The Influence of Inventory Effects and Reference Points on the Rate of Consumption

David R. Bell and Yasemin Boztuğ[1]

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[1]Wharton School, University of Pennsylvania and Institute of Marketing, Humboldt University of Berlin, respectively. We are grateful to Doug Honnold of IRI Inc., for providing us with the data and Christophe van den Bulte and Teck-Hua Ho for comments. We thank the Sonderforschungsbereich 373 for generously supporting this research.

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Abstract

The authors develop and test a model to study the influence of inventory-on-hand and price-based reference points on the consumption rate of consumers. The model is motivated by recent theoretical and empirical research which suggests inventory pressure can cause consumers to increase consumption. A second stream of research shows that purchase behavior is affected by consumer expectations about product prices. To date, no study has developed a unified assessment of both the direct (via prices) and indirect (via inventory) effect of marketing activity on consumption.

We introduce the concept of "inventory elasticity of consumption" to represent the effect of inventory on consumption rates and propose a function that allows consumption to vary with time and level of inventory on hand. The consumption function also accounts for the effect of positive and negative deviations from category price expectations.

The model is estimated on eleven product categories. The inventory elasticity of consumption is highly significant in all categories and the elasticities range from 0.28 to 2.46. Some categories (e.g., butter, crackers, margarine, paper towels, soft drinks and sugar) are consumption *inelastic* while others (e.g., bathroom tissue, detergents, hot dogs, and ice cream) are consumption *elastic* with respect to inventory.

While consumption rates in all categories are sensitive to negative deviations from the reference point (i.e., losses) the consumption rates of relatively "discretionary" products (e.g., bacon and soft drinks) show the greatest slowdown. Overall, reference effects matter less than the inventory effect in driving flexible consumption, but categories with greatest inventory effects also show the greatest reference effects. Implications for managers and researchers are discussed.

Key Words: Reference Points; Inventory; Consumption; Choice Models

1 Introduction

For many frequently purchased goods, consumers have substantial flexibility with respect to consumption and this manifests itself in two ways. First, consumers can elect to not consume a product at all, or to do so infrequently. Second, even for frequent users the individual-level usage rate may vary over time. Both conditions are certainly true for relatively discretionary products (e.g., soft drinks and ice cream). These products are not "needed" in any strict sense, and furthermore individual rates of consumption are likely to vary over time according to taste, mood and opportunity. Moreover, while relative "neccessity" products such as detergent and bathroom tissue are likely to be in the consumption set of most individuals, it is not clear that even in these cases consumption rates will be fixed within an individual over time.[1]

It is therefore surprising that very few empirical studies examine the effects of marketing activity on individual-level consumption rates. In fact, most empirical work presumes individual-level consumption rates are constant over time (e.g. Bucklin and Lattin 1991; Chiang 1991; Bucklin, Gupta and Siddarth 1998). In these studies, the estimated rate of consumption is used as a covariate to explain purchase incidence and quantity decisions and to account for heterogeneity across individuals in their predisposition to buy in a category. A notable exception is Ailawadi and Neslin (1998), hereafter AN (1998). These authors estimate a model that allows consumers to increase consumption in accordance with the level of inventory on hand. They find a strong effect for yogurt and a weaker effect for ketchup. This is an important empirical discovery because it suggests marketers may have leeway to improve the effectiveness of marketing efforts and migrate from "zero sum" activities that are solely designed to steal market share.

In constrast to the relative lack of empirical research on flexible consumption, several studies have examined "consumer adaptation" in a different, but related, domain. The notion that consumers develop reference points and that deviations from reference points influence choice outcomes has received considerable attention (e.g., Briesch et al. 1997; Hardie, Johnson

[1]Detergent containers, for example, often contain measuring devices with recommended per load usage, yet the exact amount used is still at the discretion of the individual user. In addition, users can vary other components of laundry activity – total number of loads, number of items per load, etc. As noted in a recent *Wall Street Journal* article (January 17, 2001), manufacturers have been successful at increasing consumption rates for both laundry detergents and bathroom tissue.

and Fader 1993; Winer 1986). While the vast majority of work has concentrated on reference effects in brand choice a few studies focus on category purchase (e.g., Bell and Bucklin 1999) and purchase quantity (Krishnamurthi, Mazumdar and Raj 1992). A natural question arises: Do reference effects have any bearing on individual-level consumption rates? In a partial response, AN (1998, p. 397) speculate consumption rates "could be functions of price expectations" and suggest this as an avenue for future research.

In this paper, we connect these streams of research. The following hypothetical examples serve to illustrate the potential interplay between inventory pressure and reference effects in their influence on consumption and thereby motivate the substantive content of this paper. While engaged in a shopping trip at the local supermarket, Mr. Jones notices that his favorite brand of detergent is selling at the regular price (which is much higher than his previous purchase price). He decides not to buy the product and as a result has a relatively depleted supply to use prior to his next shopping trip. Consequently, in the intervening period, he uses relatively less detergent per load and places more clothes in his machine — thus slowing his rate of consumption. Mrs. Smith, on the other hand, is pleasantly suprised to find Ben & Jerry's ice cream (her favorite brand) on deal. As a result she makes a purchase, even though she has ample supply at home. In a departure from their regular habit, Mr. and Mrs. Smith enjoy ice cream each night after dinner for the next three evenings.

The examples illustrate two mechanisms that potentially influence consumption. First, there is the inventory effect — the more of a product the consumer has on hand, the greater the potential for increased consumption (all else equal). Second, there is the reference effect — deviations from expectations influence the purchase decision directly and thereby the level of inventory. Thus, in a more indirect way, they can work to slow down or speed up consumption.

While empirical research on flexible consumption is rare, there are several theoretical rationales for why one might expect to observe it. Experimental work (e.g., Folkes, Martin and Gupta 1993; Raghubir and Krishna 1999; Wansink 1994; Wansink and Deshpandé 1994) has shown that several factors including package size, task elaboration, perceived scarcity and package shape all influence consumption rates. In addition, Assunção and Meyer (1993) show analytically that higher levels of inventory and consumption is a rational response to price promotion. In related work, Ho, Tang and Bell (1998) demonstrate that rational consumers increase consumption in response to an increase in price variation over a mean-preserving spread.

This paper offers the following contributions to the existant literature. First, we develop a parsimonious consumption function to represent the effect of inventory on hand on consumption. A key benefit of this function is that the inventory parameter has a direct interpretation as an "inventory elasticity of consumption" — this construct is particularly useful when we seek to assess our basic empirical finding across many categories. In all instances, we find the inventory effect on consumption to be correctly signed and highly significant (the magnitude of improvement in model fit is substantial for many categories).[2]

Second, we introduce reference effects in a straightforward manner and this allows us to determine the joint and separate influence of these two important constructs on consumption. Consistent with the theory of reference points in intertemporal choice (e.g., Hoch and Loewenstein 1991; Loewenstein 1988) and empirical work on category choice (e.g., Bell and Bucklin 1999) we find that negative deviations (i.e., losses) cause decelaration in consumption, while positive deviations (i.e., gains), when significant, speed up consumption. The effect of losses on consumption is negative and significant in all categories studied and is the stronger of the two effects. This follows from loss aversion applied to intertemporal choice, which implies that the "delay premium" due to a loss will exceed the "speed up cost" attributable to a gain. Moreover, reference effects appear to matter less than inventory effects as the elasticities are always smaller.

Third, we assess the robustness of the inventory effect and the reference effects by calibrating our model on eleven distinct product categories. Across categories, the parameters capturing the inventory elasticity of consumption take a plausible range of values (from 0.28 to 2.46). Some categories (e.g., butter, crackers, margarine, paper towels, soft drinks and sugar) are shown to be consumption-inelastic, while others (e.g., bathroom tissue, detergents, hot dogs and ice cream) are consumption-elastic.[3]

The remainder of the paper is organized as follows. Next, we describe rationale for the consumption effect, and the consumption function and model. Section 3 describes the data and empirical results. In section 4, we discuss the main findings and offer four stylized facts on flexible consumption. We conclude the paper with implications for managers and researchers.

[2]In the softdrink category, for example, the model log likelihood improves from $-13,163.07$ to $-12,614.01$. It is quite remarkable that the addition of a single parameter leads to this 4.2% improvement in fit.

[3]The bacon category shows unitary constant elasticity of consumption.

2 Background and Model

We first provide some context for our approach to the issue of flexible consumption and for the particular model adopted. Following this, we develop the functional form for the consumption function, and then link the model for the unobserved consumption decision to a model based on observed brand choice and purchase incidence decisions.

2.1 The Consumption Rate

Before developing an empirical model, it is important to be precise about the consumption rate. From a technical point of view it is the slope of the function which relates time and inventory. AN (1998) aside, all empirical applications using scanner panel data assume the individual level consumption rate is constant over time and that consumption function is linear. That is

$$\frac{dI}{dt} = -r. \tag{2.1}$$

The consumption rate is therefore a differential equation and the solution to equation (2.1), or the inventory function, is easily obtained as

$$I_t = I_0 - rt \tag{2.2}$$

where I_0 is the initial inventory on hand. While each household h is assumed to have a different rate of consumption, r_h, this "linear drawn down" assumption is clearly at odds with experimental research showing that the level of inventory on hand may have an important bearing on the consumption rate. That is, it is important to not only allow for heterogeneity in consumption rates across individuals, but also within individuals over time. The latter effect is particularly important if one is to capture primary demand expansion effects that may result from additional inventory. In the remainder of the paper we develop simple empirical approximations of dI/dt in order to better understand how individual level consumption rates respond to inventory levels and marketing efforts.

2.2 Factors Driving Consumption

A key premise of this paper is that the decision to consume, and therefore also the rate of consumption, is endogenous. Casual empiricism suggests this is descriptively accurate. A number of experimental studies and theoretical papers have proposed mechanisms for rationalizing and detecting the flexible consumption phenomenon. With the exception of AN (1998), however, there are no published studies that (a) show how to measure the phenomenon empirically, or (b) provide empirical assessments of the magnitude of the effect.

The key difficulty in implementing an empirical model of flexible consumption rates is that the consumption decision(s) of consumers are typically not observed. For this reason, most empirical researchers study observable decisions, such as brand choice, purchase incidence and purchase quantity. In studies of these behaviors, the "consumption rate" of individuals enters the model as an exogenous covariate (e.g., Bucklin and Gupta 1992; Chiang 1991; Chintagunta 1993).[4]

We address the observability issue in the following way. Like AN (1998) we allow consumption rates to vary within individuals over time, and impose a particular functional form on this process. The consumption function is then nested within a model of an observable behavior (i.e., purchase). Our model assumes the following about consumer behavior

1. Consumers make many *explicit* but unobserved consumption decisions between instances of purchase (e.g., by deciding how much soft drink to drink, paper towels to use, etc.).

2. The observable purchase decision may be driven, in part, by consumer expectations about likely consumption needs. By observing an explicit purchase decision, we might also be observing an *implicit* decision about consumption.

An implication of the first assumption is explicit consumption decisions are made away from the marketing environment (e.g., in the home), but may be subject to the influence of levels of inventory on hand. An implication of the second assumption is that if consumers decide to postpone or accelerate purchase it may be that they are making an implicit decision to increase or decrease consumption (at least temporarily). This motivates the need for an inventory-driven, time-varying consumption function (e.g., AN 1998). In order to facilitate the exposition and development of a model to test these ideas, we conceptualize the relationship between marketing activity, reference effects, inventory pressure, and consumption as follows:

[4]The covariate is usually calculated as a stationary "average weekly rate of consumption" equal to total purchases in some initialization period, divided by the total time for that period. These authors implicitly assume the consumption rate is of the form given in equation (2.1).

1. Changes in inventory levels in the home (perhaps as a result of marketing activity) cause changes in explicit consumption decisions made away from the point of purchase. The chain of influence is: Inventory levels $\Rightarrow$ Explicit consumption decision.

2. Deviations from price expectations may cause temporary adjustments in the rate of consumption. The chain of influence is: Marketing activity at point of purchase $\Rightarrow$ Reference effects $\Rightarrow$ Implicit consumption decision.

2.2.1 Inventory and Consumption

The challenge in an empirical setting is to create an appropriate inventory-dependent consumption function. At a minimum, the function should allow consumption to vary over time. Ideally, it should also have other properties (e.g., discriminant validity, parsimony, readily interpretable parameters, etc.). Before proposing our function, we first highlight other formulations in the literature. The simplest approach, adopted by almost all published studies on observable behaviors (i.e., brand choice, purchase incidence and purchase quantity) assumes that consumption rates vary over individuals, but within an individual are constant over time. Figure 1 illustrates this case of constant usage rates and linear consumption. The three different lines indicate low, medium and high levels of average consumption, respectively.

[Figure 1 about here]

In the first published empirical study on flexible consumption, AN (1998) propose a time-varying inventory-dependent consumption function. They investigate a spline model in which the slope of the consumption line changes part way through the consumption cycle and 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

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

$\overline{C}^h$ = average consumption by household h, and

f = flexible consumption parameter (to be estimated).

The inventory variable is calculated according to the standard recursive relationship employed in other articles (e.g., Bucklin and Lattin 1991; Chintagunta 1993).

Our proposed consumption function delivers all the benefits (e.g., parsimony, positive values for consumption, etc.) of (2.3), but offers a more natural interpretation of the inventory effect. It introduces the notion of "inventory elasticity of consumption" — a construct which is especially useful in making comparisons across categories.[5] Consumption varies with inventory according to

$$CR_t^h = \max\left\{\overline{C}^h \cdot \left[INV_t^h\right]^\beta, INV_t^h\right\}. \tag{2.4}$$

In this model, β represents the "inventory elasticity of consumption" and the formulation ensures that consumption does not exceed available inventory.[6] Note that the function also shifts up and down according to the average rate of consumption, $\overline{C}^h$, which serves to define the scale for the household. Figure 2 illustrates the properties of this function. In this figure, inventory declines over time (no purchase occurs), but the rate of decline is determined by both the elasticity and the scale (average rate) of consumption.

In the top part of the figure, consumption is inventory-inelastic ($\beta < 1$). Note that, as expected, inventory depletion increases with the average rate of consumption (from low to medium to high). In the second and third portions of the figure, we illustrate constant elasticity of consumption ($\beta = 1$) and inventory-elastic consumption ($\beta > 1$) respectively. As expected, the increase in elasticity accelerates consumption, average rate of consumption held constant. One further appealing property of our formulation is immediate from a comparison of Figure 1 and the second panel of Figure 2 (where $\beta = 1$). This shows that constant elasticity of consumption is *not* equivalent to a constant rate of consumption. The constant rate model (Figure 1) implies that consumption is everywhere independent of inventory; the constant elasticity model (Figure 2, $\beta = 1$) implies that consumption depends on inventory, but the effect (β) is constant over the range of inventory levels.

[5] Clearly, a number of nonlinear functions could be posited. Equation (2.4) is substantively appealing, and as we show subsequently, leads to substantial improvements in model fit.

[6] The consumption function is estimated as $\ln\left[CR_t^h\right] = \ln\left[\overline{C}^h\right] + \beta \cdot \ln\left[INV_t^h\right]$.

[Figure 2 about here]

2.2.2 Reference Effects and Consumption

In marketing, the reference effect stream of work focuses on the influence of reference points on observable consumer behavior (i.e., brand choices, category purchase decisions and purchase quantity decisions). The reference point itself is an unobserved or latent construct that must be inferred from the data. Three key traits characterize this stream of research. First, the overwhelming majority of papers (e.g., Briesch et al. 1997; Lattin and Bucklin 1989; Hardie, Johnson and Fader 1993; Jacobson and Obermiller 1990; Kalwani et al. 1990; Kalyanaram and Little 1994; Kalyanaram and Winer 1995; Mazumdar and Papatla 2000; Winer 1986) study reference effects in brand choice. Relatively few studies consider other behaviors such as purchase incidence (e.g., Bell and Bucklin 1999) or purchase quantity (e.g., Krishnamurthi et al. 1992).

Second, the idea that consumers respond more strongly to negative deviations (e.g., actual prices above references) and are therefore "loss averse" has gained some empirical support (e.g., Hardie et al. 1993; Kalwani et al. 1990). Third, researchers have begun to question whether early findings on reference effects and loss aversion in brand choice are artifacts of failure to account for heterogeneity (see, for example Bell and Lattin 2000; Chang et al. 1999).[7] In a recent paper on brand choice reference effects, Mazumdar and Papatla (2000) account for heterogeneity using a finite mixture model and suggest that both the type of reference point used, and the magnitude of the effect, are likely to vary across both consumers and product categories. They present a conceptual framework and empirical results which support this view.

Of particular interest to this study, is the idea that the unobserved consumption rate is also influenced by price expectations. A further benefit of our formulation of the consumption function (equation 2.4) is that reference effects can be accomodated in a very natural and appealing fashion. To see this, let EXP_t^h and OBS_t^h denote individual and time-varying expected and observed values, respectively, of marketing stimuli (e.g., prices), that capture

[7] Interestingly, the "heterogeneity bias" does not appear to be a problem when one considers the binary decision of category purchase incidence (Bell and Bucklin 1999, p. 140-141).

the attractiveness of the category to the household at a particular point in time. Consistent with prior research, we anticipate different levels of response for gains (when $OBS_t^h > EXP_t^h$) and losses (when $OBS_t^h < EXP_t^h$).[8] Further define relative gains and losses as follows

$$\begin{aligned} RGAIN_t^h &= OBS_t^h/EXP_t^h \text{ when } OBS_t^h > EXP_t^h \text{ and equal to one otherwise} \\ RLOSS_t^h &= EXP_t^h/OBS_t^h \text{ when } OBS_t^h < EXP_t^h \text{ and equal to one otherwise} \end{aligned} \quad (2.5)$$

At each time instance, t, for each household, h, either $RGAIN_t^h = 1$ or $RLOSS_t^h = 1$ when $OBS_t^h \neq EXP_t^h$. When expectations and observed values always coincide, both ratios are equal to one. We now rewrite equation (2.4) as

$$CR_t^h = \max\left\{\overline{C}^h \cdot \left[INV_t^h\right]^\beta \cdot \left[RGAIN_t^h\right]^{\delta_G} \cdot \left[RLOSS_t^h\right]^{\delta_L}, INV_t^h\right\} \quad (2.6)$$

Thus, the augmented consumption rate contains a mechanism for capturing reference effects. The parameters δ_G and δ_L are interpretable as "reference effect elasticities of consumption". This completes the development and specification of the individual-level, time-varying (but unobserved), consumption function. A final important feature of equation (2.6) is that it maps directly into a standard, empirically estimable model based on *observed* consumer behavior (i.e., purchase). In the next section, we provide the details of this relationship.

2.3 The Category Purchase Model

As noted throughout, the consumption decision(s) of consumers typically occur away from the store environment and are therefore unobserved by the analyst. The parameters of the consumption rate in equation (2.6) can only be estimated when it is connected to a model of observed behavior (i.e., purchase). It is, however, straightforward to embed this function in a standard model of brand choice and purchase incidence. To do this, we adopt a nested logit model (e.g., Bucklin and Lattin 1991) for these two decisions. In the nested logit model, the probability that alternative i is chosen at time t by household h is

$$P_t^h(i) = P_t^h(i|inc) \cdot P_t^h(inc), \quad (2.7)$$

[8] In defining a gain as $OBS_t^h > EXP_t^h$, we are saying that the value observed by the consumer is "better than expected". In the context of price, this means that the consumer encountered a prices that were *lower* than the reference prices, so that the category is relatively attractive.

where $P_t^h(i|inc)$ is the conditional brand choice probability and $P_t^h(inc)$ is the category purchase probability, given that the shopper is in the store. We focus here on the specification of the unobserved latent utility for category purchase and relegate the details for the conditional brand choice model to the Appendix. The purchase incidence probability, $P_t^h(inc)$, is given by the binary logit function

$$P_t^h(inc) = \frac{\exp(V_t^h)}{1+\exp(V_t^h)}, \tag{2.8}$$

where V_t^h is the deterministic utility associated with category purchase. In most models appearing in the literature, this deterministic utility is a function of the following covariates

$$V_t^h = \gamma_0 + \gamma_1 CR_t^h + \gamma_2 MCINV_t^h + \gamma_3 CV_t^h \tag{2.9}$$

where:

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

The standard formulation has $CR_t^h = \overline{C}^h$ so that each household is assumed to have a constant rate of consumption (see Figure 1) that is independent of either inventory levels or reference effects. The category value covariate, CV_t^h, is equivalent to the logarithm of the denominator of the conditional brand choice model, $CV_t^h = \ln\left[\sum_i \exp(U_t^h(i))\right]$, where i indexes brands in the category.

2.3.1 Alternative Models of Consumption Rate

We relate the unobserved consumption function given in equation (2.6) to the deterministic utility given in equation (2.9) as follows. First, we estimate a null model (Null) where all the parameters of the consumption function are constrained equal to zero. In this case $\beta = \delta_G = \delta_L = 0$ so $CR_t^h = \overline{C}^h$ and we have a formulation of (2.9) which is consistent with the approaches prevalent in the literature.

Second, in addition to determining whether reference effects or inventory effects have any empirically observable influence on the consumption function, we also need to determine the relative magnitude of the effects. For this reason, we start by including the parameters separately. The reference effect model (Reference) has $\beta = 0$ but estimates δ_G and δ as free parameters. Similarly, in the inventory effect model (Inventory), β is free and $\delta_G = \delta_L = 0$. In the full model (Full) all three parameters are free. To summarize, the four functions to be estimated are

$$\text{Null: } CR_t^h = \overline{C}^h \tag{2.10}$$

$$\text{Reference: } CR_t^h = \overline{C}^h \cdot \left[RGAIN_t^h\right]^{\delta_G} \cdot \left[RLOSS_t^h\right]^{\delta_L} \tag{2.11}$$

$$\text{Inventory: } CR_t^h = \overline{C}^h \cdot \left[INV_t^h\right]^{\beta} \tag{2.12}$$

$$\text{Full: } CR_t^h = \overline{C}^h \cdot \left[INV_t^h\right]^{\beta} \cdot \left[RGAIN_t^h\right]^{\delta_G} \cdot \left[RLOSS_t^h\right]^{\delta_L} \tag{2.13}$$

It is clear from equations (2.10) to (2.13) that the proposed consumption rate not only provides a straightforward interpretation of parameters, but also a simple approach to determining the value of improvements in model fit. Empirical results for the four models are reported in the next section.

2.3.2 The Formulation of Reference Effects

We now develop the mechanism for capturing reference effects and the empirical definition of the variables $RGAIN_t^h$ and $RLOSS_t^h$. An important conceptual and practical feature of our model is the relationship between the way reference effects enter the consumption rate and the form of the nested logit model of category purchase. To see the relationship, assume that we have a fully-specified consumption function (2.13) and that the consumer encounters a "gain" (i.e., $OBS_t^h > EXP_t^h \Rightarrow RGAIN_t^h > 1, RLOSS_t^h = 1$).[9] In this case,

$$\begin{aligned} CR_t^h &= \overline{C}^h \cdot \left[INV_t^h\right]^{\beta} \cdot \left[RGAIN_t^h\right]^{\delta_G} \quad \text{so that} \\ \ln\left[CR_t^h\right] &= \ln\left[\overline{C}^h\right] + \beta \cdot \ln\left[INV_t^h\right] + \delta_G \cdot \ln\left[RGAIN_t^h\right] \\ &= \ln\left[\overline{C}^h\right] + \beta \cdot \ln\left[INV_t^h\right] + \delta_G \cdot \left\{\ln\left[OBS_t^h\right] - \ln\left[EXP_t^h\right]\right\} \end{aligned} \tag{2.14}$$

Thus, after taking the log of both sides of the consumption function, the reference effect is expressed as a linear difference in logarithms. To see the relationship to the deterministic utility of the nested logit model, recall that "category value" is also a logarithmic function,

[9] The case for a loss where $EXP_t^h > OBS_t^h \Rightarrow RLOSS_t^h > 1, RGAIN_t^h = 1$ is analogous.

$CV_t^h = \ln[\sum_i \exp(U_t^h(i))]$. In behavioral terms, category value represents a time-varying and household-specific assessment of the attractiveness of making a purchase in the product category (e.g., Grover and Srinivasan 1997).

In equation (2.14) OBS_t^h and EXP_t^h are the observed and expected values associated with making a purchase in the category, but we have yet to specify an operational form for these variables that would be suitable in estimation. In their study of reference effects in the category purchase decision, Bell and Bucklin (1999) argue that CV_s^h, where s is the time of the last purchase, defines the reference point for the consumer making a *category purchase decision* at time t. If the value associated with a purchase in the category is an increasing function of the total utility available from the category, then $\ln[OBS_t^h] = \ln[\sum_i \exp(U_t^h(i))] = CV_t^h$ is a reasonable metric. Similarly, by following Bell and Bucklin (1999) and applying this logic to the reference point, $\ln[EXP_t^h] = CV_s^h = CVREF_t^h$. We can then rewrite equation (2.14) as

$$\begin{aligned}
\ln[CR_t^h] &= \ln\left[\overline{C}^h\right] + \beta \cdot \ln\left[INV_t^h\right] + \delta_G \cdot \left\{\ln\left[OBS_t^h\right] - \ln\left[EXP_t^h\right]\right\} \\
&= \ln\left[\overline{C}^h\right] + \beta \cdot \ln\left[INV_t^h\right] + \delta_G \cdot \left\{CV_t^h - CVREF_t^h\right\}. \qquad (2.15)
\end{aligned}$$

where the final term captures the effect of a "gain" on the consumption rate. Thus, our consumption function leads directly to a simple and easily estimable model which is both behaviorally reasonable and grounded in the findings of previous literature.

3 Data and Empirical Results

3.1 Database

The data come from a large mid-Western U.S. city and cover the two-year period June 1991–June 1993. A total of 548 panelists make purchases from five separate supermarkets. We use the first six months of data to initialize key model variables and the next one year for model calibration. In order to test for the presence of inventory and reference-based consumption effects across a range of contexts, we use a wide variety of product categories. These are: bacon, butter, crackers, detergent, hot dogs, ice cream, margarine, paper towels, soft drinks, sugar and bathroom tissue.

Summary statistics for these categories are provided in Table 1. In columns 2-4, we report the number of brands, sizes and unique items in each category. Column 5 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 6 gives the number of shopping trips made by the included households, while column 7 reports the total number of brand choices made by the same group.

[Table 1 about here]

3.2 Empirical Results

To establish the best fitting model, we begin by reporting the fit statistics of the four models, Null, Reference, Inventory and Full. Following this, we focus on individual parameter estimates and the substantive findings on flexible consumption provided by the best model.

3.2.1 Model Comparisons

Table 2 presents the model fits for all four models. In order to compare relative model fits, we report the log likelihood (LL) and the Bayesian Information Criterion (BIC) values. As noted earlier, the Null, Reference and Inventory models are all nested within the Full model, so we could also report the relevant χ–statistics for these comparisons, however, in the interests of space and ease of exposition, we do not do this.[10] The number of parameters, k, is also given for each model. The value of k depends primarily upon the number of brands and sizes in each category. The brand choice model (see Appendix) for the bacon category, for example, requires eleven parameters: six brand dummies, plus parameters for brand loyalty, last brand purchased, price, feature and display. As shown in equation (2.9), the purchase incidence component of the null model requires four parameters (intercept, consumption rate, mean-centered inventory and category value), for a total of $k = 15$.

[10]It is straightforward to see that both measures produce the same conclusions about relative model fit. Since the Reference and Inventory models are not nested, it is expositionally more convenient to focus on BIC for all comparisons.

In nine of eleven categories (hot dogs and sugar are exceptions), a clear pattern emerges: The Full model is the best model, then the Inventory model, then the Reference model, then the Null model.[11] In many cases (e.g., detergents, paper towels and soft drinks), the magnitude of improvement in model fit is substantial — the Full model showing as large as 4.28% improvement over the Null model. While this may seem small in absolute terms, it is worth noting that many published studies on the category purchase decision report improvements of closer to 1.0% or even less. It is also clear that the majority of the improvement in model fit is derived from the inventory effect (β) rather than from the reference effects (δ_G and δ_L). On average, the relative improvements over the Null model are 0.28%, 1.48% and 1.73% for the Reference, Inventory and Full models, respectively.

[Table 2 about here]

3.3 Parameter Estimates

Our main interest is in the parameters of the Full model, since this is the model that provides the best fit in all categories, except hot dogs. Prior to reporting these parameters, however, we also briefly examine the estimates from the other three models as they serve as a useful point of comparison.

Null Model. Table 3 reports the parameter estimates and the associated t–statistics for the Null Model. The t–statistics test the null hypothesis that the parameter estimate is equal to zero. We expect that the intercept, γ_0, should be negative, as should γ_2, the effect of mean-centered inventory. γ_1 (consumption) and γ_3 (category value) should both be positive. In accordance with expectations, we have $\gamma_0 < 0$, $\gamma_1 > 0$ and $\gamma_3 > 0$ and statistically significant in all categories. The behavior of γ_2, the response coefficient for mean-centered inventory, is negative and significant in eight of eleven cases and in the expected direction for detergent (-0.03). In soft drinks (0.01), bacon (0.07) and ice cream (0.04), it has the wrong sign and this is significant for the latter two categories.

[11] In hot dogs, the Inventory model is clearly the best ($BIC = -6,520.81$), while in sugar the Full model is the best ($BIC = -4,589.16$) and the Reference model is better than the Inventory model.

In their article on flexible consumption, AN (1998) note that the effect of inventory on purchase is potentially mis-specified in models that do not allow for time-varying consumption. As we shall subsequently show (see Tables 6 and 7), γ_2 has the correct negative sign for all categories for both the Inventory and Full models, and eleven of these estimates are statistically different from zero. Detergent (-0.07, t-ratio = -4.19) is now significantly less than zero, as are soft drinks (-0.04, t-ratio = -3.44) and bacon (-0.12, t-ratio -3.42). Finally, ice cream is also correctly signed (-0.01), but not significantly different from zero (t-ratio= -0.95).

In short, while the parameters for the Null model are in themselves, not particularly suprising, it is interesting to track the pattern across models. It is encouraging to note the considerable improvement in the behavior of γ_2 which arises in the Inventory and Full models. This is additional evidence in favor of the descriptive accuracy of these models and in the value of the time-varying consumption function given in equations (2.12) and (2.13).

[Table 3 about here]

Reference Model. Table 4 shows the parameter estimates and the t–statistics for this model. Here, we have two new parameters, δ_G and δ_L, for the gain and loss, respectively. According to the formulation given in equations (2.13) and (2.14), we expect $\delta_G > 0$ and $\delta_L < 0$. These parameters have the interpretation as "reference effect elasticities of consumption." Any positive deviation from expectations should cause temporary acceleration, while losses should cause slowdown. As in the Null model, the estimates for the effect of the consumption rate (γ_1) are correctly signed and significant. Note that some of the estimates of the inventory effect, γ_2, are still problematic (close to what they were for the Null model). The estimates for category value are only slightly affected by the new variables ($RGAIN_t^h$ and $RLOSS_t^h$). Turning to δ_G and δ_L, the first thing to note is that all parameters are less than one in absolute value, which implies that consumers are "reference-inelastic" with respect to consumption.

The estimates for δ_L are all negative as expected, and significantly different from zero. This finding is similar to that from many empirical studies, however, where the loss effect is strongly negative and always significant. In the case of gains, the estimates for δ_G do not show a clear pattern. Five are negative and significant, two are positive and significant, while the remainder are not different from zero. Since this model is not the best fitting, we return to this issue when we discuss the results from the Full model.

[Table 4 about here]

Inventory Effect Model. Table 5 gives the parameter estimates and in comparison to the Null Model, we see that the coefficients for mean-centered inventory all have the correct (negative) sign, and all but one (ice cream) are significantly less than zero. Of more interest are the estimated values for β, the inventory elasticity of consumption. We expect $\beta > 0$ and this is indeed the case for every category. All estimates are positive, and statistically greater than zero. Thus, we reject the unstated assumption of almost all prior work, namely that the consumption rate is constant and independent of inventory. Furthermore, we have a range of plausible values (from 0.26 to 2.51) suggesting both inelastic and elastic responses to inventory are present in our data (we discuss this in more detail shortly).

[Table 5 about here]

Full Model. This is the model of most interest and Table 6 provides the estimates. As noted earlier, this model beats all other models in all categories except hot dogs on the basis of model fit. (For the hot dogs category, the Inventory model fits best.) Based on our earlier analysis of the other models, three interesting points of comparison emerge.

1. In comparison to the second best (Inventory) model, the parameter estimates for consumption (γ_1) and mean-centered inventory (γ_2) change only slightly, but the t–statistics increase.

2. This is also true for the inventory elasticity of consumption parameter, β.

3. Estimates of the "reference loss elasticity of consumption", δ_L, retain the expected negative signs, but increase in magnitude.

[Table 6 about here]

4 Discussion

We have developed and estimated two new substantive and empirical constructs: the inventory elasticity of consumption and the reference effect elasticity of consumption. These constructs are of interest to marketers who believe that there may be ways to influence not only purchase, but also consumption. It is interesting to note that almost all published empirical studies implicitly ignore this possibility, and therefore adopt the view that marketing activity is a "zero sum" game which results in either brand switching, or inter-temporal substitution. In contrast, we suggest that marketing activity has a subtle effect on consumption through both inventory and reference effects.

4.1 Inventory Elasticity of Consumption

The most important empirical effect analyzed in this paper is the inventory elasticity of consumption. This elasticity is significant in all categories studied, in all models where the effect is allowed for (Inventory and Full). Thus, we strongly reject the implicit assumption in most of the empirical literature that inventory and consumption are unrelated and that the inventory elasticity of consumption is zero.

The substantive message from the empirical results is striking: every additional unit of inventory on hand will have a positive effect on the usage rate of the household. Note that the elasticity estimates also imply the converse effect: when consumers have less inventory, they use products at a slower rate. It could well be that our sample of eleven products are insufficiently representative of all consumer goods, nevertheless, this finding is of practical interest. The following table shows the estimated inventory elasticity of consumption parameter, β, and the t-statistics for the null hypothesis of unitary elasticity $H_0 : \beta = 1$. Categories are listed in increasing order of elasticity.

Inelastic Categories			Elastic Categories		
Category	β	t-ratio	*Category*	β	t-ratio
Crackers	0.28	-8.05	Bathroom tissue	1.18	2.64
Paper towels	0.39	-16.50	Ice cream	1.44	4.18
Sugar	0.41	-4.82	Hot dogs	2.05	4.48
Margarine	0.46	-10.55	Detergent	2.46	5.79
Butter	0.64	-4.59			
Soft drinks	0.82	-2.87			

The final category, bacon, has an estimated inventory elasticity of consumption that is not significantly different from one (β = 0.83, t-ratio = -1.58). Of particular interest are the inventory-elastic categories: bathroom tissue, ice cream, hot dogs and detergents. In these categories, the key for marketers is getting additional units of inventory into the home. In our model, all quantities are measured in standard units, so inventory loading could be accomplished by encouraging consumers to purchase larger sized packages.

While many of us will identify with the Smith family ice cream vignette in the Introduction, it is also easy to imagine increased usage as a function of inventory, for a category like hot dogs. On the surface, the effects for tissue ($\beta = 1.18$) and detergent ($\beta = 2.46$) seem perhaps more difficult to rationalize. On reflection, however, is not uncommon for households to adjust their usage of such products in accordance with inventories, as anyone running low on these goods can attest. Proctor and Gamble has had considerable success recently in stimulating changes in consumption through changes in cap sizes and packaging for laundry detergents (*Wall Street Journal*, January 17, 2001).

4.2 Reference Effect Elasticity of Consumption

The reference effect elasticities are in general, less important in describing behavior (as evidenced by model fits) and typically inelastic with respect to consumption. As noted previously, the empirical results for the gain parameters are somewhat inconclusive. Four of the food categories (butter, crackers, ice cream, margarine) show the expected positive sign, implying that favorable deviations from expectations lead to an increase in the rate of consumption. In two of these categories (crackers and margarine) the effects are statistically significant. A further five categories (bacon, detergent, hot dogs, sugar and tissue) show insignificant effects and the remaining categories (papers towels and soft drinks) are negatively signed and significant.

In contrast to gains, the reference elasticities of consumption for losses all show the expected negative sign, and all are statistically significant. The following table shows the estimated loss elasticity of consumption parameter, δ_L, and the t-statistics for the null hypothesis of unitary elasticity $H_0 : \delta_L = -1$. Categories are listed in increasing order of elasticity.

Inelastic Categories			Unitary-Elasticity Categories		
Category	δ_L	t-ratio	*Category*	δ_L	t-ratio
Crackers	-0.35	6.80	Detergent	-0.82	1.12
Sugar	-0.38	10.10	Bathroom tissue	-0.84	1.98
Margarine	-0.51	4.62	Bacon	-0.90	0.59
Hot dogs	-0.57	2.38	Soft drinks	-1.22	-1.33
Butter	-0.61	3.63			
Ice cream	-0.73	2.47			
Paper towels	-0.76	3.53			

In all cases, deviations from expectations cause a slowdown in the rate of consumption. This slowdown is most pronounced in the categories on the right side of the table (detergent, tissue, bacon and soft drinks), where the estimated loss elasticity of consumption is statistically not different from one (unitary elasticity). The interplay between the inventory elasticity of consumption and reference effect elasticities of consumption is illustrated in Figure 3. Here we show the consumption curve moving outwards to the right (slowing down) in response to a loss, and moving inwards to the left (speeding up) in response to a gain. Consistent with the literature and our empirical findings, the loss effect dominates that of the gain. Conceptually (and empirically) it seems reasonable to conclude the inventory elasticity of consumption is the primary effect, but may be moderated by reference effects.

[Figure 3 about here]

4.3 Summary

This paper offers the following stylized facts on flexible consumption:

1. Consumption rates of consumers are endogenous. The model fits and estimated parameters strongly endorse this idea, for all categories studied. In fact, the magnitude of fit improvements are striking and in general, much better than those routinely encountered in the literature.

2. The inventory elasticity of consumption is an important measure of how inventory on hand affects usage rates. Some categories (butter, crackers, margarine, paper towels, soft drinks and sugar) are inventory-inelastic, while others (detergent, hot dogs, detergent and tissue) are inventory-elastic. Bacon has a unitary inventory elasticity of consumption. Thus, in all product categories, consumption rates respond to inventory—but the magnitude of the elasticity varies across categories. The cross-category average inventory elasticity of consumption, $\overline{\beta}$, is equal to 1.15.

3. Reference effect elasticities of consumption are less statistically important to model fit and are smaller in magnitude than the corresponding inventory effects. The empirical results for gains are mixed and the cross-category average gain elasticity of consumption is small ($\overline{\delta_G} = -0.11$). The findings for loss elasticity of consumption are consistent across categories–always negatively signed and significant. The cross-category average loss elasticity of consumption is far larger in magnitude than that for gains, and less than the analogous value for the inventory effect ($\overline{\delta_L} = -0.76$).

4. Collectively, our results give rise to the notion of "consumption sensitivity" at the category level. Categories that are more sensitive to inventory effects, will also be more sensitive to loss effects. The correlation between β and δ_L is -0.55, which is significantly less than zero on a one-tailed test ($p < 0.03$).[12] A median split on the total responsiveness of the consumption function (i.e., the sum of the absolute value of all elasticities) offers further insight and some additional support for our approach. Consistent with intuition, sugar, crackers, butter, margarine, paper towels and bacon have the least sensitive consumption rates. Again, in order of increasing sensitivity, bathroom tissue, ice cream, soft drinks, hot dogs, and detergents have the most sensitive consumption rates.

5 Conclusion

Over several years, a number of researchers in marketing (e.g., Bucklin and Lattin 1991; Chiang 1991; Chintagunta 1993; Gupta 1988) have used scanner panel data to build models of *observable* consumer decisions. The goal of these studies was to determine the drivers of brand, category and purchase quantity decisions of consumers. 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, a number of experimental and analytical 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 in fact endogenous. Two of the key variables to emerge from this work were (a) level of inventory on hand, and (b) price variation in the environment. Causal empiricism also suggests that for many products, it is quite probable that consumers evolve their consumption rates in an economically meaningful and empirically detectable manner. Thus, it is important that empirical researchers develop models which allow for this possibility.

[12] Recall that $\beta > 0$ and $\delta_L < 0$ so this correlation should be negative: larger positive values of the inventory effect are associated with larger negative values of the loss effect.

The first published empirical study to measure changes in the rate of consumption is AN (1998). 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. In this paper, we build on this earlier work in several ways.

1. We propose a more intuitive consumption function and explicitly introduce the notion of an "inventory elasticity of consumption". This concept is particularly useful when we compare findings across many categories. We also benchmark our model against AN (1998), to make sure that it is at least comparable in terms of model fit. As shown in Table 7, the Inventory model has a superior fit in 10 of eleven categories for an average improvement of 1.06%. The Full model is better in all eleven cases with an average margin of 1.28

2. We extend the conceptual domain of flexible consumption to include the influence of reference effects. While the study of reference effects has a long tradition in marketing (see Kalyanaram and Winer 1995; Meyer and Johnson 1995) there exist no models that incorporate and estimate these effects as they relate to consumption. A particularly appealing property of our approach is the functional form of the consumption function which allows reference effects to be introduced in a natural way (see equation 2.14).

3. Our study is extensive in that we estimate our model across eleven product categories. The remarkable consistency in improvements in model fit points to the robust nature of the phenomenon.

[Table 7 about here]

5.1 Implications and Future Research

Our goal was to motivate a model of flexible consumption and to provide empirical estimates of two important drivers of this phenomenon: (a) inventory on hand, and (b) deviations from price expectations. In doing so, we developed a model that is straightforward to estimate and has parameters that are easily interpreted.

The modeling effort represents a number of trade-offs and leaves several avenues open for future research. While the research is motivated by both experimental and analytical findings, no formal theory is developed. Such an effort is likely to produce additional insight into the behavioral drivers of the flexible consumption mechanism. Second, we utilize a simple reduced form approach to model specification. In order to make specific policy evaluations, a structural esimation approach could prove useful.

Third, like AN (1998), we do not attempt to model unobserved parameter heterogeneity directly. We do, however, capture heterogeneity by allowing each consumer to have an individual consumption rate. As can be seen in Figure 2, a single β value allows various consumption speeds to be modeled in accordance with individual–specific average consumption rates. Thus, we leave the estimation of individual-specific consumption elasticity parameters as a topic for future research, and focus instead on understanding sample-wide effects and differences in behavior across several product categories. The remarkably consistent patterns of results and improvements in model fit suggest that the basic empirical message and substantive implications are unlikely to change.

6 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

$$P_t^h(i|inc) = \frac{\exp(U_t^h(i))}{\sum_k \exp(U_t^h(k))}, \tag{6.1}$$

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:

$$\begin{aligned} U_t^h(i) &= \alpha_i + \beta_1 BLOY_i^h + \beta_2 LBP_{ti}^h + \beta_3 SLOY_i^h + \beta_4 LSP_{ti}^h + \\ & \quad \beta_5 PRICE_{ti} + \beta_6 FEAT_{it} + \beta_7 DISP_{it} \end{aligned} \tag{6.2}$$

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
Bathroom tissue	9	4	26	495	33,402	6221
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

Category		*Null Model*	*k*	*Reference Model*	*k*	*Inventory Model*	*k*	*Full Model*	*k*
Bacon	LL	-4,944.31	15	-4,930.92	17	-4,916.95	16	-4,897.66	18
	BIC	-5,014.85		-5,010.86		-4,992.19		-4,982.30	
Bathroom tissue	LL	-22,998.73	22	-22,907.59	24	-22,565.52	23	-22,485.13	25
	BIC	-23,113.31		-23,032.59		-22,685.31		-22,615.34	
Butter	LL	-3,661.66	13	-3,637.36	15	-3,587.52	14	-3,566.10	16
	BIC	-3,721.56		-3,706.47		-3,652.02		-3,639.82	
Crackers	LL	-3,067.59	14	-3,042.59	16	-3,010.46	15	-2,992.84	17
	BIC	-3,132.25		-3,116.49		-3,079.74		-3,071.36	
Detergent	LL	-6,259.15	22	-6,235.87	24	-6,141.12	23	-6,121.89	25
	BIC	-6,364.73		-6,351.05		-6,251.50		-6,241.87	
Hot dogs	LL	-6,524.84	21	-6,519.08	23	-6,415.26	22	-6,409.40	24
	BIC	-6,625.59		-6,629.42		-6,520.81		-6,524.54	
Ice cream	LL	-8,684.17	24	-8,657.80	26	-8,542.38	25	-8,511.93	27
	BIC	-8,802.09		-8,785.55		-8,665.22		-8,644.59	
Margarine	LL	-13,612.15	19	-13,592.14	21	-13,544.51	20	-13,521.69	22
	BIC	-13,708.59		-13,698.74		-13,646.03		-13,633.37	
Paper towels	LL	-16,034.65	19	-15,953.74	21	-15,781.17	20	-15,695.31	22
	BIC	-16,131.79		-16,061.11		-15,883.42		-15,807.79	
Soft drinks	LL	-13,163.07	23	-13,105.91	25	-12,614.01	24	-12,580.80	26
	BIC	-13,274.12		-13,226.62		-12,729.89		-12,706.33	
Sugar	LL	-4,536.35	15	-4,511.93	17	-4,527.47	16	-4,503.68	18
	BIC	-4,607.59		-4,592.67		-4,603.45		-4,589.16	

Table 2: Model Fit Statistics

Category	*Intercept* (γ_0)	CR_t^h (γ_1)	$MCINV_t^h$ (γ_2)	CV_t^h (γ_3)
Bacon	-3.73	2.67	0.07	0.44
	-34.88	13.99	2.67	9.39
Bathroom tissue	-4.13	0.24	-0.03	0.55
	-62.06	23.38	-3.89	35.49
Butter	-2.71	2.53	-0.11	0.59
	-52.03	16.29	-3.92	15.08
Crackers	-4.04	2.82	-0.30	0.47
	-22.91	12.57	-5.57	8.08
Detergent	-3.96	0.40	-0.03	0.41
	-43.25	13.27	-1.53	12.82
Hot dogs	-4.09	2.19	-0.06	0.42
	-27.93	17.93	-2.30	9.30
Ice cream	-3.91	0.67	0.04	0.36
	-40.78	21.37	3.00	13.00
Margarine	-2.50	1.63	-0.06	0.34
	-82.00	21.79	-4.51	12.93
Paper towels	-3.10	0.76	-0.02	0.50
	-65.93	28.08	-2.09	23.99
Soft drinks	-3.12	0.31	0.01	0.28
	-38.89	33.15	0.72	14.16
Sugar	-2.36	0.73	-0.05	0.33
	-31.01	19.15	-2.99	11.31

Table 3: Parameter Estimates and t–Statistics for the Null Model

Category	*Intercept* (γ_0)	CR_t^h (γ_1)	$MCINV_t^h$ (γ_2)	CV_t^h (γ_3)	$RGAIN_t^h$ (δ_G)	$RLOSS_t^h$ (δ_L)
Bacon	-3.43	2.68	0.07	0.36	-0.04	-0.38
	-29.97	15.13	2.45	6.30	-0.45	-4.80
Bathroom tissue	-3.74	0.23	-0.04	0.50	-0.09	-0.39
	-38.16	22.25	-4.76	20.65	-2.25	-12.96
Butter	-2.51	2.50	-0.10	0.45	0.01	-0.39
	-38.08	16.56	-3.51	8.79	0.12	-6.77
Crackers	-3.31	2.93	-0.29	0.22	0.35	-0.35
	-14.81	12.93	-5.17	2.60	2.65	-3.86
Detergent	-3.56	0.40	-0.03	0.32	0.02	-0.39
	-29.10	13.70	-1.81	6.94	0.28	-6.46
Hot dogs	-4.06	2.16	-0.06	0.45	-0.21	-0.22
	-23.50	15.19	-2.47	8.16	-2.21	-2.97
Ice cream	-3.48	0.69	0.04	0.27	0.04	-0.37
	-31.14	22.15	2.68	8.08	0.60	-6.82
Margarine	-2.44	1.63	-0.06	0.27	0.13	-0.24
	-66.49	21.94	-3.71	9.35	2.51	-5.05
Paper towels	-2.80	0.73	-0.03	0.46	-0.15	-0.41
	-54.39	28.29	-2.39	20.08	-3.58	-11.96
Soft drinks	-2.67	0.30	0.00	0.23	-0.30	-0.60
	-21.18	31.76	0.02	7.23	-4.83	-10.02
Sugar	-2.30	0.73	-0.05	0.27	-0.06	-0.30
	-18.39	18.93	-3.07	6.18	-1.03	-6.77

Table 4: Parameter Estimates and t–Statistics for the Reference Effect Model

Category	*Intercept* (γ_0)	CR_t^h (γ_1)	$MCINV_t^h$ (γ_2)	CV_t^h (γ_3)	INV_t^h (β)
Bacon	-2.30	0.50	-0.11	0.39	0.80
	-18.52	12.18	-3.18	8.93	7.34
Bathroom tissue	-3.87	0.45	-0.06	0.53	1.15
	-51.91	25.21	-6.60	29.66	17.90
Butter	-1.20	0.60	-0.24	0.56	0.65
	-13.55	14.23	-6.63	14.70	7.73
Crackers	-1.80	0.99	-0.37	0.49	0.26
	-6.76	10.30	-5.98	8.47	2.94
Detergent	-3.54	0.45	-0.07	0.43	2.51
	-30.97	11.50	-3.99	11.62	9.89
Hot dogs	-2.54	0.44	-0.13	0.32	2.05
	-13.98	11.24	-4.92	7.11	8.83
Ice cream	-3.03	0.51	-0.01	0.32	1.52
	-26.34	17.50	-0.78	10.30	13.86
Margarine	-1.37	0.49	-0.15	0.31	0.45
	-30.83	20.57	-8.43	11.93	8.69
Paper towels	-2.16	0.58	-0.08	0.46	0.38
	-37.53	28.23	-6.36	24.68	10.17
Soft drinks	-3.09	0.41	-0.03	0.28	0.83
	-26.90	20.21	-3.44	9.88	14.04
Sugar	-1.39	0.77	-0.04	0.32	0.44
	-24.23	17.89	-2.22	12.22	3.52

Table 5: Parameter Estimates and t–Statistics for the Inventory Effect Model

Category	*Intercept* (γ_0)	CR_t^h (γ_1)	$MCINV_t^h$ (γ_2)	CV_t^h (γ_3)	$RGAIN_t^h$ (δ_G)	$RLOSS_t^h$ (δ_L)	INV_t^h (β)
Bacon	-1.94	0.51	-0.12	0.29	-0.10	-0.90	0.83
	-13.51	12.60	-3.42	4.87	-0.63	-5.29	7.71
Bathroom tissue	-3.45	0.44	-0.06	0.46	-0.09	-0.84	1.18
	-42.02	22.97	-8.23	22.71	-1.05	-10.38	17.32
Butter	-1.03	0.59	-0.23	0.44	0.01	-0.61	0.64
	-12.05	14.75	-7.25	8.32	0.09	-5.68	8.16
Crackers	-1.14	1.00	-0.37	0.29	0.26	-0.35	0.28
	-3.87	11.15	-6.07	3.52	2.00	-3.66	3.13
Detergent	-3.20	0.45	-0.07	0.37	-0.10	-0.82	2.46
	-24.48	11.35	-4.19	8.25	-0.57	-5.08	9.76
Hot dogs	-2.40	0.44	-0.13	0.31	-0.23	-0.57	2.05
	-11.85	11.69	-5.30	5.64	-1.07	-3.15	8.75
Ice cream	-2.52	0.54	-0.01	0.21	0.13	-0.73	1.44
	-21.12	18.39	-0.95	6.42	1.15	-6.67	13.68
Margarine	-1.32	0.49	-0.15	0.23	0.32	-0.51	0.46
	-28.08	20.75	-8.27	7.73	2.76	-4.81	8.99
Paper towels	-1.86	0.56	-0.09	0.40	-0.18	-0.76	0.39
	-31.19	28.90	-6.38	16.15	-2.36	-11.17	10.55
Soft drinks	-2.67	0.40	-0.04	0.22	-0.43	-1.22	0.82
	-18.43	19.34	-3.44	6.39	-2.75	-7.39	13.06
Sugar	-1.31	0.78	-0.05	0.27	-0.08	-0.38	0.41
	-11.60	17.72	-2.61	6.08	-1.13	-6.19	3.35

Table 6: Parameter Estimates and t–Statistics for the Full Model

	BIC Values			*% Improvement*	
	AN (1998)	*Inventory*	*Full*	*Inventory over AN*	*Full over AN*
Bacon	-5,016.15	-4,992.19	-4,982.30	0.48%	0.67%
Bathroom tissue	-22,904.69	-22,685.31	-22,615.34	0.96%	1.26%
Butter	-3,731.54	-3,652.02	-3,639.82	2.13%	2.46%
Crackers	-3,142.76	-3,079.74	-3,071.36	2.01%	2.27%
Detergent	-6,269.97	-6,251.50	-6,241.87	0.29%	0.45%
Hot dogs	-6,537.93	-6,520.81	-6,524.54	0.26%	0.20%
Ice cream	-8,677.96	-8,665.22	-8,644.59	0.15%	0.38%
Margarine	-13,694.18	-13,646.03	-13,633.37	0.35%	0.44%
Paper towels	-16,132.58	-15,883.42	-15,807.79	1.54%	2.01%
Soft drinks	-13,225.57	-12,729.89	-12,706.33	3.75%	3.93%
Sugar	-4,589.34	-4,603.45	-4,589.16	-0.31%	0.00%
Mean				1.06%	1.28%

Table 7: A Comparison of the Proposed Models and Ailawadi and Neslin (1998)

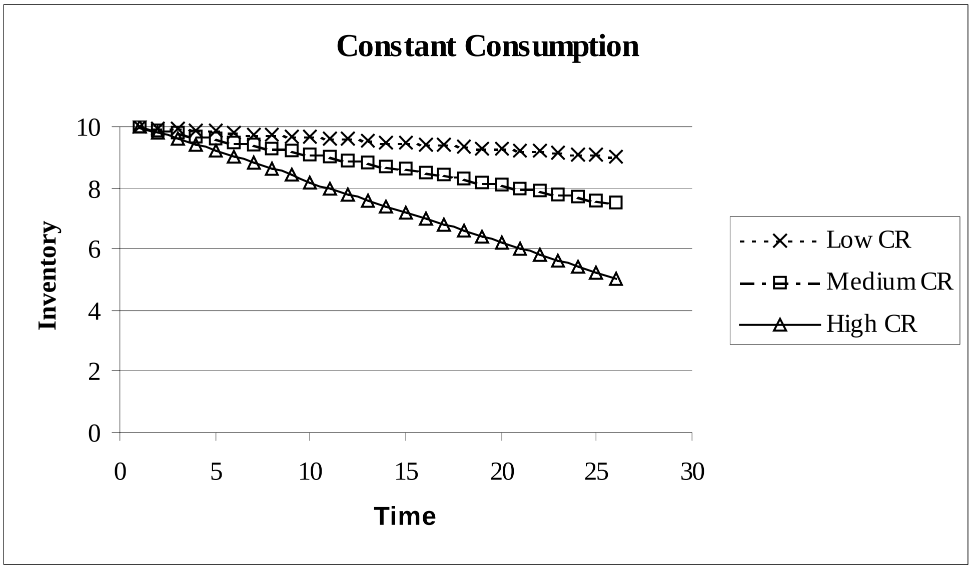

Figure 1: Inventory elasticity for constant consumption

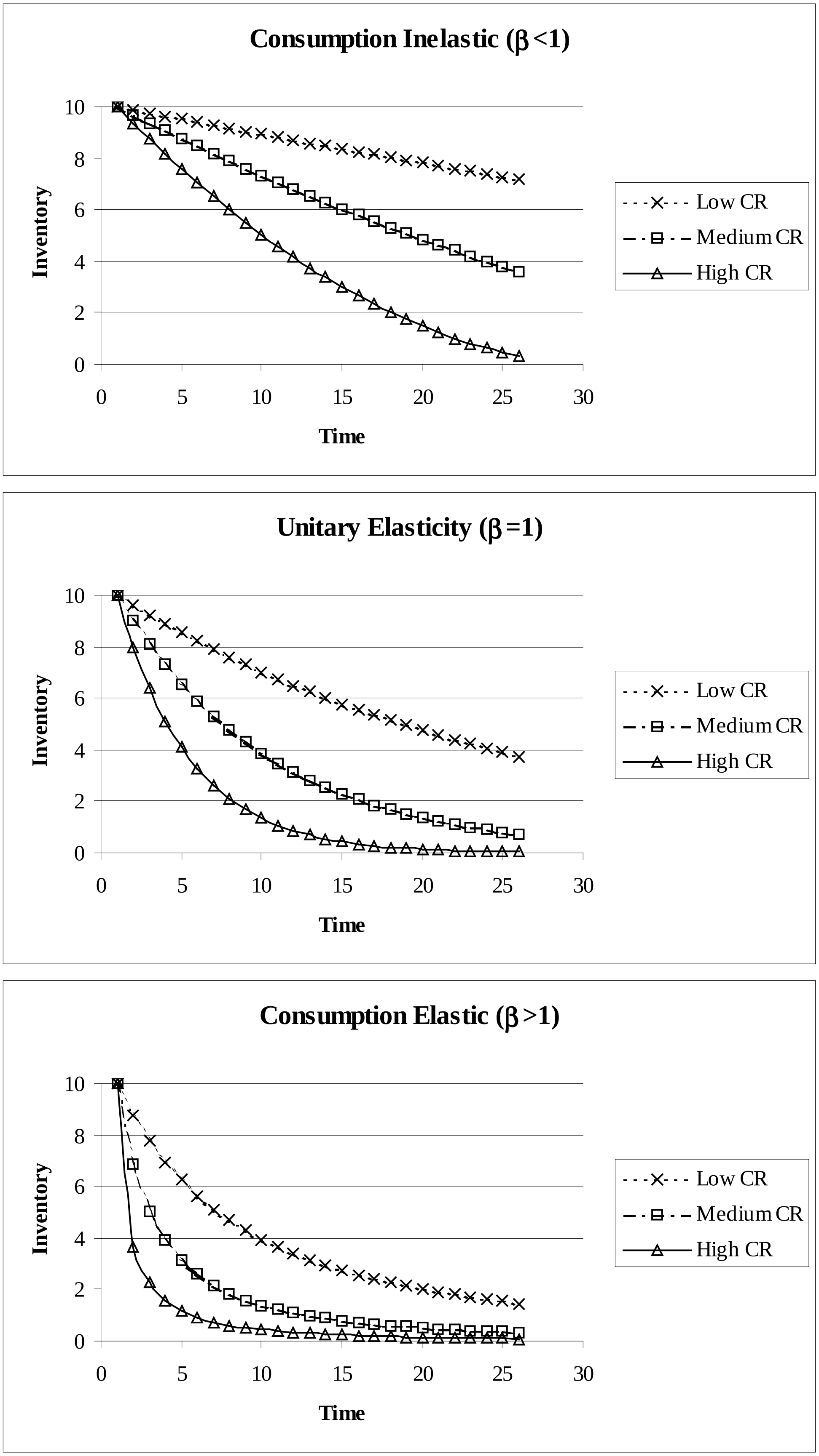

Figure 2: The inventory elasticity of consumption

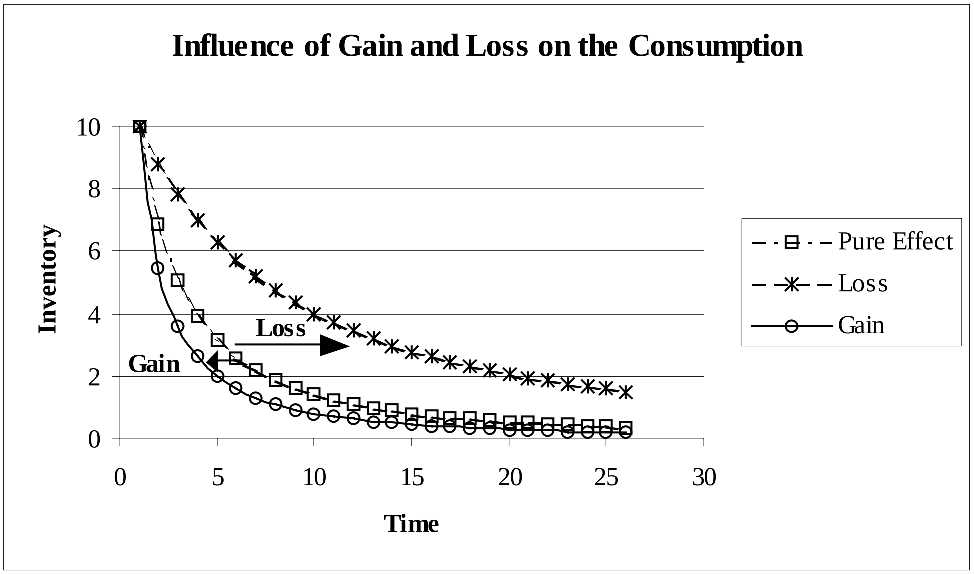

Figure 3: Influence of loss and gain to the inventory elasticity