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The Effect of Inventory on Purchase Incidence: Empirical Analysis of Opposing Forces of Storage and Consumption

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Abstract

Behavioral studies and recent empirical research suggest higher levels of inventory on hand can lead consumers to increase consumption. Inventory on hand is therefore posited to exert two countervailing forces on the probability of purchase incidence. First, higher levels of inventory *reduce* the likelihood of purchase as the consumer feels less pressure to buy. At the same time however, theory suggests higher levels of inventory may drive up the rate of consumption, thereby *increasing* the probability of incidence.

We develop an empirical model that explicitly captures these two effects. The elasticity of purchase incidence with respect to inventory derived from the model is shown to capture these opposing forces in a simple and intuitive way. The analytical expression allows calculation of a threshold below (above) which the net effect is positive (negative). The model is estimated on ten product categories from the Stanford Market Basket database and is shown to fit better than both the standard nested logit approach and an alternative formulation developed by Ailawadi and Neslin (1998). The threshold values have plausible magnitudes and are intuitive across categories: butter, margarine and crackers have relatively low thresholds implying that inventory build up does not drive consumption; ice cream and soft drinks have relatively large thresholds (below which the inventory pressure to consume more outweighs the effect to delay purchase). Implications for retail management are discussed.

Key Words: *Choice Models, Consumption, Inventory, Purchase Incidence*

1 Introduction

In recent years managers have expressed interest and faith in an important intuition about consumer behavior: Greater volumes of product on hand can lead to higher overall levels of consumption. This phenomenon — the inventory effect — occurs not only for products where it might be expected ex ante (such as ice cream and soft drinks), but also in seemingly mundane consumption-invariant categories such as dryer softeners.[1] Marketing academics have provided theoretical, experimental and empirical support for this conjecture. Assunção and Meyer (1993) show that higher levels of inventory and consumption is a rational response to price promotion and Ho, Tang and Bell (1998) prove that consumption increases rationally with price variation (over a mean-preserving spread). Experimental work (e.g., Folkes, Martin and Gupta 1993; Raghubir and Krishna 1999; Wansink 1994; Wansink and Deshpandé 1994) shows that package size, package shape, task elaboration, and perceptions of (lack of) scarcity can all have a positive effect on consumption.

In an empirical study that motivates our paper, Ailawadi and Neslin (1998), hereafter AN, find that consumption of yogurt increases when consumers have more inventory on hand. Sun (2004) provides a dynamic structural model to offer a behavioral underpinning for the conditions under which stockpiling is rational, and how such an effect can be identified in secondary data. She develops a number of substantive insights including: The effect of promotion on consumption is greater for stronger brands, and the general phenomenon may be behind the well-known lack of a "post promotion dip."

Chandon and Wansink (2002) develop a conceptual framework and terminology that further refines our understanding of this kind of inventory effect. They introduce and distinguish the notions of *exogenous* and *endogenous* inventory effects on consumption — concepts that will be very helpful in interpreting our empirical findings. An exogenous effect occurs when consumers use more of the product simply because they have excess inventory on hand. Chandon and Wansink conjecture that food products such as juices and cookies might be susceptible to such an effect. An endogenous effect occurs because of an anticipated increase in household

[1] This particular example was communicated to the authors by a brand manager at Proctor and Gamble in Toronto who was able to drive consumption of dryer softening sheets by selling them in larger boxes. His lay theory was that consumers with larger inventories (as a result of buying greater volumes) were less "frugal" in their use of his product.

demand. They claim and show the endogenous effect could occur for both food and non-food products. For example, hosting a party leads to an increased need for food products; additional household guests or a promise to launder the clothing for a partner's rugby team leads to an increased need for detergent. Using scanner panel data they show exogenous effects for juices and cookies only — having more detergent on hand does not lead one to use it at a faster rate. All three categories do however show significant endogenous effects. An important implication is that stockpiling is necessary but not sufficient for exogenous effects to occur. The cross-category differences reported in Bell, Chiang and Padmanabhan (1999) can also be reassessed in light of this new work by Chandon and Wansink (2002). In particular, one would now predict that the "stockpiling only" categories (e.g., detergents and paper towels) might exhibit endogenous effects, but will not show exogenous effects. Conversely, the so called "consumption categories" (e.g., soft drinks) might be expected to show both.

It is important to note that econometric work in which the effect of inventory on consumption is estimated directly is relatively scarce — AN and Sun (2004) represent the exception rather than the rule. It is also critical to note that the ultimate dependent variable is *not* consumption itself, but an observable outcome such as purchase incidence. All prior studies using scanner panel data that model purchase incidence and employ a proxy for consumption as an individual-level covariate assume this measure is constant over time. A sample of papers include Bucklin and Lattin (1991), Bucklin, Gupta and Siddarth (1998), Chiang (1991) and Chintagunta (1993). An important consequence of these formulations is that the elasticity of purchase incidence with respect to average consumption is always positive, and the elasticity with respect to some estimate of current inventory is always negative.[2] That is, the higher the average consumption, the greater the probability of purchase incidence and the higher the level of inventory the lower the probability of incidence. What these models do not capture is the relationship between inventory and consumption itself, and the effect of this relationship on the purchase incidence probability.

The two key contributions of our paper are as follows. First, we develop a very parsimonious and easily interpretable model to capture the relationship between inventory, consumption and purchase incidence. While AN demonstrate the existence of the inventory effect, the complex and highly non-linear relationship between this construct and the purchase incidence

[2]This assumes that the parameters for these variables have the theoretically correct signs and are statistically different from zero, a condition which holds in all these studies.

probability implied by their model makes interpretation relatively more difficult.[3] We formalize the countervailing effects of inventory on purchase incidence by deriving the elasticity of purchase incidence with respect to inventory. Unlike prior studies, we capture both the traditional negative effect and also the additional positive effect. The former occurs because everything else equal, the more inventory the household has, the less pressure there is to replenish. However, consumer behavior theory tells us the more inventory on hand, the greater the likelihood of spontaneous consumption (an exogenous effect) and also that the household is preparing for a period of higher than usual demand (an endogenous effect).

Second, while we are not able to directly separate whether the inventory effect is for exogenous or endogenous reasons, we estimate the net influence of inventory for ten different product categories. This faciliates some degree of generalization and we use the results of Bell, Chiang and Padmanabhan (1999) and the Chandon and Wansink (2002) framework to help organize and interpret the empirical findings. The cross-category results are intuitively plausible: Beginning at relatively low levels of inventory, butter, margarine and crackers all show a net negative effect of inventory on the probability of purchase incidence. This implies that on average, the consumption rates in these categories are mostly invariant to the level of inventory on hand.[4] Conversely, for hot dogs, ice cream and soft drinks the positive effect of inventory on consumption is present (and outweighs the negative effect of inventory on purchase incidence) even at relatively high stock levels. In other words, the pressure to consume more for both exogenous and endogenous reasons is high for these goods. Finally, like Chandon and Wansink (2002) we find evidence consistent with endogenous consumption effects for two categories that are frequently stockpiled: Laundry detergent and paper towels.

The remainder of the paper is organized as follows. Next, we describe the purchase incidence model, the relationship between inventory and consumption, and the analytics for the net effect of inventory on incidence probabilities. Section 3 presents the data and section 4 reports the empirical findings and summarizes the implications for management practice.

[3]We discuss this in the next section.

[4]This result is also consistent with the findings in Bell, Chiang and Padamanabhan (1999, p. 511).

2 Model

We begin with the specification of the purchase incidence probability and proceed to the formalization of the relationship between inventory and consumption. The proposed model is compared to AN and the net effect of inventory on purchase incidence probabilities is derived as the elasticity of incidence with respect to inventory.

2.1 Purchase Incidence

The dependent variable of interest is a binary indicator of purchase incidence. The probability that household h purchases in a given product category at time t is modeled as binary logit

$$P_t^h(inc) = \frac{\exp(V_t^h)}{1+\exp(V_t^h)}, \tag{2.1}$$

where V_t^h represents the deterministic component of a reduced form purchase incidence utility that is household and time-dependent. It is standard in the literature (e.g., AN, Bucklin and Lattin 1991; Chintagunta 1993) to specify V_t^h as a linear-in-parameters function as follows

$$V_t^h = \gamma_0 + \gamma_1 CR^h + \gamma_2 MCINV_t^h + \gamma_3 CV_t^h \tag{2.2}$$

where:

$$\begin{aligned}
CR^h &= \text{estimated average consumption rate for household } h,\\
MCINV_t^h &= \text{relative (mean-centered) inventory for household } h \text{ at time } t,\\
CV_t^h &= \text{category value for household } h \text{ at time } t, \text{ and}\\
\gamma_0, \gamma_1, \gamma_2, \gamma_3 &= \text{parameters to be estimated.}
\end{aligned}$$

The category value covariate, CV_t^h, is equivalent to ln $[\sum_i \exp(U_{it}^h)]$ where U_{it}^h is a household and time-varying deterministic component of the brand choice model for items $i = 1, \ldots, I$ in the multinomial model of brand choice nested beneath the binary model of incidence. In our empirical analysis we follow the standard approach and estimate the brand choice and purchase incidence parameters simultaneously, however as brand choice is not of direct interest in this study we relegate the details of this model to the Appendix. In the articles referenced above (and in similar studies) the incidence parameters are signed as follows: $\gamma_0, \gamma_2 < 0; \gamma_1 > 0$ and $0 < \gamma_3 < 1$.

CR^h is measured using initialization data that are not included in the estimation sample. The common approach is to compute the total volume of product purchased by household h in (say) the first six months of the data and use this to define a daily or weekly average usage. Having computed CR^h from the data, one can then develop an estimate of INV_t^h, a time-varying and household-specific estimate of the inventory on hand. Again, there is a standard approach to estimating inventory and this is reported in equation (1) of AN. Inventory in the current period is simply previous period inventory, plus any new purchases less the consumption that has occurred in the interim.

Prior to documentation by Wansink (1994) and others of the within individual "inventory effect" — higher inventories lead to greater rates of consumption — most empirical studies used estimated consumption rates and inventory on hand purely to control for observed heterogeneity across individuals in their propensity to purchase in the category. Moreover, the time-dependent inventory estimate was mean-centered to reflect "relative inventory on hand." This controls for observed heterogeneity across individuals in their usage levels. AN was the first empirical study to modify the basic setup and reflect the possibility of inventory effects in the underlying purchase incidence model.

2.2 Inventory and Consumption

In all empirical studies prior to AN, the rate of consumption CR^h estimated from initialization data did not vary with time and was assumed *independent* of the level of inventory on hand. AN propose a time-varying inventory-dependent consumption function and investigate two alternative forms: (1) a spline model in which the slope of the consumption line changes part way through the consumption cycle, and (2) a "continuous nonlinear function". This latter function provides a superior fit to the data and is given by

$$CR_t^h = INV_t^h \cdot \left[\frac{\overline{C}^h}{\overline{C}^h + (INV_t^h)^f} \right], \tag{2.3}$$

where

$$\begin{aligned} CR_t^h &= \text{consumption by household } h \text{ at time } t, \\ INV_t^h &= \text{inventory for household } h \text{ at time } t, \\ \overline{C}^h &= \text{average consumption by household } h, \text{ and} \end{aligned}$$

$$f \quad = \quad \text{flexible consumption parameter (to be estimated).}$$

AN demonstrate that this new formulation: (1) provides a better fit to the data than a model specified according to equation (2.2), and (2) that one can draw interesting insights about the ability of promotions to stimulate additional demand. While these are important contributions, the implied elasticity is highly non-linear and cross-category comparisons are not intuitive. It is these two issues in particular that we address in our formulation. While our model (like AN) is a reduced form approximation, we demonstrate its empirical merit through: (1) superior model fit, and (2) intuitive cross-category comparisons.

Assume that the consumption rate behaves according to a Cobb-Douglas like formulation

$$CR_t^h = C^h \cdot (INV_t^h)^\beta, \tag{2.4}$$

and taking logs

$$\log(CR_t^h) = \log(C^h) + \beta \log(INV_t^h), \tag{2.5}$$

so that the consumption rate is set with the average level of consumption in the initialization period and is proportional to inventory on hand. Inserting the new consumption function into equation (2.2), the deterministic utility for the incidence model is changed as follows

$$\begin{aligned} V_t^h &= \gamma_0 + \gamma_1 \log(CR_t^h) + \gamma_2 MCINV_t^h + \gamma_3 CV_t^h \\ &= \gamma_0 + \gamma_1 \left\{ \log(C^h) + \beta \log(INV_t^h) \right\} + \gamma_2 MCINV_t^h + \gamma_3 CV_t^h. \end{aligned}$$

In order to properly identify the parameters, we reparameterize the model as

$$V_t^h \quad = \quad \alpha_0 + \alpha_1 \log(C^h) + \alpha_2 \log(INV_t^h) + \alpha_3 MCINV_t^h + \alpha_4 CV_t^h, \tag{2.6}$$

where $\alpha_2 = \alpha_1 \cdot \beta$ so that β can be derived from α_1 and α_2 after estimation and the associated standard error obtained using Kramer's Theorem.[5]

[5] We estimate the consumption rate parameters in log form according to equation (2.6) and we set inventory to 0.01 in instances where our estimate of inventory hits zero. We checked the number of times this occurred for each category and found it to be very rare (less than 4% of observations for all categories). We re-estimated the models under a condition where these observations were ignored. That is, we stopped using observations for households once the estimate of inventory hit a very small but positive value and then only re-started using the particular household when inventory was again replenished (by the next purchase). This resulted in a small window of "inactivity" for the household. Under this condition our proposed model still fits the data better than the null model (all categories) and better than AN (all categories except sugar). The statistical significance of the results is unchanged and the quantitative effects virtually identical. We thank an anonymous reviewer for drawing our attention to this matter.

2.3 Inventory Elasticity and Quantitative Effects

The substantive value of equation (2.6) is evident when we compute the elasticity of purchase incidence with respect to inventory. Dropping the household and time specific subscripts for ease of exposition, we have

$$\eta = \frac{dP}{dINV} \cdot \frac{INV}{P} \tag{2.7}$$

Again, for ease of exposition we denote the deterministic component of utility in the purchase incidence probability as simply V. Working with the chain rule and the quotient rule we obtain the derivative of the purchase incidence probability with respect to inventory as

$$\begin{aligned} \frac{dP}{dINV} &= \frac{e^V(\alpha_2/INV + \alpha_3)(1+e^V) - e^V e^V(\alpha_2/INV + \alpha_3)}{(1+e^V)^2} \\ &= (\alpha_2/INV + \alpha_3)P(1-P) \\ \Rightarrow \qquad \frac{dP}{dINV} \cdot \frac{INV}{P} &= (1-P)(\alpha_2 + \alpha_3 INV) \end{aligned} \tag{2.8}$$

The final expression in equation (2.8) reveals the following. First, net elasticity can be *either* positive or negative. This is because the term $(1 - P)$ is always positive, however the term $(\alpha_2 + \alpha_3 INV)$ can be positive or negative: $\alpha_2 > 0$ and $INV \geq 0$ and $\alpha_3 < 0$. The sign of the elasticity is therefore driven by relative magnitudes of the effects captured by α_2 and α_3 and also the level of inventory on hand, INV. Recall that $\alpha_2 = \alpha_1 \cdot \beta$ is positive, captures the "inventory pressure effect" and causes one to speed up the likelihood of purchase incidence. Alternatively, α_3 is negative and represents the "slowing down" effect of inventory as the consumer with inventory on hand feels less pressure to buy in the category, all else equal. In standard models the elasticity of incidence with respect to inventory is *always* negative. AN offers an intuition similar to ours, however the expression is highly non-linear and difficult to evaluate due to the formulation of the consumption rate according to equation (2.3).

For given parameter estimates, equation (2.8) reveals a critical level of inventory, INV^*, below which the net effect is positive, and above which the effect is negative. When the net effect is negative this says that the consumer has a level of inventory that is large enough to cause a delay in the probability of incidence *even accounting for the pressure of inventory on increased consumption*. In the empirical section we compute the INV^* for ten different product categories and show that not only are the effects plausible, but also consistent with intuition about how different product categories (e.g., ice cream and paper towels) are consumed.

3 Data and Empirical Results

We begin with a brief description of the database and product categories used in the analysis and then proceed to the empirical findings. Specifically, a comparison of AN and the proposed model in terms of fit, followed by a discussion of the parameter estimates and quantitative effects.

3.1 Database

We utilize ten product categories from the Stanford Market Basket Database. A total of 548 panelists make purchases from five separate supermarkets over a two-year period. We use the first six months of data to initialize the average rate of consumption and other the loyalty variables that are used in the brand choice model. The next one year of data are set aside for model calibration. Our selection of product categories is guided by prior research (Bell, Chiang and Padmanabhan 1999; Chandon and Wansink 2002). A priori, we would expect relatively weak effects for bacon, butter, crackers, margarine and sugar due to perishability and usage issues. Given the findings of Chandon and Wansink (2002) we might anticipate inventory effects that are endogenous in detergent and paper towels. Finally, hot dogs, ice cream and soft drinks should show the strongest effects as these categories could be subject to both endogenous and exogenous consumption effects.

Summary statistics for the categories are provided in Table 1. In columns two through four we report the number of brands, sizes and unique items (brand-size combinations) in each category. Column five provides the number of households who make a choice in the category (we include any household that makes at least one purchase in both the initialization and calibration periods). Note that the penetration rate varies considerably across categories, with butter and tissue being the low and high categories, respectively. Column six gives the number of shopping trips made by the included households, while column seven reports the total number of brand choices made by the same group.

[Table 1 about here]

3.2 Empirical Findings

Model Fits. Table 2 reports a comparison of the model fits for AN and for our proposed model. In the interests of brevity we do not include the fits for the standard model (where the consumption rate is independent of time and inventory) but both AN and our proposed model fit better for all categories (results are available from the authors upon request). The number of parameters is the same for AN and our model, which provides a better fit for nine of the ten categories (sugar is the one exception).

[Table 2 about here]

Parameter Estimates. Table 3 contains the parameter estimates for our proposed model. All parameter estimates have the expected signs and are statistically different from zero (with the exception of α_3 for ice cream). AN note that purchase incidence models that do not allow consumption to vary with inventory are likely to have downwards biased estimates for mean-centered inventory ($MCINV_t^h$) and consumption (C^h). We also find evidence of this as our estimates of α_1 and α_3 have larger magnitudes and smaller standard errors in our proposed model (relative to a standard null model of equation 2.2).

[Table 3 about here]

Column five reports the effect of inventory on consumption, recovered as $\beta = \alpha_2/\alpha_1$. The statistical significance of this parameter for all categories implies that consumption is not independent of inventory, and that this manifests as a mechanism for speeding up purchase incidence. The effect is strongest for ice cream and soft drinks — implying that inventory pressure to consume more is particularly strong in these categories. Collectively, the cross-category findings are consistent with the empirical work of AN and with the many behavioral theories which suggest consumption is not independent of inventory.

Quantitative Effects. The derivation of the purchase incidence elasticity with respect to inventory allows one to recover the critical value of inventory INV^* below which the elasticity is positive. That is, the threshold value below which the pressure to consume more outweighs the need to delay due to inventory on hand. Note that the inventory threshold values for bacon, butter, crackers, margarine and sugar are relatively low, both in absolute terms and in comparison to the size of a standard package. This implies that in these categories the consumer needs to only have a relatively small store of inventory on hand before the purchase incidence probability is reduced. Consumers who "stockpile" these categories (if at all) will become less likely to purchase as a consequence of inventory. They will not be induced to consume more of the category.

Detergents and paper towels show relatively higher thresholds. This suggests that the presence of inventory (about one standard package of detergent and four rolls of paper towels) is likely to signal an increase in consumption. Following Chandon and Wansink (2002) we would infer that this is for endogenous reasons — the presence of inventory signals an upcoming period of higher than usual demand — and *not* for exogenous reasons (more inventory itself leads to more consumption). The final three categories, hot dogs, ice cream and softdrinks show relatively high thresholds. The inference is that the consumer needs to have "quite a lot" of product on hand before the volume of inventory causes a slow down in the purchase incidence probability. For moderate values of inventory the pressure to consume more dominates and leads to an increase in the likelihood of purchase. Ice cream is a particularly interesting case. The quantitative effect suggests that a consumer needs to have more than nine 16 oz containers (a standard pack) on hand before a slowdown occurs. Because such a level of inventory is rare the interpretation is that the presence of ice cream inventory on hand almost always causes a speeding up in consumption and therefore the likelihood of purchase. This empirical result suggests ice cream is a prototypical "inventory effect category."

4 Discussion and Conclusion

Over several years, a number of authors (e.g., Bucklin and Lattin 1991; Chiang 1991; Chintagunta 1993; Gupta 1988) have used scanner panel data to build models of purchase incidence. Implicit in all this work was the notion that individual-level consumption rates vary over individuals, but not within individuals over time. At the same time analytical and experimental studies (e.g., Assunção and Meyer 1993, Folkes et al. 1993; Ho et al. 1998; Raghubir and Krishna 1999; Wansink 1994; Wansink and Deshpandé 1994) began to accumulate evidence that consumption rates are not independent of inventory.

AN is the first published empirical study to allow consumption to depend on inventory in a model of purchase incidence. The authors specify the function given in equation (2.3) and show a large degree of flexibility in the yogurt category and a smaller effect for ketchup. Sun (2004) provides a structural model which finds the same kind of effect for canned tuna.

In this paper, we offer a parsimonious reduced form model to capture the effect of inventory on consumption and the total effect of inventory on purchase incidence. Two opposing forces: (1) the inventory pressure effect where more inventory leads to higher consumption, and (2) the direct inventory effect – where higher levels of inventory reduce the need for purchase, are incorporated into the model. The formulation is consistent with behavioral theories of consumption and purchase, and the empirical findings concur with those of AN and also later work by Sun (2004). An important outcome of the formulation is the analytical expression for the elasticity of purchase incidence with respect to inventory. The expression given in equation (2.8) captures the two opposing forces explicitly, and facilitates calculation of a critical value of inventory below which consumers will feel pressure to increase consumption. Intuitively, when inventory levels get “too high” the *net* effect on purchase incidence should be negative.

The empirical findings for all categories reject the assumption that consumption is independent of inventory. The findings also reveal important differences across categories with hot dogs, ice cream and soft drinks the categories that are most likely to be subject to exogenous effects. That is, in all these categories higher levels of inventory — which can induce the pressure to consume more — will have a net positive effect on the probability of purchase. One implication is that retailers and manufacturers could fruitfully exploit this phenomenon through a combination of price promotions and larger package sizes. For categories like detergents and paper towels higher levels of inventory will likely be accompanied by higher levels of consumption, but for endogenous reasons. Such endogenous reasons are idiosyncratic to the household and therefore less subject to influence via price promotions. It may, however, still be worthwhile for firms to investigate via market research, whether there is any systematic pattern to these reasons, and if so how they could be addressed through advertising and communication.

Future Research. The contribution of this paper lies in the simple partitioning of the overall effect of inventory on purchase incidence and in the cross-category results. We offer further validation of the various behavioral theories that advance a relationship between inventory and consumption, however, several avenues remain open for future research. First, one could attempt to develop more complex structural models as this kind of model is purportedly superior for policy experiments (Sun 2004). Such experiments would allow researchers to quantify the long term impact of an inventory-consumption relationship on primary demand. The findings presented here point to large cross-category differences which are likely to be of substantive interest to managers and are worthy of further exploration.

Second, we have not addressed the issue of parameter heterogeneity and there are undoubtedly "segments" of consumers who exhibit stronger or weaker effects. Identification of such segments would be highly useful for targeting. It is well known that failure to account for unobserved heterogeneity typically causes attenuation of the parameter estimates so it is highly unlikely that our findings on the average effect are spurious.[6]

[6] AN do not consider parameter heterogeneity either. Also, the estimates for other model parameters (for average consumption, mean-centered inventory and category value) all improve in our formulation — relative to the standard null model.

5 Appendix

To complete the specification of the nested logit model, we briefly describe the brand choice component. The multinomial logit model specifies the probability of brand choice, given purchase incidence, for household h at time t as

$$P_t^h(i|inc) = \frac{\exp(U_t^h(i))}{\sum_k \exp(U_t^h(k))}, \tag{5.1}$$

where $U_t^h(i)$ denotes the deterministic component of utility for each alternative i. In categories where brands offer multiple sizes, each alternative becomes a brand-size combination (Guadagni and Little 1983). To estimate the intercept portion of utility for specific brand-size combinations, we follow the formulation given in Fader and Hardie (1996), using constants pertaining to brands or sizes, as opposed to brand-sizes (see Table 1 for a description of categories with multiple sizes).

The brand choice utility is:

$$\begin{aligned} U_t^h(i) &= \alpha_i + \beta_1 BLOY_i^h + \beta_2 LBP_{ti}^h + \beta_3 SLOY_i^h + \beta_4 LSP_{ti}^h + \\ & \quad \beta_5 PRICE_{ti} + \beta_6 FEAT_{it} + \beta_7 DISP_{it} \end{aligned} \tag{5.2}$$

where:

$$\begin{aligned} BLOY_i^h &= \text{loyalty of household } h \text{ to brand of brand–size } i, \\ LBP_{it}^h &= 1 \text{ if } i \text{ was last brand purchased, 0 otherwise,} \\ SLOY_i^h &= \text{loyalty of household } h \text{ to size of brand–size } i, \\ LSP_{it}^h &= 1 \text{ if } i \text{ was last size purchased, 0 otherwise,} \\ PRICE_{it} &= \text{the actual shelf price of brand–size } i \text{ at time } t, \\ FEAT_{it} &= 1 \text{ if brand–size } i \text{ appeared in a feature at time } t, \text{ 0 otherwise and} \\ DISP_{it} &= 1 \text{ if brand–size } i \text{ was specially displayed at time } t, \text{ 0 otherwise.} \end{aligned}$$

We expect $\beta_1, \beta_2, \beta_3, \beta_4, \beta_6, \beta_7, > 0$ and $\beta_5 < 0$. In the interests of space, these brand choice estimates are not reported in the paper. All parameter values for all categories have the expected sign and are statistically different from zero. Details are available from the authors upon request.

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Category	*Number of Elements*					
	Brands	*Sizes*	*Items*	*Households*	*Observations*	*Choices*
Bacon	7	1	7	206	12,149	1442
Butter	5	1	5	163	10,048	1421
Crackers	6	1	6	170	10,277	1033
Detergent	9	4	32	243	14,742	1562
Hot dogs	10	2	16	255	14,694	1790
Ice cream	12	3	18	304	18,523	2528
Margarine	11	1	11	393	25,639	3693
Paper towels	11	1	11	430	27,598	4649
Soft drinks	7	7	29	257	15,624	3544
Sugar	7	1	7	244	13,339	1460

Table 1: Summary Statistics for Product Categories

	BIC Values	
	AN (1998)	*Proposed*
Bacon	-5,016.15	-4,992.19
Butter	-3,731.54	-3,652.02
Crackers	-3,142.76	-3,079.74
Detergent	-6,269.97	-6,251.50
Hot dogs	-6,537.93	-6,520.81
Ice cream	-8,677.96	-8,665.22
Margarine	-13,694.18	-13,646.03
Paper towels	-16,132.58	-15,883.42
Soft drinks	-13,225.57	-12,729.89
Sugar	-4,589.34	-4,603.45

Table 2: A Comparison of AN (1998) and the Proposed Model

Category	*Intercept* (α_0)	CR_t^h (α_1)	$MCINV_t^h$ (α_3)	CV_t^h (α_4)	INV_t^h (β)	*Threshold* (INV^*)
Bacon	-2.30	0.50	-0.11	0.39	1.60	7.27 oz
	-18.52	12.18	-3.18	8.93	6.29	
Butter	-1.20	0.60	-0.24	0.56	1.08	2.70 oz
	-13.55	14.23	-6.63	14.70	6.79	
Crackers	-1.80	0.99	-0.37	0.49	0.26	0.70 oz
	-6.76	10.30	-5.98	8.47	2.83	
Detergent	-3.54	0.45	-0.07	0.43	5.58	35.87 oz
	-30.97	11.50	-3.99	11.62	7.50	
Hot dogs	-2.54	0.44	-0.13	0.32	4.66	15.77 oz
	-13.98	11.24	-4.92	7.11	6.94	
Ice cream	-3.03	0.51	-0.01	0.32	2.98	151.98 oz
	-26.34	17.50	-0.78	10.30	10.87	
Margarine	-1.37	0.49	-0.15	0.31	0.92	3.01 oz
	-30.83	20.57	-8.43	11.93	8.00	
Paper towels	-2.16	0.58	-0.08	0.46	0.66	4.79 rolls
	-37.53	28.23	-6.36	24.68	9.57	
Soft drinks	-3.09	0.41	-0.03	0.28	2.02	27.61 oz
	-26.90	20.21	-3.44	9.88	11.53	
Sugar	-1.39	0.77	-0.04	0.32	0.57	10.97 oz
	-24.23	17.89	-2.22	12.22	3.45	

Table 3: Parameter Estimates, t-Statistics and Inventory Threshold