (1987). By testing the two-state model against a one-state nested logit model, we aim to provide a relatively clean assessment of the impact of incorporating planned and opportunistic decisions states into an integrated incidence/choice model.

The one-state nested logit model is given by the following set of equations:

$$P_t^h(i) = P_t^h(\text{inc})P_t^h(i \mid \text{inc}), \tag{10}$$

$$P_t^h(i \mid \text{inc}) = \frac{\exp(U_i)}{\sum_k \exp(U_k)}, \tag{11}$$

$$\begin{aligned} U_i = {} & \alpha_i + \beta_1 \text{LOY}_i^h + \beta_2 \text{LP}_{it}^h + \beta_3 \text{PRICE}_{it} \\ & + \beta_4 \text{PROMO}_{it} + \beta_5(\text{PRICE}_{it} \times \text{PROMO}_{it}), \end{aligned} \tag{12}$$

$$P_t^h(\text{inc}) = \frac{\exp(V)}{1 + \exp(V)}, \tag{13}$$

$$V = \theta_4 + \theta_1 \text{CR}^h + \theta_2 \text{INV}_t^h + \theta_5 \text{CV}, \qquad \text{and} \tag{14}$$

$$\text{CV} = \ln\left(\sum_k \exp(U_k)\right). \tag{15}$$

Note that the utility function for the brand choice component in equation (12) is slightly different from that in the opportunistic component of the two-state model; for completeness, we have included the term $\beta_2 \text{LP}_{it}^h$. The form for V is functionally identical to the form for V_{opp} in the two-state model; however, the measure CV will take on different values depending upon the coefficient estimates from the brand choice component of the model.

We calibrate the one-state model following the maximum likelihood procedure described by Guadagni and Little (1987). Table 2 reports estimates and asymptotic t-statistics for the 14 model parameters. Interestingly, the coefficient for PRICE_{it} is barely significant and the coefficient for $\text{PRICE}_{it} \times \text{PROMO}_{it}$ is not significant at the 0.05 level. While the same may not be true for other categories, failing to account for planned purchasing behavior in saltines might lead us to conclude that price does not have a significant impact on brand choice behavior. With the two-state model, we avoid this potentially misleading conclusion.

The overall fit statistics for the two-state model and the one-state model are shown below for the calibration sample (152 households).

	Two-State	One-State
Log Likelihood	−3696.4	−3803.4
Akaike Information Criterion	−3721.4	−3817.4
U^2	0.207	0.184

Since the two models are not nested, we compare them following an approach proposed by Rust and Schmittlein (1985): the Akaike Information Criterion (AIC) favors the two-state model over the one-state model by a comfortable margin. Note that our U^2 values are lower than those found in Guadagni and Little (1983) because our model also incorporates purchase incidence, which is more difficult to predict than brand choice alone.

Using the parameter estimates obtained from the calibration sample, we calculated log likelihood function values for both the one-state and two-state models for the hold-out sample of 100 households. These are

TABLE 2

Parameter Estimates for the One-State Nested Logit Reference Model

$P_t^h(i \mid \text{inc})$			$P_t^h(\text{inc})$		
Store Private Label 1	α_1	1.073 (2.63)[a]	Intercept	θ_4	−4.350 (−41.66)
Store Private Label 2	α_2	0.837 (2.14)	CR^h	θ_1	2.629 (9.24)
Sunshine	α_3	−0.209 (−1.06)	INV_t^h	θ_2	−0.446 (−11.51)
Zesta	α_4	0.450 (2.54)	CV	θ_3	0.398 (14.06)
Premium 1	α_5	−0.259 (−1.18)			
LOY_i^h Loyalty)	β_1	3.058 (14.23)			
LP_{it}^h (Last Purchase)	β_2	1.476 (12.05)			
PRICE_{it}	β_3	−1.001 (−1.68)			
PROMO_{it}	β_4	1.603 (2.51)			
$\text{PRICE}_{it} \times \text{PROMO}_{it}$	β_5	0.022 (0.04)			

(a) Asymptotic t-statistics in parentheses.

	Two-State	One-State
Log Likelihood	−2397.4	−2441.2

Thus, the improved fit of the two-state model over the one-state approach carries through to an independent sample of households.[9]

5. Implications

Like other models of purchase incidence and brand choice, the two-state model can be used to gain insight into the nature of consumer purchase behavior by tracking response to promotion and calculating price elasticities. Because of our focus on shopping behavior, however, the two-state model also addresses other issues of theoretical interest to researchers and with practical implications for retailers.

Across Category

The two-state model permits us to infer decision state from the observed shopping behavior of the household. For any given shopping trip, the probability of planned purchase tells us in part how likely it is that the consumer will not respond to point-of-purchase promotion in the category. By looking at the distribution of P_t^h(plan) we can get an idea of the promotion-responsiveness of the category as a whole. Figure 2a shows the distribution of P_t^h(plan) for saltine crackers across all 15,023 shopping trips in the calibration sample. The probability of being in the planned state is symmetrically distributed and roughly uniform in shape; thus, we conclude that shopping for saltines is not highly skewed towards either opportunistic or planned behavior.

We can compare the distribution of P_t^h(plan) across categories to look for differences in shopping behavior and promotion responsiveness. For the purposes of illustration, we recalibrated the two-state model using the IRI coffee data.[10] Figure 2b shows the distribution of P_t^h(plan) for four major national brands of ground coffee (Hills Brothers, Folgers, Maxwell House, Chock Full O'Nuts) across a sample of 82 households. Compared to saltine crackers, the distribution is much more highly skewed towards opportunistic behavior: on nearly 80 percent of occasions, the household is more likely to exhibit opportunistic shopping behavior for ground coffee (versus 50 percent for saltines).

This type of cross-category finding is of potential interest to modelers and managers. Academics might use the two-state model to uncover the differences in shopping behavior across categories in order to study the determinants of deal responsiveness. Retailers, too, should be able to use these findings in deciding which categories to feature in their attempts to build store traffic. Once we better understand the determinants of shopping behavior, we can build better normative models of cross-category promotional strategy.

[9] One possible concern is that the improvement in fit of the two-state model over the reference model is due not to its structure, but to the fact that the two-state model embodies additional information regarding store loyalty and deal loyalty. To account for these possible effects in a one-state framework, we modified the reference model to include these two factors. When we recalibrated the model, we found that although the fit improved it was significantly short of that achieved by the two-state model.

[10] Because these data do not include store trip information, we focused on a single store environment and explicitly modeled the probability that a household would visit the target store in any given week. We also modified our measure of store loyalty as the proportion of all category-related expenditures made by household h in store s. Our findings were very similar to those for saltines. In the functional form for P_t^h(plan), both deal loyalty and inventory were correctly signed and significant; store loyalty, however, was not significant, possibly due to the error variance introduced by the category-specific measure.

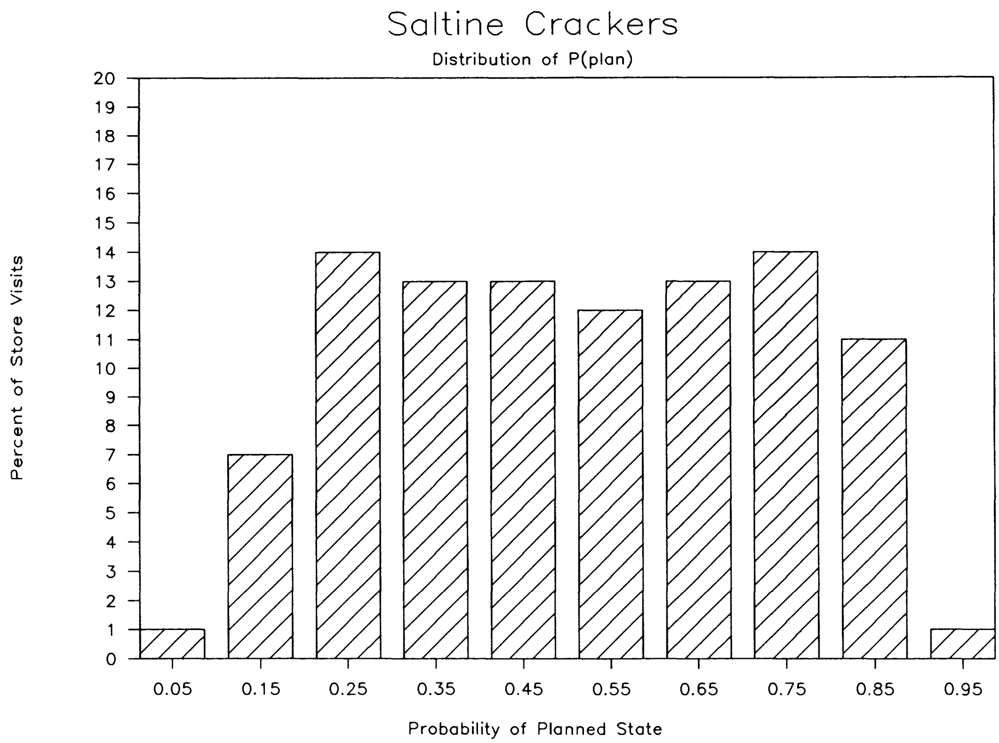

FIGURE 2a.

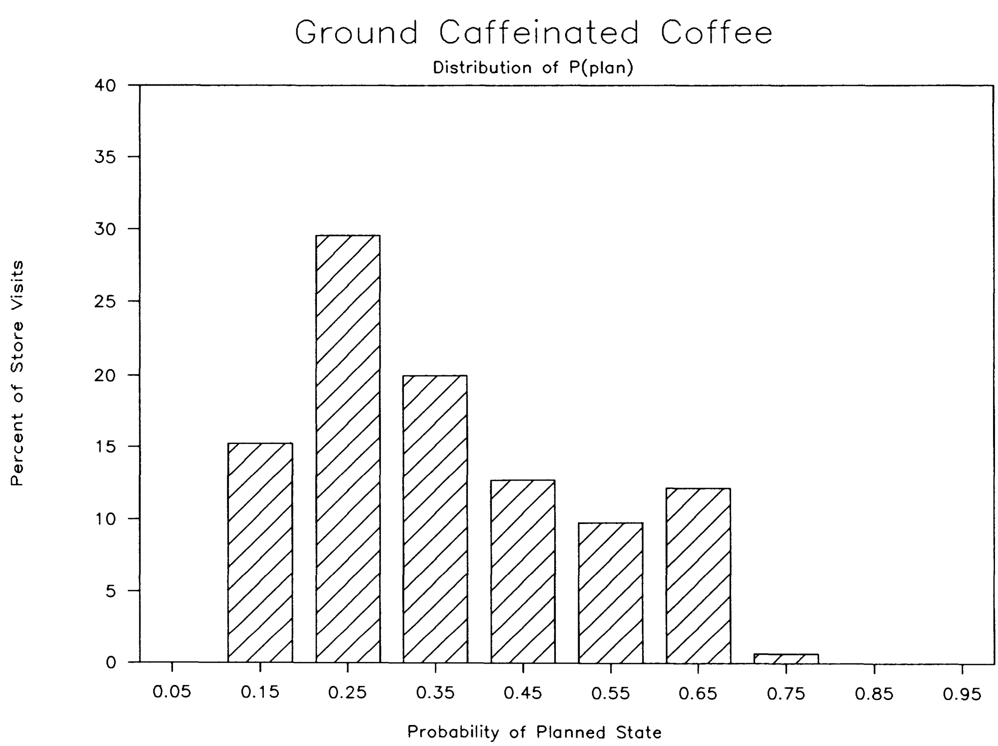

FIGURE 2b.

Within Category

The two-state model also provides insight into the role of store loyalty and its relationship to consumer response. As the retailer works to build traffic, the store receives more visits from store switching customers (i.e., those whose expenditures are spread across several stores). Since these households are more likely to exhibit opportunistic shopping behavior in a different store environment, the result is an increase in promotion responsiveness at the category level.

Consider store 107, where 64 households from our calibration sample made a total of 1836 visits during the year. Of the 64 households, 23 exhibit high loyalty to the store ($SL_{it}^h > 0.60$); they account for more than 70 percent of all visits to the store during the year. According to the two-state model, we can expect these households to purchase 2.32 pounds of saltines per week when all brands are at regular price and there is no promotion. When the store offers a promotional price on Premium Saltines, the expected category volume increases to 3.48 pounds, a 50 percent increase. The remaining 41 households (those with $SL_{it}^h < 0.60$) purchase only 0.55 pounds per week at regular prices; in the presence of a price promotion on Premium, however, the expected category volume increases to 1.46 pounds, a 163 percent increase. Thus, if the retailer is successful in bringing in store switchers, he will increase consumer response to promotion at the category level.

6. Conclusion

We have developed a conceptualization of consumer shopping behavior and its relationship to purchase incidence and brand choice grounded in the theory of consumer information processing. Stated simply, our contribution is that a model which permits two different ways of shopping for brands should be better than a model with only one. Thus, we try to improve on the "one-state" view of the world that implies consumers *always* make their incidence and choice decisions combining *all* factors in a compensatory fashion. We drew from the literature on consumer shopping behavior to develop the appropriate decision states to model. The extensive documentation of planned versus unplanned purchasing and its heterogeneity across consumers provided both logical and empirical support for our distinction between planned and opportunistic shopping modes.

We calibrated and validated the two-state model on purchase panel data for the saltine cracker product category. Our hypotheses are supported by the significance of the coefficients, the model's overall fit, and its predictive performance in a hold-out sample. The two-state model's fit is superior to nested logit, currently one of the better technologies for modeling purchase incidence and brand choice. More specifically, we demonstrate the ability of three measures crafted entirely from the panel data—store loyalty, deal loyalty, and inventory—to discriminate between decision states. In future research, we may be able to improve state discrimination through the development of other measures and the integration of survey and scanner panel data.[11]

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