Hysteresis, Price Acceptance, and Reference Prices

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1 Introduction

Shelf prices are not always the stimulus consumers use to guide their decision making. Rather, the existence of reference prices, or mental benchmarks consumers use to assess what is a "normal" or expected price, is well-documented (Lattin and Bucklin 1989; Hardie, Johnson, and Fader 1993; Kalyanaram and Winer 1995; Bell and Lattin 2000; Erdem, Mayhew, and Sun 2001; Mazumdar, Raj, and Sinha 2005; Pauwels, Srinivasan, and Franses 2007). From a practical standpoint, however, practitioners are more interested in what happens when prices move away from the reference level? Empirical studies reveal zones of inactivity around reference prices, or "latitudes of price acceptance" (Gupta and Cooper 1992; Kalwani and Yim 1992; Kalyanaram and Little 1994; Han, Gupta, and Lehmann 2001; Terui and Dahana 2006) in which retail prices change, but consumers do not appear to respond as we would expect them to. That is, consumers appear to be insensitive to price changes between an upper and lower threshold surrounding the reference price. One popular explanation for the existence of such price-thresholds is the Assimilation-Contrast Theory (ACT, Sherif 1963) in which "a new stimulus encountered by an individual is judged against a background of previous experience in the category" (Kalyanaram and Little 1994). Price variations within the region of acceptance are assimilated, or ignored, and price changes outside of this region are contrasted with the consumer's previous experience, thereby inducing a behavioral response. Others explain the fundamental asymmetry in consumer response around their reference price in terms of either Prospect Theory (PT, Kahneman and Tversky 1979) or Adaptation Level Theory (ALT, Helson 1964). Prospect Theory maintains that consumers develop an expected or reference price, and that any price changes above that level will leave them in the domain of losses, while price reductions below their reference level will leave them in the domain of gains. Because losses are perceived as more onerous than gains are beneficial, according to Prospect Theory, loss aversion leads to a revealed asymmetry in price response that appears as a kinked demand curve. Adaptation Level Theory, on the other hand, argues that consumers will not respond to a stimulus if it is not deemed to be either too high or too low relative to some benchmark price that they have become adapted to. However, each of these theories presumes some sort of behavioral component that contradicts the underlying tenets of rational economic behavior. While such violations are possible, and well-documented, the burden of proof in documenting their existence is high because they remove the ability of theory to generalize and to explain market phenomenon that result from individual behavior.[1] In this study, we offer an alternative that is grounded in rational economic behavior.

Our explanation, on the other hand, does not require that we assume the market fails when thresholds arise. Rather, if consumers face uncertain retail prices, and incur fixed costs in searching for grocery products (Mehta, Rajiv, and Srinivasan 2003; Hong and Shum 2006; Moraga-Gonzalez and Wildenbeest 2008; Kim, Albuquerque, and Bronnenberg 2010; Wildenbeest 2011; De los Santos, Hortacsu, and Wildenbeest 2012), then the purchase decision embodies a real option value. Akin to a financial option to buy a share of stock (or currency, commodity contract, or other financial instrument) at a fixed price for a fixed time period, the ability to wait until the uncertainty surrounding the retail price is resolved creates a potentially significant value for the option holder. Consequently, the decision to purchase the product when shelf prices are either above or below the reference price involves exercising the option and giving up a substantial amount of value in doing so. Allowing the shelf price to change either upward or downward sufficient to make exercising this option worthwhile creates a zone of apparent acceptance around the reference price in which the consumer neither capitalizes on the opportunity to take advantage of a perceived "deal" on the product, nor reluctantly responds to an underlying need for a product that is deemed relatively expensive. Intuitively, consumers know that if retail prices are volatile, there is a chance that the price will fall far enough to make immediate purchase a wise decision, and that there is also a chance that the price will rise far enough to cause them to have to fulfill a need at an apparently usurious price. Waiting for either to happen creates inactivity that is referred to as hysteresis (Dixit and Pyndick 1994), or the persistence of a phenomenon even after its initial cause has disappeared. Identifying hysteresis, as opposed to either ACT, PT, or ALT, requires that we estimate a threshold econometric model in which the location of the thresholds depends on factors that drive real option values, namely past price volatility. None of the alternative explanations for the existence of price thresholds depends on the volatility of retail prices in this sense, so if retail price volatility is found to be a significant determinant of the price thresholds, then the data support our hysteretic theory of threshold formation.[2]

[1] For example, if everyone in the market possesses a different reference price, then there is no reason to explain why thresholds arise in aggregate data, despite evidence that they do (Pauwels, Srinivasan, and Franses 2007) and empirical evidence that heterogeneity explains much of the evidence of reference prices, traditionally defined (Lattin and Bucklin 1989).

[2] Others conjecture that the size of the zone of price acceptance depends, in part, on price volatility (Mazumdar and Jun 1992), but do not formalize why this might be the case.

We test our hysteretic explanation for the presence of a latitude of price acceptance using household-level scanner data from four frequently-purchased product categories (that vary in their purchase frequency; cereal, yogurt, and laundry soap) in a variant of an econometric friction model (Rosett 1959). A friction model is appropriate for testing the theory that underlies threshold pricing because it explicitly accounts for the existence of thresholds in the data that separate households into regimes of gains, losses, and indifference based on some endogenous source of censoring. In our model, the selection mechanism derives from price volatility and a real option effect. Terui and Dehana (2006) is the only other study that explicitly accounts for the data-censoring implied by threshold behavior, but their model presumes a Bayesian separation mechanism and normally distributed preferences. We allow for randomness in the formation of price thresholds as in Han, Gupta and Lehmann (2001), but the latter do not account for the underlying censoring of the data caused by thresholds. While their model is an extension of a logit model of brand choice, ours represents a fundamentally different approach to accounting for threshold-price behavior. Accounting for unobserved heterogeneity in the hysteretic effect addresses the issue of whether price acceptance is an artefact of heterogeneity in our data (Bell and Lattin 2000), or are inherently probabilistic constructs (Han, Gupta, and Lehmann 2001). If removing unobserved heterogeneity causes thresholds to disappear, then it is clear that thresholds are due to failing to account for unobserved factors that otherwise explain reference-price effects.

We compare our model to other possible explanations – ACT, PT, ALT – in order to establish the validity of our model. The primary differentiating factor between the hysteretic and other models is that the threshold driven by an implicit real option will widen when the variability of prices is high. That is, when a retail price is relatively volatile, the real option will be higher, so the hysteretic effect will be stronger, and the threshold wider than would otherwise be the case. The other explanations for reference-price behavior are silent on the effect of two-sided volatility on the existence and magnitude of price-thresholds. We compare these models using commonly-accepted models that embed reference prices, and use the specification for the formation of reference prices that has been found to fit the data from several categories best (Briesch et al. 1997). Consequently, observations of market-level threshold effects must be explained by something other than micro-level household behavior.

Our findings have practical importance. Marketing practitioners use the concept of "threshold effects" as if it was of the order of a stylized fact (Management Science Associates 2013). That is, the implicit assumption among practitioners is that demand response is not smooth over a range of prices, but rather there exists pricing thresholds beyond which demand elasticities change in a fundamental way. Whether this is true or not is critically important for setting retail prices, because elasticities clearly drive the relationship between pricing and sales revenue. In order to be useful, a method of estimating demand models that accounts for, and is able to test for and locate, such thresholds, must be relatively simple and tractable in a relatively large demand system. In this research, we develop an approach for estimating pricing thresholds and demonstrate its usefulness in four frequently purchased consumer good categories. Many studies identify the existence of reservation prices and thresholds at the micro, household-level (Mazumdar, Raj, and Sinha 2005). While individual behavior may be the source of any reservation price behavior, marketers are more interested in the aggregate, market-level implications of individual-level reservation prices. Pauwels, Srinivasan and Franses (2007) address this problem by estimating a reservation-price model in aggregate data, but with a demand model that is not grounded in utility maximization. Bell and Lattin (2000) show that much of the reservation price evidence disappears once heterogeneity is properly accounted for, but not all. The question remains, therefore, are threshold-prices a product of aggregate, store-level data? Rather than estimate with store-level data, we estimate our threshold-price model at the individual household level, and then simulate a market equilibrium over an assumed distribution for unobserved consumer heterogeneity. Any thresholds that remain, therefore, are both consistent with individual utility maximization, and the distribution of heterogeneity that is relevant for practitioners.

We find that the data are consistent with our hysteretic explanation for threshold prices. One of the primary implications of the hysteretic model that differentiates it from others is that the size of the latitude of price acceptance rises in the volatility of retail prices. Because option values rise in volatility, the implicit cost of excercising the option by making a purchase is higher the more variable retail prices. We find strong evidence in support of this outcome in each of the product categories. Second, we find evidence of asymmetric price response above and below the threshold. This finding suggests that, while Prospect Theory may not provide a complete explanation of threshold-price behavior, its predictions are nonetheless relevant in data. Third, we find that consumers do appear to respond to variations in retail prices around reference levels, even after controlling for heterogeneity in both the threshold and in price response. This finding is significant as reference-price formation does not appear to be an artefact of failing to control for unobserved heterogeneity. Finally, we find that our household-level estimates do indeed imply aggregate, or store-level, threshold price behavior. Because store-level data remains the workhorse of marketing analytics in practice, our findings are relevant to decision-makers.

Our findings contribute to both the theoretical and methodological literatures on reference prices and price thresholds. Conceptually, finding support for our hysteretic model of threshold price effects adds an explanation for an oft-observed phenomenon that does not rely on some sort of a behavioral deviation from neo-classical economic assumptions. Although it is not our intent to discredit behavioral models in general, nor to justify traditional economic modeling, our model shows how predictions based on simple postulates of consumer behavior are sufficiently general and should not be ruled out. Our approach also adds to the existing literature on this topic by synthesizing theory from financial economics with marketing theory to arrive at an alternative explanation for what is generally regarded as a stylized fact. On a methodological level, we contribute to the debate on whether the existence of reference prices and price thresholds are artifacts of failing to control for unobserved heterogeneity. In our model, we allow for two sources of consumer heterogeneity and still find evidence of reference-price behavior. We also explicitly account for the implications of threshold-price behavior for censoring effects in the underlying data, and offer a tractable, easily-estimated alternative to existing Bayesian methods of estimating multi-threshold demand models. Finally, we contribute to the body of empirical evidence on the asymmetry of price-response to either side of price thresholds. Specifically, Prospect Theory suggests that consumers respond much more aggressively to price increases than to price reductions, and we find evidence to support this hypothesis in frequently-purchased consumer-packaged goods data.

In the second section, we provide a brief background to the theoretical and empirical literature on reference prices and price thresholds. We use this background to motivate the development of an alternative model in section three that is based in real option pricing theory, and its primary implication for purchase behavior, purchase hysteresis. We present our econometric model of purchase hysteresis in the fourth section, and describe how we implement the model in data covering four categories of consumer packaged goods. The application and relevant data are presented in a fifth section. We offer detailed estimation results from one category in the sixth section, and compare our findings to alternative model specifications. We also discuss our results in the context of other empirical research on this issue. A final section concludes, and suggests some avenues for future research that may help resolve some of the fundamental debates that remain.

2 Background on Reference Prices and Price Thresholds

In this section, we summarize the theories used to explain the existence of reference prices, and how they may give rise to thresholds in consumer decision making. These theories are grouped into three broad classifications as to their origin: (1) neo-classical economics, (2) consumer behavior and applied psychology, and (3) financial economics. We summarize the first two in this section, and offer our alternative as part of the third group of explanations in the next section. There we describe how our new theory of threshold prices compares with existing theories in terms of its implications for observed pricing patterns, and retail practice.

2.1 Neo-Classical Economic Theories

While demand curves in principles of economics are typically represented as smooth and continuous, the notion of a "kinked" demand curve arose early in the theory of imperfect competition with differentiated products. Sweezy (1939) was the first to advance the notion that rival firms in oligopoly will match price increases, but not price reductions. Therefore, if an individual firm tries to raise its price, it loses a large amount of market share, but cannot gain much market share by reducing its price. In the kinked-demand story, however, it is difficult to disentangle whether the observed response in demand derives from consumer behavior, or a rational firm response to expectations of consumer behavior.[3] Similarly, more recent research on the apparent fixity of retail prices cites the existence of fixed costs (termed "menu costs") of changing prices as an explanation for apparent thresholds in price response. Such fixed costs introduce a fundamental non-convexity to firms' price-change decision so that prices will not change smoothly in response to underlying changes in demand or costs, but rather follow an (s_L, S, s_U) bounds rule (Sheshinski and Weiss 1977; Caballero and Engel 1999; Slade 1998, 1999). According to this rule, a retailer may want to change her price

[3] Subsequent empirical research by Stigler (1947) and Simon (1969) discredited the kinked-demand curve theory by finding that oligopoly firms do not necessarily respond in the most dis-advantageous way to the initiator of a price change.

toward an "ideal" level, S, but she will only do so when the benefit of a change exceeds the total adjustment cost. Once the desired price reaches either an upper or lower threshold, it is immediately changed to the target value. Putler (1992) also demonstrates the implications of reference-price behavior for neo-classical market equilibrium, but does not attempt to explain why reference prices arise in the first place.

2.2 Behavioral Theories

Several theories in consumer behavior and applied psychology have been developed to explain reference prices and their link to the existence of thresholds in consumer decision making. The first was Adaptation Level Theory (ALT), put forward in pioneering research by Helson (1964). In the context of reference prices, ALT posits that a consumer's price reference point is determined by her exposure and recollection of prior prices. Monroe (1971) and Della, Bitta and Monroe (1974) empirically test this theory in experimental settings to show that consumers respond differently when prices are above the reference price than when they are below the reference price. Subsequent research based in ALT focused on implications to price advertising (Gotlieb and Dubinsky 1991), pricing of new products (Della, Bitta and Monroe 1974), the role of retail prices suggested by suppliers (Lichtenstein and Bearden 1988), and pricing tactics (Kinard, Capella and Bonner 2013), among others. While this stream of research points out to the importance of the level of retail price relative to the reference price of consumers, it is silent regarding how large the difference between reference and actual prices should be to trigger changes in purchase decisions.

Various theories have been developed to examine the nuances of identifying reference price structure, relying on quantitative methods for testing (Winer 1986). By far, the most popular among these are Assimilation Contrast Theory (ACT, Sherif and Hovland 1961; Sherif 1963) and Prospect Theory (PT, Kahneman and Tversky 1979). The two theories differ in their assumptions about the influence of the reference price, in particular regarding the existence of discontinuities in the relationship among reference prices, actual prices and consumer response (Boztug and Hildebrand 2005). Most research has focused on PT, although a large body of consumer behavior literature suggests that reference price may be a region and should not be described as a point (Emery 1969; Kalwani and Yim 1992; Klein and Oglethorpe 1987; Monroe 1971; Sawyer and Dickson 1984). Moreover, a growing number of empirical studies confirm the existence of price thresholds (Han, Gupta, and Lehmann 2001; Kalyanaram and Little 1994; Raman and Bass 2002; Pauwels, Franses, and Srinivasan 2004).

Assimilation Contrast Theory (ACT) was introduced Sherif and Hovland (1961) based on the psychological principle that individuals have a range of indifference around a reference point. According to ACT, a stimulus inside this indifference range is perceived as smaller than its real value (i.e., assimilation effect). On the other hand, stimulus outside the range of indifference is perceived as larger than its real value (i.e., contrast effect) triggering behavioral changes of individuals. Sherif (1963) was the first in applying ACT to consumer price perception and in measuring the range of indifference in an experimental setting. Lichtenstein and Bearden (1989) examine the range of acceptance around the expected market price. The authors assume an asymmetric range of indifference around the reference price. Kalyanaram and Little (1994), integrate ACT with a consumer choice model assuming a symmetric range of indifference to gaps between actual prices and the reference price. They also included price variability when determining the width of the indifference range. The primary challenge of using ACT to build a consumer choice model is to determine the width of the range of indifference, which has to be estimated from experiments or from consumer purchase data.

Contrary to ACT, Prospect Theory (PT, Kahneman and Tversky 1979) generally assumes a range of zero around the reference price and the indifference region thus becomes a point (Boztug and Hildebrand 2005). A fundamental characteristic of PT is that individuals tend to value losses more than gains (i.e. when prices are lower and higher than the reference price, respectively). The theory assumes that consumer utility is concave for gains and convex for losses; and that individuals are loss-averse with the loss function being steeper than the gains function (Edwards, 1996; Tversky and Kahneman 1981). PT has been often employed to describe pricing decisions under risk (Levy and Wiener 2013; Urbany and Dickson 1990; Edwards 1996).

Most empirical applications of PT have focused on financial markets, particularly on the price of financial assets and the evaluation of investment alternatives (e.g., Loughran and McDonald 2013; Henderson 2012; Gurevich, Kliger and Levy 2009). However, empirical applications offer a number of managerial and marketing implications. For example, Kalyanaram and Winer (1995) and Choi et al. (2013) employ PT to show that the timing and magnitude of price promotions should take into account the existence of reference prices and their resulting demand impacts. Janiszewski and Lichtenstein (1999) demonstrate that the range of evoked prices moderates the effect of reference price and has implications for "high-low" and "every-day-low price" pricing strategies. Moreover, researchers have shown that reference prices, together with the way they are shaped, influence brand choices and purchase quantity decisions (Kumar, Kirande and Reinartz 1998). PT has also been used to show that macroeconomic factors such as interest rates, unemployment and inflation influence the formation of reference prices and should therefore be taken into account in the evaluation of alternative pricing strategies (Estelami, Lehmann and Holden 2001).

Neither neo-classical nor behavioral theories of threshold pricing are entirely satisfactory. While neo-classical models offer a rigorous explanation for how thresholds can arise from rational, optimizing behavior, they are silent on how the value of the thresholds is determined. On the other hand, behavioral theories implicitly assume a failure on the part of consumers to rationally consider all available information, or to respond in less-than-rational ways to price changes. In the next section, we offer an alternative to both that is grounded in optimizing behavior, and provides estimates of threshold values that are empirically tractable.

3 Conceptual Model of Purchase Hysteresis

The theory of purchase hysteresis derives from the concept of a real option from the financial economics literature (Dixit 1989; 1992). In this section, we demonstrate how a real option arises in a household's purchase decision, and how this gives rise to a hysteretic effect. This hysteretic effect, in turn, is observationally equivalent to the latitude of price acceptance observed by other authors.

In an uncertain retail-price environment, the fixed costs of searching for and purchasing a good embed a real option in the purchase decision. The value of this real option rises in the level of price volatility, which provides a convenient way to test for the existence of a real option. Before testing econometrically for the presence of a real option effect, we argue why, logically, shopping for and purchasing consumer goods must include a real option component. Specifically, there are three necessary conditions that must exist for a real option value to arise: (1) ongoing uncertainty, (2) fixed costs, and (3) a unique opportunity to make a decision (Dixit 1989). The long-term volatility of retail prices is not controversial. Whether from retail promotions, retailers passing through trade promotions, cost increases, or meeting competitive challenges, there are many factors that may cause retail prices to vary over time. Second, Mehta, Rajiv, and Srinivasan

(2003) document the magnitude of search costs in a retail grocery environment. Third, individual consumers clearly have sovereignty over their purchase decisions, so there is no market mechanism through which the real option value will be arbitraged away. In summary, the appropriate conditions exist for a purchase decision to embody a real option value, one that is significant relative to the shelf price of the product. In this section, therefore, we develop a simple mathematical model of how real options can be expected to arise in grocery purchases, and derive an econometric model that can test for their presence in household-level scanner data.

Solving for the dynamically optimal purchase process under price uncertainty results in a discontinuous purchase path similar to one that would arise with a model of economic friction (Rosett 1959). If the cost of purchasing a consumer product in a retail store includes a real-option component, then we expect to see a consumer respond to prices that rise above his or her reference price only if a certain threshold "price gap" (difference between the shelf price and reference price) has been reached, and respond to a price reduction only if the price gap falls below a different threshold value. When retail purchases are subject to price thresholds, consumers are in the domain of gains when the shelf price falls below the reference price (Kahneman and Tversky 1979), or in the domain of losses when self prices rise above their reference price. Because the size of the threshold includes both a generalized measure of search costs and a real option value, the consumer follows a discontinuous purchase strategy wherein the gap between the upper and lower purchase-price thresholds widens with the value of the option. We show how this result occurs by deriving a consumer's reference price and then demonstrating how it is likely to differ from the observed stimulus price, or the price that leads to either purchasing or switching.

To make our concept of the source of volatility concrete, consider a retail food product such as coffee or cereal, where the production cost is largely driven the price of the underlying commodity, and production labor. While labor is relatively stable, and predictable, the commodity cost can lead to wide variation in the costs of production. Witness the general price of groceries during the 2008 commodity boom, the 2009 bust, and the subsequent resurgence of commodity prices. Wholesale prices over this period were particularly volatile, and recent research on retail pass-through rates (Eichenbaum et al 2011; Gopinath et al 2011) suggest the same was true at retail. Define the gap between a consumer's reference price and the observed shelf price as follows: $g_{jt}^h = rp_{jt}^h - p_{jt}$ for consumer h, brand j, and period t. Reference prices are assumed to be brand-specific given the empirical evidence on the preferred specification for reference-prices (Briesch et al. 1997). Note that this definition is not standard, but we feel it is more intuitive as the consumer gains if shelf prices fall below the reference price (or the value of g_{jt}^h rises). If retail prices are indeed uncertain, then they are expected to follow a stochastic process over time. For simplicity, we assume the relationship between a consumer's reference price and the retail price follows a Geometric Brownian Motion process:

$$dg_j^h = \mu_j g_j^h dt + \sigma_j g_j^h dz, \tag{1}$$

suppressing the time subscript, where μ is the mean drift rate, σ is the standard deviation of the process, and dz defines the Wiener increment with properties: $E(dz) = 0, E(dz^2) = dt$. Search costs consist of opportunity costs of the consumer's time, travel costs, or even cognitive processing costs that are incurred in finding a product, considering alternatives, and making a purchase (Roberts and Lattin 1991), each of which is sunk, or irretrievable after the search process has been completed. Define these costs generically as c_t^h as they vary across consumers, and over time.

From a consumer's perspective, his or her wealth is conceptualized as the present value of a stream of lifetime consumption decisions, plus the value of other investments. If the consumer's objective is to maximize the wealth, or the value, of his or her household by making optimal purchase decisions, the fundamental arbitrage condition that determines the value of the real option compares the value of a household that purchases ($V^{p,h}$) with one that does not purchase ($V^{n,h}$). Faced with a decision of purchasing or not purchasing at each period, the maximum value a household can attain is the maximum of whether it purchases or does not purchase, or:

$$V^{0,h}(g_j^h, p_{jt}, t) = \max[V^{n,h}(g_j^h, p_{jt}), V^{p,h}(p_{jt}) - \lambda c_t^h], \tag{2}$$

where λ is the marginal cost of search, assuming search takes place only when a purchase occurs.[4] The solution to this problem provides upper and lower threshold values of g_{jt}^h that constitute optimal switching points between responding and not responding to a particular value of the price gap.

[4] A shopping trip is defined as a purchase occasion in which the household is observed making at least one purchase, not necessarily in the focal category.

Unlike other price-threshold models, ours maintains that in order for a consumer to purchase a brand, the difference between the shelf and reference prices must be large enough to not only cover the direct costs of search, but also the implicit option value of waiting to make a purchase. Exercising this option (and thus purchasing or switching) means sacrificing an asset of real value to the household, therefore, doing so represents a real and significant opportunity cost. Indeed, even for small search costs, ongoing uncertainty in the price gap can cause a wide gap between the latent desire to purchase and observed purchase behavior. Given the stochastic process governing price gaps, there may be a long wait for the shelf price to either rise or fall enough to induce a stimulus for purchase behavior, where "wait" is defined in terms of a range of retail prices between the upper and lower response thresholds. This wait is interpreted as the latitude of price acceptance (Kalyanaram and Little 1994), or hysteresis in purchase behavior.

The problem described in (2) above can be solved using dynamic programming techniques (Caballero and Engel 1999; Slade 1999), but a contingent claims approach (Dixit 1989, 1992) provides analytical expressions for the threshold values of g_j^h that are amenable to econometric estimation. Contingent claims analysis treats the value of waiting to make a purchase as a contingent security – contingent on the underlying price-process upon which the decision depends. Compare the value of a household that decides to purchase with one that does not using the value functions in (2). With search costs, and uncertainty of the form shown in (1), the value of a household that does not purchase consists of one capitalized stream of purchase decisions, plus the value of the option to purchase, while the value of a household that does purchase is the discounted value of a consumption stream that includes the most current decision. Given the process for g_{jt}^h shown in (1), the equilibrium condition for a household that decides not to purchase is found by first equating the instantaneous expected return on household wealth due to a change in the price gap with the required return on the household's wealth (ρV^n). In this case, the instantaneous expected return consists only of the expected rise in the value of the household (Dixit 1989) so the partial differential equation becomes:[5]

$$(1/2)\sigma^2 g^2 V_{gg}^n + \mu g V_g^n - \rho V^n = 0, \tag{3}$$

where we note that subscripts indicate partial differentiation, we suppress the household indices for clarity,

[5] The rise in the net worth of the household is akin to holding equity in a publicly-traded firm only for its expected capital gain.

ρ is the required rate of return, and the other variables are as previously defined. The general solution to (3) is then found by substituting $g^\theta = V^n$ and solving the resulting quadratic equation:

$$\phi(\theta) = (1/2)\sigma^2\theta(\theta - 1) + \mu\theta - \rho = 0, \tag{4}$$

where θ is a constant to be determined. This equation has two roots: $\beta_1 < 0$, and $\beta_2 > 1$ such that:

$$\beta_1, \beta_2 = 1/2\left(\frac{1-2\mu}{\sigma^2} + / - \left(\left(1 - \frac{2\mu}{\sigma^2}\right)^2 + \frac{8\rho}{\sigma^2}\right)^{1/2}\right). \tag{5}$$

the general solution to the differential equation (3) for a household that does not purchase must reflect this fact so we write:

$$V^n = A^n g^{\beta_1} + B^n g^{\beta_2}, \tag{6}$$

which must then be solved for values of A^n and B^n. The fact that this expression solves (3) can be verified by taking the first and second derivatives of V^n in (6) and substituting the result into (3). As in Dixit (1989), the two terms on the right-side of (6) represent the option to purchase, while the value of not purchasing is normalized to zero by assumption.

We determine the value of the option by applying the value-matching and smooth pasting conditions to the expressions for the value of a non-purchasing household, and one that responds to the price-gap stimulus. The value of a household that decides to purchase is determined solely by the flow of services provided by the good as they have already exercised the option to buy. The value of the good, in turn, is assumed to be equal to the price gap as it represents the difference between what a household is willing to pay for the good, and what the market requires them to pay. Because the price gap is assumed to drift at an average rate of μ, the present value of this stream of benefits to the household is found as:

$$V^a = \frac{g}{\rho - \mu}, \tag{7}$$

for a constant α, so the value of the household is comprised entirely of the value of purchasing the good in question. Solving for the constant terms is possible if we recognize that for small values of g the value of the option to wait will be very low, so $A^n = 0$. Further, at a sufficiently high level of g, call it the upper-threshold, or g^U, a household will immediately purchase so the value of a non-purchasing household must equal the value of a household that does purchase less the fixed cost of search:

$$V^n(g^U) = B^n(g^U)^{\beta_2} = \frac{g^U + p - rp}{\rho - \mu} - \lambda c = V^a(g^U), \tag{8}$$

because the value of a household that purchases is equal to the capitalized value of all desired consumption. Next, the smooth pasting condition requires that the incremental value of waiting to purchase as g rises must be equal to the incremental value of a household that has already purchased, or:

$$V_g^n(g^U) = \beta^2 B^n(g^U)^{\beta_2 - 1} = 1/(\rho - \mu) = V_g^a(g^U). \tag{9}$$

The smooth pasting and value matching conditions yield two equations and two unknowns. Solving these for g^U gives a closed-form expression for the threshold price gap as a function of the parameters of the model:

$$g^U = \left(\frac{\beta_2}{\beta_2 - 1}\right)(\lambda c(\rho - \mu) - \rho/\mu)\,, \tag{10}$$

where β_2 is a function of both the drift rate and volatility of the price gap, and is strictly greater than one in value.

Using traditional economic decision rules, a household in this environment purchases if the gains are greater than the annualized fixed cost of shopping and buying: $g^U > \lambda c(\rho - \mu)$. However, because β_2 is greater than one, the existence of a real option creates a wedge between the traditional and "full cost" thresholds that depends on the volatility of underlying prices and the magnitude of search costs (Dixit 1992; Dixit and Pindyck 1994). A similar line of reasoning applies in calculating the value of g^L. If retail prices are falling, consumers will wait until the observed price falls below not only the reference price, but also the cost of shopping and the a real option of not purchasing. As a result, the lower threshold price gap is significantly below zero. Combining both upper and lower thresholds, observed price gaps imply a discontinuous pattern of purchasing with no activity over a wide range of observed shelf prices. Defining the indirect utility associated with a price gap of g_t as $U(g_t)$, a consumer's purchase behavior maximizes the indirect utility function given by:

$$U(g_t) = \left(\begin{array}{ll} U(g_t - g_t^U - u_t); & g_t - g_t^U - u_t > 0 \\ U(g_t - u_t); & g_t - g_t^U - u_t < 0 < g_t - g_t^L - u_t \\ U(g_t - g_t^L - u_t); & g_t - g_t^L - u_t < 0 \end{array} \right), \tag{11}$$

where $g_t^L < 0$, $g_t^U > 0$, and u_t is an independent, identically distributed random variable in time period t. Because the price gap varies randomly over time, it will likely take some time before the threshold level is exceeded. This, in turn, represents the effect that the real option value exerts over the household's response to changes in the price gap – an effect we interpret as a latitude as price acceptance, or purchase hysteresis.

4 Econometric Model of Threshold Prices

4.1 Overview

Our conceptual model suggests that rational consumers will respond to price changes in a way that can be described by three distinct regions, or zones of activity, or inactivity, as the case may be. In the first region, consumers perceive a reduction in the shelf price as sufficient to warrant exercising the real option they hold on not making a purchase, respond to the price stimulus, and buy the product. In the second region, any variation in shelf price is not sufficient to trigger a purchase, so we observe a relative insensitivity to normal price variation. In the third region, the shelf price rises sufficiently to induce a different response, whether to buy the product only out of a fundamental need, in spite of the higher price, or to buy a competing product. Of course, identifying these regions is conditional on perceived need: Consumption rate, interpurchase time, and the resulting level of household inventory clearly drives both the need to purchase an alternative brand, or to stay out of the category altogether.

4.2 Econometric Model of Purchase Hysteresis

Equation (11) defines a model of economic friction, which we use as the basis for econometric tests of the existence of a hysteretic effect. Among other models of economic rigidity, Willis (2000), Slade (1999), Caballero and Engel (1999), and Cecchetti (1986) each estimate different types of "adjustment hazard function" to determine the factors that influence the probability that a firm changes either its price or stock of capital goods. For current purposes, however, our interest lies in estimating the size of the thresholds caused by the real option embedded in searching for, and purchasing, a desired item. A friction model is appropriate when the dependent variable responds in a discontinuous way to changes in an independent variable – when the latent stimulus for activity must exceed a certain threshold level before a response is observed (Rosett 1959; Maddala 1983). In Rosett's (1959) example, he models the response of asset holdings to changes in their yield. Due to unobservable transactions costs, only relatively large changes in yield cause a reallocation. With this approach, we are able to estimate the size of each threshold as well as test the effect of each explanatory variable on the real option value that is likely present.

There are a number of econometric implications of the real option effect that are manifest in the friction model. First, we will not observe a consumer response to a price gap despite considerable variation in a latent (unobservable utility) desire to do so. Second, the extent to which latent utility fluctuates before a response occurs, or the threshold price gap, will rise with its expected volatility. Third, the gap between the upper and lower thresholds will widen with the magnitude of search costs. Fourth, purchases will exhibit significant inertia, meaning that when purchases do occur, the underlying decision will not change even after their apparent cause has disappeared, and fifth, upward price changes need bear no quantitative relationship to the size of downward price changes so response will appear to be asymmetric (Kahneman and Tversky 1979). Each of these hypotheses is tested within an estimable form of (11) wherein we do not observe purchases or switches until the difference between reference and shelf prices either rises above, or falls below a certain threshold level. To arrive at this form of the model, however, we first define each of the theoretical constructs that are thought to underlie purchase hysteresis.

Utility is a function of not only the price gap, but elements of the marketing mix, brand-specific preference, brand loyalty, and category inventory. We define household-specific reference prices as a brand-level, geometric weighted average of past prices. In doing so, we follow Briesch et al. (1997) who test a number of specifications for the reference price, and find that a household-specific, geometric weighted average provided the best fit. The friction model suggests that there is no reason why price response should be symmetric on either side of the full-cost thresholds, so we let the parameters of interest vary across regimes of rising, falling, and staying the same.

In order to test the purchase hysteresis model outlined above, we disaggregate the price gap into observable and unobservable components, and the observable part into regimes in which the reference price is above the current shelf price, below the shelf price, and equal to the shelf price. Define this part of the price gap as lying in the domain of gains (G) when the shelf price is below the household-specific reference price ($g_{jt}^{h,G}$), in the domain of losses (S) when the shelf price is above the reference price ($g_{jt}^{h,S}$), or neither (A) when the observed price is equal to the reference price. The unobservable component, however, it what separates our model from others in the price-acceptance literature. Namely, we define the upper and lower threshold price gaps to be parametric functions of the underlying volatility of prices: $g_{jt}^U = \gamma_U \sigma_g$ and $g_{jt}^L = \gamma_L \sigma_g$. Although Han, Gupta, and Lehmann (2001) allow their probabilistic thresholds to depend on price volatility, their motivation is empirical, and not grounded in a model of option pricing as is ours. With this specification, if $\gamma_U \neq 0$ and $\gamma_L \neq 0$, then our data support the theory of purchase hysteresis when controlling for all other possible explanations for the existence of a zone of price acceptance.

We bring each of these elements together in a random utility model of brand choice defined over the three price-gap regimes. Indirect utility, therefore, is written as:

$$U(g_{jt}^h, X_{jt}|\gamma, \beta) = \left(\begin{array}{ll} U(\alpha_j^{h,G} + X_{jt}^h \beta^G + \eta^G g_{jt}^{h,G} - g_{jt}^{h,U}(\sigma_g) + u_{jt}); & g_{jt}^{h,G} - g_{jt}^{h,U} - u_{jt} > 0 \\ U(\alpha_j^{h,A} + X_{jt}^h \beta^A + \eta^A g_{jt}^{h,A} + u_{jt}); & g_{jt}^{h,G} - g_{jt}^{h,U} - u_{jt} < 0 < g_{jt}^{h,S} - g_{jt}^{h,L} - u_{jt} \\ U(\alpha_j^{h,S} + X_{jt}^h \beta^S + \eta^S g_{jt}^{h,S} - g_{jt}^{h,L}(\sigma_g) + u_{jt}); & g_{jt}^{h,S} - g_{jt}^{h,L} - u_{jt} < 0 \end{array} \right), \tag{12}$$

where $\alpha_j^{h,k}$ are household-and-brand specific preference parameters in regime $k = G, A, S$, β^k is a vector of marketing-mix, loyalty, and inventory effects in regime k, η^k is the price-response parameter in regime k, and the other variables are as defined above. Assuming the iid error term is Type I Extreme Value distributed, the choice model assumes the usual logit form. However, in this problem we account for the discontinuous nature of the expected purchase pattern.

In this model, note that the γ_U and γ_L parameters provide a means of directly testing the phenomenon Dixit (1989) describes as hysteresis, or the inertia that some economic variables tend to possess after their originating cause has disappeared. Further, by writing (12) in this way, the structural parameters of (10) are not identified, *per se*, and the solution is a highly non-linear function of volatility. Therefore, the γ_i parameters are in reduced form with typical element: $\gamma_i = (\beta_2/(\beta_2 - 1))\lambda_i$, and we estimate a linear approximation to the true impact of volatility on each threshold. Numerical simulations described in Dixit and Pindyck (1994) suggest that this approximation is likely to be a good one.

4.3 Estimation Method

The entire model is estimated over all regimes (domain of gains, domain of losses, and no price gap) using maximum likelihood. Because the error term in (12) represents the distribution of consumer tastes in our sample market, the probability that household h purchases good j, written as $P^h(j = 1)$, is derived by invoking a random-utility assumption such that:

$$P^h(j=1) = \left(\begin{array}{l} P[U(\alpha_j^{h,G} + X_{jt}^h \beta^G + \eta^G g_{jt}^{h,G} - g_{jt}^{h,U}(\sigma_g)) - U(\alpha_k^{h,G} + X_{kt}^h \beta^G + \eta^G g_{kt}^{h,G} - g_{kt}^{h,U}(\sigma_g)) > u_{kt} - u_{jt}]; \\ \quad g_{jt}^{h,G} - g_{jt}^{h,U} - u_{jt} > 0 \\ P[U(\alpha_j^{h,A} + X_{jt}^h \beta^A + \eta^A g_{jt}^{h,A}) - U(\alpha_k^{h,A} + X_{kt}^h \beta^A + \eta^A g_{kt}^{h,A}) > u_{kt} - u_{jt}]; \\ \quad g_{jt}^{h,G} - g_{jt}^{h,U} - u_{jt} < 0 < g_{jt}^{h,S} - g_{jt}^{h,L} - u_{jt} \\ P[U(\alpha_j^{h,S} + X_{jt}^h \beta^S + \eta^S g_{jt}^{h,G} - g_{jt}^{h,L}(\sigma_g)) - U(\alpha_k^{h,S} + X_{kt}^h \beta^S + \eta^S g_{kt}^{h,G} - g_{kt}^{h,L}(\sigma_g)) > u_{kt} - u_{jt}]; \\ \quad g_{jt}^{h,S} - g_{jt}^{h,L} - u_{jt} < 0 \end{array} \right), \tag{13}$$

where the specific form of the likelihood function is determined by our distributional assumption regarding u_{jt}. Terui and Dahana (2006) estimate a similar discontinuous-utility model under the assumption of normality (yielding a probit model), but the probit is not appropriate for modeling price response as it implies some density on each side of zero (Train 2003). Therefore, we assume instead that the distribution of consumer tastes is Type I EV distributed. Assuming Ψ is the EV cumulative density function, ψ is the EV probability density function, and the mean utility for brand j in regime k is $\delta_j^{h,k} = \alpha_j^k + X_{jt}^h \beta^k + \eta^k g_{jt}^k - g_{jt}^k(\sigma_g)$, then $P^{h,k}(j = 1)$ represents the probability that household h purchases brand j in regime k. Therefore, the likelihood function for the friction model is:

$$\begin{aligned} L(g_{jt}^h, X_{jt}|\gamma, \beta) &= \prod_{n_1} \left(P^{h,G}(j=1)\right)^{\tau_1} \prod_{n_2} \left(P^{h,A}(j=1)\right)^{\tau_2} \prod_{n_3} \left(P^{h,S}(j=1)\right)^{\tau_3} \qquad (14) \\ &= \prod_{n_1} \psi[\delta_j^{h,U}] \prod_{n_2} \left(\Psi[\delta_j^{h,L}] - \Psi[\delta_j^{h,U}]\right) \prod_{n_3} \psi[\delta_j^{h,L}], \quad h = 1, 2, ..., H, \; t = 1, 2, ..., T \end{aligned}$$

defined over regimes of n_1 observations where the shelf price is below the reference price, n_3 observations where it is below, and n_2 observations where it is equal, where $\tau_k, k = 1, 2, 3$ are binary indicators for purchases in the domain of gains, indifference, and losses, respectively. The likelihood to be maximized is the sum of (14) over all households and time-periods. Applying this model to high-frequency, household-level data on a specific grocery product, we are able to estimate the potentially persistent effects of search costs and retail price volatility on the existence and size of the latitude of price acceptance.

4.4 Operationalizing Utility Arguments

Operationalizing the model of utility that underlies our threshold model involves a number of constructs. In each case, we adhere to the extant literature as closely as possible in order to differentiate our model only with the inclusion of the threshold term. In the econometric model above, we define mean utility in regime k for brand j as $\delta_j^{h,k} = \alpha_j^k + X_{jt}^h \beta^k + \eta^k g_{jt}^k - \gamma_l^h \sigma_g$, where α_j^k are brand-specific preference parameters, X_{jt}^h are elements of the marketing mix which may or may not be unique to the household, g_{jt}^k is the price-gap (reference price less shelf price) in regime k, $\gamma_l^h, l = G, S$ are the household-specific upper- and lower-price thresholds that depend on the volatility of the gap term (σ_g). The specific variables that are included in the matrix X_{jt}^h are defined as follows:

p_j = shelf-price of brand j,

fea_j = a binary indicator variable that equals 1 when brand j is featured,

dis_j = a binary indicator variable that equals 1 when brand j is on display,

pro_j = a binary indicator variable that equals 1 when brand j is on promotion,

lp_{hj} = a binary indicator variable that equals 1 when household h purchased brand j on the last purchase occasion,

bl_{hj} = a the within-household market share of brand j for household h,

inv_h = category inventory held by household h on the date of purchase,

st_s = a binary indicator variable that equals 1 if the brand is purchased in store s.

Note that by including the shelf-price among the arguments of X_{jt}^h,our maintained model is the "sticker-shock" model of Winer (1986), Bell and Lattin (2000), and Chang, Siddarth, and Weinberg (1999). Among the other variables, we calculate inventory in a relatively simple way. First, we use the entire data set to calculate the average consumption rate (at the category level) of each household. We then estimate the initial amount on hand from the observed consumption rate, and the date of the first purchase. We then calculate a running inventory by adding new purchases, and subtracting consumption over the entire sample period. We measure loyalty in two ways, following Han, Gupta, and Lehmann (2001). The first measure, lp_{hj}, is a state-dependent measure that is defined in repeat-purchase terms. That is, a household is deemed loyal to a specific brand if it is purchased on the previous shopping trip. The second measure, bl_{hj}, is a cross-sectional measure of brand loyalty in that it represents the share of brand j for household h calculated over a burn-in period. For this purpose, we use the first 52 weeks of data. Each of these measures are well-accepted in the reference-price literature (Mayhew and Winer 1992; Kalwani and Yim 1992).

Allowing the volatility parameter to vary randomly over households addresses the concern expressed by Bell and Lattin (2000) that the sticker shock effect is largely a result of failing to account for unobserved household heterogeneity. Doing so also reflects the probabilistic nature of thresholds captured by Han, Gupta, and Lehmann (2001), but in a different way. In the utility model (12), the threshold parameters ($\gamma^h_{U,L}$) are modeled as random-normal variates: $\gamma^h_l = \gamma_l + \sigma_\gamma \nu_h$, where $\nu_h \tilde{} N(0, 1)$. Because the γ^h_l parameter multiplies the price-volatility term, the mean-threshold parameter, γ_l, measures the extent to which volatility causes the threshold price to widen or contract. Our primary hypothesis, therefore, is that $\gamma_l > 0$, or that greater volatility causes the threshold price to widen, and lower volatility reduces the threshold effect. Of course, ERthe validity of this hypothesis is conditional on the existence of reference prices around which thresholds are formed.

Consumers form reference prices either according to an internal reference price (IRP), or external reference price (ERP) mechanism, or both (Rajendran and Tellis 1994; Bell and Bucklin 1999; Mazumdar and Papatla 2000; Kopalle, and Lindsey-Mullikin 2003). If the consumer uses an IRP, then his or her notion of what a product's price should be is shaped by recent experience, memory, and expectations. On the other hand, ERPs depend more on notions of what is reasonable in either a competitive sense, or as an absolute "willingness-to-pay." Within both IRP and ERP, reference prices can be either "stimulus-based" if grounded in a consumer's current experience, or "memory-based" if grounded in previous experience with the brand in question, or a rival brand (Briesh et al. 1997). Based on prior empirical research in similar categories, we calculate reference prices using the brand-specific, last-purchase method that Briesch et al (1997) find to be the preferred specification and applied in a context similar to ours by Han, Gupta and Lehmann (2001). That is, each household's reference price for brand j is an exponentially-weighted average of the previous reference price value, and the current shelf price:

$$rp_{jt}^h = \kappa rp_{jt-1}^h + (1-\kappa)p_{jt-1}, \tag{15}$$

where rp_{jt}^h is the reference price for brand j and household h in time period t, p_{jt} is the shelf price in period t, and κ is the constant smoothing parameter. While there are potentially infinite ways in which households can conceivably form reference prices based on their past exposure experience, this specification represents a parsimonious combination of households' current and recent past experience. Including shelf prices from further back in time may capture the distributed-lag effect of memory more carefully, but the empirical results reported by Dickson and Sawyer (1990) suggest that consumers do not remember shelf prices from shopping trips in the distant past. Estimating κ in panel data is somewhat problematic. While Lattin and Bucklin (1989) assume a value of 0.7 in calculating a series of reference prices for each household, and compare to a naive specification in which $\kappa = 0$, others estimate the lag-weight parameter using a grid-search procedure and choose the value that maximizes the likelihood function in a discrete fashion (Han, Gupta and Lehmann 2001). In this study, we follow the latter and find a κ value of 0.6 provides a superior goodness of fit to other non-zero values, and to the naive value $\kappa = 0$. Because this result is well-established in the literature, the results reported below for all models make this same assumption.

5 Data Description

We estimate the model using data from four categories of products represented in the IRI Academic Data Set (Bronnenburg, Kruger, and Mela 2008). We use household panel data from Eau Claire, WI for the years 2009 - 2011, focusing first on purchases from the ready-to-eat cereal category, and Infoscan (store-level) data over the same period in order to impute missing prices in the household panel data. After completing our analysis of the cereal data, we replicate our estimation approach with coffee, yogurt, and laundry detergent data in order to establish the validity and robustness of the model. We use the first dataset, cereal, to investigate whether or not there exists a stylized fact, or an observation that is clear from summary data only, that suggests our explanation may be valid even before econometric estimation.

There are a number of reasons why cereal provides an excellent context with which to study reference prices. First, cereal is purchased with sufficient frequency that the notion of consumers forming internal reference prices is both intuitive and plausible. If consumers shop frequently, they are more likely to be able to recall prices paid in the recent past (Briesch, et al. 1997). Further, cereal manufacturers introduce new products every month, and offer frequent manufacturer promotions. Although frequent promotions can reduce reference prices, the variation in retail prices they imply helps researchers identify behavior when prices change either above the reference price or below. Third, the cereal category is dominated by two manufacturers, Kelloggs and General Mills, who are well-known to behave strategically through both prices and product introductions (Nevo 2001). When there is a closely-competitive product for consumers to switch into, the notion of a "kinked demand curve" is more likely to arise. Fourth, cereal is an important category to retailers, so tends to reflect a retailers' overall pricing strategy. If a retailer claims to operate some form of everyday-low-price (EDLP) strategy, then cereal prices will generally be lower and more stable than at other retailers. Stable prices, of course, are more conducive to consumers' forming reference prices based on their own memories. In sum, if consumers do indeed form reference prices for frequently-purchased consumer packaged goods, then cereal is likely a good context in which they will be revealed.

In panel data, it is necessary to have data on prices for not only the product that was purchased, but those that were not purchased as well. Both the household-purchase and store-level contains a masked store code that allowed us to merge both data sets by store, week, and UPC. By combining the household and store-level data sets, we observe the complete set of prices, and other marketing mix variables, for all UPCs available on a given purchase trip. We include only households who purchase cereal from the two most popular stores in the data set because the other stores do not provide price information to IRI, so we are unable to impute price for non-purchased items in a consistent way. The resulting merged data set provides sufficient variation in prices and choice probabilities across brands and over time in order to identify the reference-price mechansisms we investigate (see tables 1 and 2).

[tables 1 and 2 in here]

Household data is necessary for our analysis because we model household-specific reference prices, and require household-level choice-variation to identify the model. While tables 1 and 2 provide aggregated-evidence in support of variation in choice probabilities, table 3 shows the characteristics of the households in our sample. The data in this table reveals that our sample skews slightly higher in mean income relative to the U.S. average, and exhibits less racial diversity than a more general sample would, but the Eau Claire data are nonetheless well-accepted for quantitative analyses such as the one we present here.

[table 3 in here]

If reference prices are indeed a feature of the data, they should be apparent from simply examining price data and the associated sales volumes. If small changes in the price of a particular brand are met with only small changes in volume, but larger changes induce substantial changes, then this would provide evidence for the existence of reference prices, if not volatility-induced price thresholds. Table 4 presents stylized facts employing the twenty cereal brands in the study for the years 2009−2011. The table illustrates switching behavior of consumers as they face small gains/losses (i.e., the reference price is relatively close to the prevailing retail price), as well as relative large losses and gains (i.e. large negative and positive distances between reference and retail prices). The table indicates that consumers are quite unlikely to change behavior when they face small gains or losses. When losses are small, in average, only 3.0 percent of consumers stop purchasing brand i. In contrast, when losses are relatively large, 15.7 percent of consumers switch to alternative brands, in average. The differences in consumer response are more considerable in the realm of gains (i.e. when reference prices are greater than retail prices). When gains are small, in average, only 2.4 percent of consumers switch to purchase brand i; whereas, in average, 19.9 percent of consumers switch to brand i when gains are relatively large. These stylized facts indicate differences across brands, probably due to such factors as brand loyalty and frequency of purchase, among others. Although these summary results are suggestive of reference-price behavior, we can only isolate the specific effect of reference prices if all other marketing-mix, and unobserved factors, are properly taken into account in the more complete econometric model econometric model. In the next section, we present the results obtained from estimating our model.

[table 4 in here]

6 Results and Discussion

We first present and interpret the results obtained with data from our focal category – ready-to-eat cereal – and then compare the results from our maintained model with estimates from other categories, and from other, plausible alternatives.

6.1 Estimation Results

The sticker shock model maintains that shelf prices will continue to have a negative effect on utility, even when reference prices are appropriately taken into account. And, defined as we do here, the price-gap term should be positively related to utility as reductions in the shelf price below the reference price represent benefits for the consumer. Our version of the sticker shock model further maintains that the price-gap term must reach a certain value before consumers change their behavior. We specify this threshold term as a function of the variance of the price-gap variable. In table 5, the left-most four columns show the estimation results for the base sticker shock model that includes price-thresholds, but does not allow for unobserved heterogeneity (Model 1). In this model, we see that each of the sticker-shock parameters are of the expected sign and significantly different from zero. Most importantly, the threshold parameter estimates suggest that consumers require shelf prices to rise significantly above the reference price before changing their behavior, or fall significantly below, and that the size of this "latitude of acceptance" widens in the volatility of the price-gap. Indeed, the threshold parameter estimates in table 5 imply a region of between \$0.151 / oz and \$0.267 / oz wherein consumers' response to variations in the reference remains the same. In other words, when consumers are in the domain of gains, or when the shelf-price falls below the reference price, consumers do not alter their behavior until a shelf price of \$0.151 / oz is reached. On the other hand, when they are in the domain of losses, they do not respond until an upper-threshold price of \$0.267 / oz is reached. These initial results also support the predictions of Prospect Theory (Kahneman and Tversky 1979) as the magnitude of the Gain / Loss parameter is larger when consumers are in the domain of losses than in the domain of gains. These results, however, assume there is no unobserved heterogeneity in response to variations in either price or price-gap volatility.

[table 5 in here]

Accounting for heterogeneity in volatility-response has a significant impact on our parameter estimates, but not in the same qualitative way as others have found (Bell and Lattin 2000). Based on a likelihood ratio (LR) specification test, accounting for unobserved heterogeneity in response to reference-price volatility improves the fit substantially (Model 2 in table 5). With two degrees of freedom the critical chi-square test statistic for a LR test between Model 1 and Model 2 is 5.991, while the calculated test statistic value comparing the two models is 1,523.16. Unlike Bell and Lattin (2000), we find that including this source of heterogeneity does not weaken the reference-price effect. In fact, the latitude of price acceptance is larger with this model than the fixed-coefficient version as the gap now widens to \$0.152 / oz to \$0.279 / oz. In terms of the relevant point-estimates, we find that the price-gap term in the domain of gains is only slightly attenuated (2.217 compared to 2.255) while in the domain of losses, it is considerably smaller (2.507 versus 2.698). However, the volatility-effect estimate falls to 24.414 compared to 25.045 in the domain of gains, and rises to 31.908 relative to 26.966 in the domain of losses. It is this effect that is primarily responsible for the dramatic widening in the latitude of price acceptance. In the sticker-shock model, however, it is assumed that consumers respond to not only differences between their reference price and the observed shelf price, but the level of shelf prices as well. Therefore, it is reasonable to assume heterogeneity in response to shelf prices as well.

Model 3 in table 5 presents the results from estimating a model that accounts for heterogeneity in both the response to price volatility and shelf prices. Again comparing models 2 and 3 using a LR test, we find a calculated chi-square statistic of 6,228.36 relative to the same critical chi-square statistic of 5.991. Therefore, we prefer Model 3 to either Model 2 or Model 1 and conclude that both sources of heterogeneity are important. Compared to the previous models, however, we find a latitude of price acceptance closer to Model 1 – the model that did not account for heterogeneity – than in Model 2. Specifically, the lower shelf-price threshold in the domain of gains is now \$0.151 / oz, while the upper threshold is \$0.270 / oz. While the mean price-volatility parameter in the domain of gains rises slightly to 25.009, the corresponding parameter estimate in the domain of losses falls to 28.164. Estimates of the price-gap parameter are also closer to those in Model 1, which suggests that the direction of bias induced by failing to account for heterogeneity in price-response is opposite the direction of bias caused by not allowing for heterogeneity in response to volatility. Again, it is difficult to say that the presence of heterogeneity weakens the reference-price effect. Similar to Model 1, this preferred model also provides evidence in support of the predictions of Prospect Theory as the magnitude of the response to price-gaps is larger when consumers are in the domain of losses relative to the domain of gains.

With these estimation results, we are able to address the question raised by Pauwels, Srinivasan and Franses (2007). Namely, they are concerned with whether reference prices and response thresholds are an artefact of household-level data, or whether they can be expected to arise in aggregate data as well? While most of the empirical analyses of this question use household-level data, where threshold behavior is apparent even from casual inspection, many market analysts work with aggregate data, and still operate on the assumption that price-response is subject to threshold-like behavior. Because we are able to explicitly estimate threshold parameters with our friction-model approach, and the distribution of consumer heterogeneity that governs the location of the thresholds, we examine whether they are likely to be apparent in aggregate, store-level data by simulating empirical threshold values. We analyze these simulated data in two ways in order to determine whether there is any evidence of threshold behavior – one qualitative and another more quantitative.

First, figure 1 shows the simulated data for one brand (General Mills Cheerios) over the sample period. The figure shows the position of the upper and lower thresholds implied by our estimates for this brand, the observed price, and the ratio of the implied market share among consumers who are in the domain of gains (shelf price below their reference price) to those who are in the domain of losses (shelf price above the reference price). While the aggregated shares necessarily show considerable variation from week to week, some patterns are in evidence. Namely, when the observed price goes above the upper threshold, consumers in the domain of losses appear to respond by reducing their purchases, and the relative share among those in the domain of gains rises (see weeks 117 - 145). Consumers who are in the domain of gains have relatively high reference prices (for the same shelf price, they perceive the price to be relatively low) so when the price falls below the lower threshold, consumers in the domain of losses are induced into the market, and their relative share rises. Although this graphical analysis is suggestive of threshold-type behavior among two groups of consumers, it is not definitive.

[figure 1 in here]

Second, we use the simulated aggregate data to estimate simple models of threshold price behavior for each brand. From a practitioner's perspective, price-thresholds exist when the response elasticity differs in a meaningful away above and below a certain price level. We use the price thresholds in figure 1 to define these regions, and estimate simple own-price elasticities above and below the threshold price levels. We show the estimation results from a sample of 10 brands in table 6. These results show that, in each case, the aggregate price elasticity differs significantly between consumers in the domain of gains relative to those in the domain of losses. In particular, the response elasticity is lower (in absolute value) when the shelf price is below the lower threshold (domain of gains), relative to when the price is above the upper threshold (domain of losses). As with the household-level estimates, these findings support the predictions of Prospect Theory (Kahneman and Tversky 1979) and suggest that consumers are more sensitive to variations in price when experiencing losses, than when they perceive observed price to be offering "a good deal." From a revenue-management perspective, these findings are also interesting in that the gains-elasticity is uniformly below 1.0 (in absolute value) and the loss-elasticity is above 1.0. This outcome suggests that retailers can increase revenue by raising shelf prices when the "aggregate consumer" perceives himself to be in a positive position, and can increase revenue by reducing shelf prices when the representative consumer perceives losses. This is neither shocking nor counter-intuitive, but does provide a formal empirical rationale for sound retailing behavior.

[table 6 in here]

6.2 Comparison to Alternative Models

We compare the fit of our maintained model against three alternatives. To ensure the comparison is valid, however, we restrict our attention to the class of models that explicitly account for the multiple-regime nature of the threshold model. Because models that do not control for the censored nature of the data that is implied by threshold behavior are fundamentally inconsistent, any comparison between our model and a single-regime model would be comparing apples and oranges. Maintaining the multiple-regime structure implied by the threshold model, the primary differences between our utility model and others in the literature (Lattin and Bucklin 2001; Han, Gupta, and Lehmann 2001) are the inclusion of the shelf price in addition to the price-gap term (the "sticker-shock" model), modeling price-thresholds as dependent upon price volatility, and allowing for unobserved heterogeneity in the size of the thresholds. Therefore, the first alternative contains neither the sticker-shock term, volatility, nor unobserved heterogeneity. In the second alternative, we include a volatility term, but not the sticker-shock term or unobserved heterogeneity. In the third, we allow for unobserved heterogeneity. We also estimated fixed-coefficient and random coefficient versions of the three-regime sticker shock model (see table 5), in addition to one in which both thresholds and price-response are random parameters. Because these models are nested, we compare the goodness-of-fit using standard likelihood-ratio tests. We also estimate the preferred two-regime specification in three other categories (yogurt, coffee, and laundry detergent) in order to examine the robustness of our results across different product categories.

In table 7, we show estimation results obtained from models that do not include the shelf-price term, but do include various forms of the price-gap volatility term that forms the core of our maintained model. The first two models (Models 4 and 5) compare the fit of a non-sticker-shock model that includes price-gap volatility (Model 5) with one that does not (Model 4). With a calculated LR statistic of 3,719.22, we easily reject Model 4 in favor of the alternative. Combined with the individual significance of the threshold-volatility terms in Model 5, we conclude that Model 5 provides a better fit to the data. Next, we compare Model 5 to an alternative that accounts for unobserved heterogeneity in the location of the price thresholds (Model 6). The LR statistic for this comparison is 7,682.32, so we again favor the random-coefficient to the fixed-coefficient variant. Consistent with the results reported in table 5, but contrary to Bell and Lattin (2000), including heterogeneity causes the Gain / Loss terms to become more statistically significant, albeit slightly smaller in magnitude. Finally, we compare the preferred non-sticker-shock specification (Model 6) to the preferred sticker-shock alternative. Again using a LR test, we find a calculated chi-square statistic of 506.40, which suggests that the best sticker-shock model provides a better fit to the data than a comparable model that does not include both the price-gap and shelf-price.

[table 7 in here]

In table 8, we present estimation results from categories that are more frequently purchased than cereal (yogurt) and less frequently purchased (coffee and laundry detergent). Reference price-response is likely to be relatively sensitive to frequency of purchase (or the wavelength of the purchase cycle) because our reference-price mechanism is based on the consumer's ability to recall the price paid on the focal brand at the last purchase occasion. The longer the time since last purchase, the less likely the consumer is to be able to recall the price paid. For all three categories, we present estimates from our maintained sticker-shock specification that accounts for heterogeneity in response to both price and price-gap volatility. Again, our key parameter estimates are the price-gap responses and estimated threshold (volatility) parameters. In each case, the estimates in table 8 show that the price-gap term has a positive effect whether households are in the domain of gains or losses, and that the marginal effect differs significantly between regimes. Finding that the price-gap is not statistically significant in the "gain" regime for coffee and detergent supports the conjecture that consumers have a more difficult time forming reference prices for relatively long-cycle products. Moreover, the asymmetry of this outcome lends further support to the notion that consumers behave in fundamentally different ways when experiencing gains instead of losses. While they do not appear to care whether shelf prices fall below their reference price, their behavior changes significantly when shelf prices rise above reference prices. Further, the location of the implied threshold effect depends on the volatility of the price-gap term, confirming the real-option hypothesis maintained throughout. That is, the size of the latitude of acceptance between the upper and lower price-thresholds appears to widen in the variability of the difference between reference and shelf prices.

[table 8 in here]

6.3 Implications

These results support the hypothesis that consumers appear to respond to not only shelf prices, but also to the difference between shelf prices and some notion of what the price of a product "should be." More specifically, they behave as if there are thresholds around this reference price that induce fundamentally different behavior depending upon whether shelf prices rise above the upper threshold, or fall below the lower threshold. While these insights are not unique, we also show that these thresholds are driven largely by the existence of a real option that consumers are reluctant to exercise too early, or too late.

Our findings have important implications for both research in this area and marketing of consumer packaged goods in general. First, while others include price-volatility as an argument of threshold functions in empirical models similar to ours (Han, Gupta, and Lehmann 2001, for example) we offer a theoretical explanation and an empirical approach that is grounded in threshold-price behavior. The importance of this advance is less in the technical details of the econometric model, but that we offer an explanation for consumer behavior that is grounded in rational, optimizing behavior and not in a violation of rational economic behavior. This finding suggests that apparent violations of economic rationality may not necessarily be due to pathological consumer behavior, but rather the failure to adequately model the complexity of the decision process.

Second, from a practitioner's standpoint our findings suggest that price thresholds are indeed important, and that the latitude of price acceptance around reference prices is relatively large. This, in turn, means that retailers have some cover in changing prices for frequently-purchased goods when the cost of search is high, and prices volatile, but the cost of exceeding either the upper or lower price threshold is higher than previously believed in terms of lost revenue.

Third, our findings suggest that there is some scope for strategic obfuscation on the part of retailers (Ellison and Ellison 2009). Although it is well understood that frequent promotions can erode brand equity, inducing price variability can widen the latitude of price acceptance, providing retailers more flexibility to change prices before consumers will notice changes in the shelf price.

Fourth, although our model is grounded in optimizing economic behavior, our findings are fully consistent with the behavioral theories of Kahneman and Tversky (1979) in that consumers appear to be more averse to retail prices rising above their upper threshold than they are appreciative of prices that fall below their lower threshold. In some sense, this finding provides both theoretical and empirical support for the kinked demand curve of Sweezy (1939) and has dramatic effects on retailer pricing strategies (Kopalle, Rao, and Assungdo 1996). If demand is more elastic above the upper threshold than it is below the lower threshold, then aggregate demand curves will exhibit a "kink" around the reference price. The reference price then becomes a natural choice for rival retailers to regard as the industry-standard price, and a focal point for tacitly collusive pricing behavior. Moreover, von Massow and Hassini (2013) show that threshold-price behavior can generate cyclical optimal price-paths, as opposed to a single-price policy.

7 Conclusion

In this paper, we document a new explanation for the existence of threshold effects in consumers' purchases of consumer packaged goods. If consumers face a fixed cost of search, and if retail prices are volatile around consumers' reference prices, then their shopping decisions will embody a real option. A real option implies that consumers will rationally wait for observed prices to either rise above an upper threshold or fall below a lower threshold before exercising their option to respond to an observed price change. These thresholds form a zone of inaction that has been described as the latitude of price acceptance in the behavioral literature. As a behavioral construct, price acceptance depends on idiosyncractic behavior that may be difficult to exploit from a practical perspective. Rather, our theory suggests that the zone of inaction widens in the volatility of retail prices, or more precisely the difference between retail prices and consumers' reference prices, so can be used by retailers to set prices strategically.

We test our theory of threshold price behavior using an extension of the friction model of Rosett (1959) that accounts for unobserved household heterogeneity and extreme-value errors. Rather than segment the price-response term in a traditional model of brand choice, our econometric model explicitly recognizes the censored nature of data generated by threshold-price behavior. We estimate our econometric model using household-level data from the cereal, yogurt, coffee, and detergent categories. In each case, we find evidence in support of reference price behavior, and support for the real option explanation for the existence of threshold prices. Because retailers are generally more concerned with aggregate behavior than individual choices, we show that our findings aggregate out to the market level, and that our findings are not an artefact of focusing only on household behavior. In this sense, our model provides an operational tool that practitioners can exploit to improve pricing strategy.

There are many implications that follow from these results, but perhaps the most important concern the opportunity afforded retailers to price strategically. Inaction by consumers implies that they assimilate price changes into a pattern of perceived "normal" prices, an assimilation process that is economically-optimal according to the theory advanced here, and do not change their behavior in a significant way. If retailers are able to estimate the location of the thresholds beyond which consumers no longer assimilate price changes, they can raise prices up to a point just below the upper threshold, and maximize revenue without losing traffic. If all retailers price this way, then a common price point can arise in a way that is observationally equivalent to tacit collusion. Hysteretic behavior on the part of consumers, therefore, represents a source of retail market power that has not been previously identified. Retailers can exploit this form of market power by either raising search costs, or causing prices to become more volatile over time.

Future research in this area may extend our approach to products other than consumer packaged goods. Consumer durables, for example, represent purchases that are more discrete, lumpy, and a longer-term commitment of household resources. For these reasons, the real option phenomenon described here is likely to be more significant for consumer durables than for consumer packaged goods. Because the zone of inaction induced by price variability rises in both volatility and the cost of search, categories that are subject to relatively high search costs may also exhibit sharper threshold results than those shown here. Healthcare insurance, retirement plans, and other inherently complicated products are likely to exhibit relatively wide pricing thresholds.

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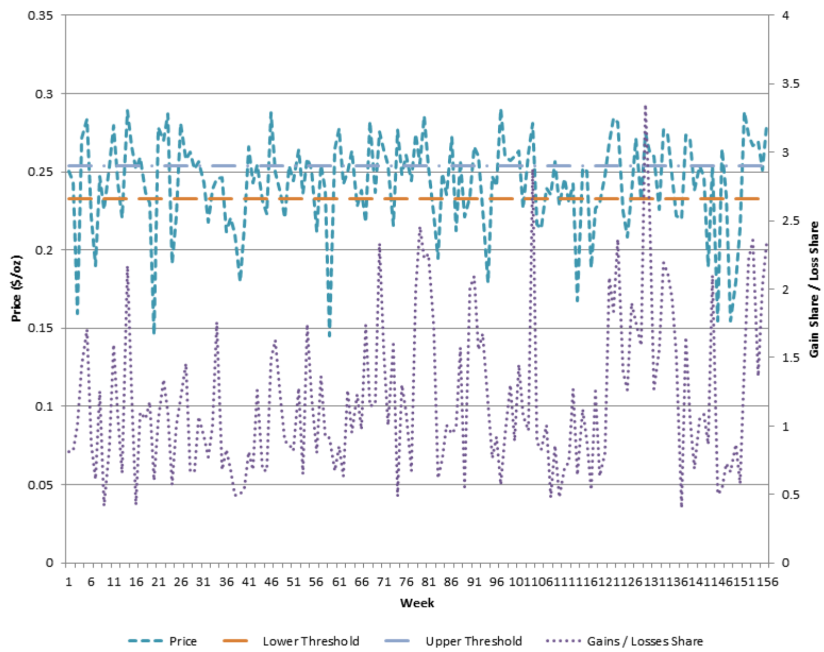

Figure 1: Reference Price Threshold Simulation

Table 1: Descriptive Statistics of Cereal Purchase Data

	Vol Share (%)		Volume (M oz)		Feature (%)		Display (%)		Promotion (%)		Price ($/oz)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
GM Cheerios	0.215	0.411	5.696	15.145	0.323	0.468	0.432	0.495	0.733	0.443	0.241	0.058
Private Label	0.061	0.240	1.576	7.394	0.114	0.317	0.121	0.326	0.318	0.466	0.227	0.028
K Raisin Bran	0.019	0.136	0.415	3.522	0.180	0.384	0.150	0.357	0.413	0.492	0.226	0.049
K Frosted Mini-Wheats	0.016	0.125	0.345	3.338	0.152	0.359	0.125	0.331	0.346	0.476	0.207	0.036
Q Cap N Crunch	0.031	0.174	0.794	5.775	0.191	0.393	0.183	0.387	0.399	0.490	0.196	0.038
K Rice Krispies	0.030	0.170	0.549	3.784	0.074	0.261	0.229	0.420	0.222	0.416	0.197	0.038
K Special K	0.014	0.118	0.236	2.248	0.239	0.426	0.463	0.499	0.646	0.478	0.229	0.065
G Chex	0.036	0.187	0.995	6.043	0.210	0.407	0.455	0.498	0.671	0.470	0.169	0.045
P Honey Bunches of Oats	0.036	0.187	0.909	5.876	0.119	0.324	0.121	0.326	0.221	0.415	0.182	0.029
K Frosted Flakes	0.060	0.237	1.120	5.659	0.191	0.393	0.356	0.479	0.575	0.494	0.248	0.051
G Cinnamon Toast Crunch	0.043	0.203	1.225	7.012	0.111	0.315	0.249	0.433	0.359	0.480	0.168	0.036
Q Life	0.079	0.270	1.570	6.481	0.143	0.350	0.126	0.331	0.304	0.460	0.254	0.046
G Lucky Charms	0.016	0.125	0.535	5.375	0.022	0.147	0.025	0.156	0.238	0.426	0.159	0.031
G Reeses Puffs	0.064	0.245	1.588	7.266	0.060	0.237	0.141	0.348	0.543	0.498	0.227	0.044
P Shredded Wheat	0.027	0.163	0.612	4.335	0.069	0.254	0.213	0.409	0.549	0.498	0.237	0.055
K Corn Flakes	0.023	0.151	0.593	4.921	0.031	0.174	0.052	0.223	0.312	0.463	0.207	0.037
P Grape Nuts	0.138	0.345	4.392	14.753	0.050	0.217	0.461	0.499	0.759	0.428	0.155	0.049
K Froot Loops	0.032	0.176	0.769	5.228	0.095	0.293	0.297	0.457	0.673	0.469	0.191	0.044
P Pebbles	0.042	0.200	1.020	5.756	0.097	0.297	0.251	0.434	0.639	0.480	0.196	0.038
Q Oatmeal Squares	0.016	0.125	0.433	4.181	0.069	0.253	0.063	0.243	0.385	0.487	0.235	0.047

Note: G = General Mills, K = Kelloggs, P = Post, and Q = Quaker Oats.

Table 2: Descriptive Statistics of Cereal Share, Price and Promotion by Store

	Store 1						Store 2					
	Vol Share (%)		Price ($/oz)		Promotion (%)		Vol Share (%)		Price ($/oz)		Promotion (%)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
GM Cheerios	0.053	0.225	0.245	0.039	0.853	0.354	0.093	0.290	0.225	0.036	0.674	0.469
Private Label	0.014	0.118	0.224	0.023	0.281	0.449	0.028	0.166	0.233	0.025	0.341	0.474
K Raisin Bran	0.004	0.062	0.241	0.039	0.529	0.499	0.006	0.079	0.217	0.031	0.359	0.480
K Frosted Mini-Wheats	0.005	0.069	0.215	0.032	0.579	0.494	0.004	0.061	0.198	0.026	0.223	0.416
Q Cap N Crunch	0.005	0.073	0.201	0.025	0.474	0.499	0.012	0.108	0.189	0.030	0.375	0.484
K Rice Krispies	0.007	0.083	0.218	0.029	0.418	0.493	0.015	0.120	0.171	0.011	0.109	0.312
K Special K	0.004	0.062	0.221	0.057	0.843	0.363	0.005	0.070	0.213	0.026	0.549	0.498
G Chex	0.011	0.104	0.166	0.035	0.861	0.346	0.013	0.115	0.161	0.023	0.579	0.494
P Honey Bunches of Oats	0.011	0.106	0.195	0.024	0.502	0.500	0.011	0.105	0.169	0.005	0.073	0.260
K Frosted Flakes	0.017	0.131	0.248	0.039	0.859	0.348	0.025	0.157	0.224	0.021	0.436	0.496
G Cinnamon Toast Crunch	0.011	0.103	0.171	0.025	0.589	0.492	0.022	0.146	0.155	0.010	0.257	0.437
Q Life	0.029	0.169	0.277	0.031	0.381	0.486	0.027	0.163	0.233	0.012	0.278	0.448
G Lucky Charms	0.004	0.060	0.155	0.015	0.157	0.364	0.006	0.078	0.149	0.015	0.290	0.454
G Reeses Puffs	0.015	0.121	0.238	0.036	0.395	0.489	0.029	0.167	0.221	0.032	0.656	0.475
P Shredded Wheat	0.005	0.073	0.242	0.053	0.495	0.500	0.009	0.096	0.235	0.045	0.612	0.487
K Corn Flakes	0.005	0.072	0.211	0.029	0.233	0.423	0.011	0.105	0.197	0.031	0.368	0.482
P Grape Nuts	0.046	0.211	0.148	0.029	0.782	0.413	0.059	0.237	0.147	0.031	0.758	0.428
K Froot Loops	0.008	0.087	0.208	0.046	0.655	0.475	0.015	0.120	0.180	0.026	0.691	0.462
P Pebbles	0.009	0.096	0.206	0.040	0.580	0.494	0.017	0.130	0.188	0.026	0.700	0.458
Q Oatmeal Squares	0.002	0.043	0.251	0.041	0.171	0.377	0.007	0.081	0.224	0.045	0.522	0.500

Note: G = General Mills, K = Kelloggs, P = Post, and Q = Quaker Oats.

Table 3: Summary of Demographic and Choice Data

	Units	Mean	Std. Dev.	Minimum	Maximum	N
Income	\$000 / yr.	56.3518	36.1528	5.0000	125.0000	15,101
Household Size	#	2.5161	1.1816	1.0000	6.0000	15,101
Black	%	0.0045	0.0670	0.0000	1.0000	15,101
Hispanic	%	0.0032	0.0564	0.0000	1.0000	15,101
Asian	%	0.0043	0.0657	0.0000	1.0000	15,101
White	%	0.9880	0.1091	0.0000	1.0000	15,101
Age	years	58.0906	10.8207	29.5000	69.5000	15,101
Education	years	12.5411	2.1531	6.0000	18.0000	15,101
Marital Status	% Single	0.0630	0.2429	0.0000	1.0000	15,101
Number of Shopping Trips	#	24.9329	15.2957	10.0000	105.0000	15,101
Store 1	%	0.3805	0.4855	0.0000	1.0000	15,101
Store 2	%	0.5919	0.4915	0.0000	1.0000	15,101
Volume Purchased	oz	25.3723	19.9730	1.3008	252.0000	15,101
Consumption Rate	oz	0.6709	0.4011	0.1025	2.4118	15,101
Number Brands: Store 1	#	250.9097	15.8375	186.0000	275.0000	15,101
Number Brands: Store 2	#	353.5829	7.8247	338.0000	380.000	15,101
Distance to Store 1	miles	2.3933	3.1205	1.2274	89.6697	15,101
Distance to Store 2	miles	2.7561	4.9350	1.5495	145.7904	15,101

Note: Distance calculated from centroid of household ZIP code to exact store address. Store brands are UPCs.

Table 4: Brand Switching and Extent of Gains or Losses

Brand	% Consumers Switching From i		% Consumers Switching To i	
	'Small' Loss	'Large' Loss	'Small' Gain	'Large' Gain
1	9.8	31.5	8.6	35.1
2	3.7	13.3	2.7	30.4
3	1.4	11.5	0.9	15.9
4	1.3	12.4	1.0	13.6
5	2.4	17.6	1.6	18.9
6	1.9	15.3	2.0	14.8
7	1.3	12.2	1.0	14.3
8	2.8	14.8	2.0	18.8
9	2.5	16.3	2.2	17.5
10	4.6	12.3	3.9	13.5
11	3.2	16.1	2.4	20.8
12	3.9	17.5	3.3	23.3
13	0.9	11.1	0.7	15.8
14	4.2	10.3	2.6	20.6
15	2.1	14.2	1.3	19.5
16	1.5	13.9	1.0	18.6
17	6.9	28.1	5.0	34.8
18	2.5	15.7	2.1	18.3
19	2.6	15.5	1.9	17.3
20	1.2	13.9	0.8	15.2
Average	3.0	15.7	2.4	19.9

Note: A small / large loss or gain is defined as a price-gap that is larger than one standard deviation from the mean.

Table 5: Threshold Model Estimates: Sticker-Shock Model

	Sticker-Shock Model: Fixed Coefficient Model 1				Sticker-Shock: Random Coefficient Model 2				Sticker-Shock: Two Random Coefficients Model 3			
	Gains		Losses		Gains		Losses		Gains		Losses	
	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
G Cheerios	2.3535*	5.5605	2.4439*	10.0800	2.2273*	16.4080	2.4755*	32.6680	2.2975*	18.9404	2.6026*	38.9872
Private Label	3.2459*	7.6500	3.1932*	12.9619	3.2094*	23.5900	3.2142*	40.7398	3.3393*	27.3044	3.1227*	44.6601
K Raisin Bran	2.5471*	5.9695	2.5855*	9.3909	2.4526*	17.9260	2.4857*	29.3319	2.4601*	20.0373	2.4676*	33.2612
K Frosted Mini-Wheats	2.2800*	5.3423	2.2839*	8.5094	2.1410*	15.6739	2.1985*	26.6358	2.1543*	17.5801	2.3352*	32.2215
Q Cap N Crunch	2.7785*	6.5819	2.4366*	9.7243	2.7249*	20.1535	2.3819*	30.7030	2.8210*	23.2339	2.3772*	34.4682
K Rice Krispies	2.5408*	5.9642	2.3534*	9.6561	2.3640*	17.3498	2.3999*	31.5603	2.4037*	19.6195	2.5055*	37.0201
K Special K	2.1033*	4.9492	2.1747*	8.0883	2.0854*	15.2726	2.0387*	24.5429	2.2659*	18.4543	2.1128*	29.1186
G Chex	1.8959*	4.5374	1.7166*	7.2581	1.8825*	14.0878	1.7044*	23.1736	2.0747*	17.3170	1.8287*	28.1177
P Honey Bunches of Oats	2.6691*	6.2618	2.6019*	10.7071	2.6745*	19.5715	2.6284*	34.7354	2.5986*	21.3070	2.6117*	39.0606
K Frosted Flakes	3.1958*	7.5072	3.5173*	13.5625	3.0272*	22.1614	3.5095*	43.3125	3.2504*	26.4929	3.5024*	49.2603
G Cinnamon Toast Crunch	2.4818*	5.9198	2.1787*	9.0819	2.4122*	17.9946	2.2114*	29.5844	2.4800*	20.6434	2.2089*	33.3432
Q Life	3.1475*	7.3247	3.0412*	11.8973	2.8986*	21.0664	3.0623*	38.3017	2.9665*	24.0633	3.0609*	43.6783
G Lucky Charms	2.1492*	5.1027	2.1119*	8.0981	2.1016*	15.6033	1.9979*	24.9858	2.1340*	17.6279	1.9880*	27.8606
G Reeses Puffs	3.1613*	7.4772	3.0928*	12.2757	3.0712*	22.6823	3.0693*	39.0383	3.2283*	26.5938	3.0672*	44.3799
P Shredded Wheat	2.9270*	6.8904	2.7068*	9.7668	2.7096*	19.9214	2.6049*	30.5223	2.9420*	24.0402	3.4426*	40.0225
K Corn Flakes	2.7629*	6.5069	1.3944*	5.8672	2.5901*	19.0781	1.3041*	17.6642	2.5919*	21.2594	1.5964*	23.9707
P Grape Nuts	1.8412*	4.4310	1.8198*	8.0919	1.7842*	13.4373	1.7342*	24.8199	1.9038*	16.0417	2.0126*	32.2446
K Froot Loops	2.2794*	5.4280	2.1607*	8.9990	2.2633*	16.8357	2.1219*	28.4357	2.4865*	20.6047	2.1609*	32.5363
P Pebbles	2.5194*	5.9868	2.7572*	11.0829	2.4609*	18.2722	2.7512*	35.5066	2.6479*	21.9097	3.9750*	49.0982
Gain / Loss	2.2549*	4.7803	2.6984*	4.6764	2.2171*	14.1473	2.5066*	13.2700	2.4324*	16.0204	2.7106*	18.4281
Display	-0.2676*	-8.6281	0.5550*	11.6722	-0.2153*	-21.0710	0.5159*	35.1331	0.0255*	2.6709	0.0260*	2.3831
Feature	0.0371	1.3155	0.7682*	10.9777	0.0431*	4.6203	0.7307*	34.1121	-0.0214*	-2.3184	0.7448*	47.4380
Promotion	-1.4801*	-26.6081	-0.5104*	-12.4151	-1.4643*	-76.9375	-0.4464*	-34.9341	-1.4386*	-78.1727	-0.4084*	-37.4727
Last Purchase	-0.4934*	-14.2959	-0.0640	-1.4837	-0.5609*	-50.0517	-0.0673*	-4.9943	-0.7652*	-77.2172	-0.0812*	-7.5540
Brand Loyalty	7.0396*	52.9247	1.3236*	13.7005	6.6142*	155.4262	1.2357*	41.5152	3.8312*	124.0841	-0.0438*	-1.9772
Inventory	0.4269*	13.5779	0.4257*	8.5877	0.2955*	31.4489	0.3901*	26.2770	0.5273*	48.0154	0.5249*	40.3392
Store 1	-1.0273*	-2.4883	-0.8192*	-4.0071	-1.0718*	-8.1384	-0.8885*	-14.0488	-1.2540*	-10.6451	-1.4042*	-24.1399
Store 2	-1.8349*	-4.4529	-1.5230*	-7.5517	-1.7896*	-13.6177	-1.5363*	-24.6066	-1.6199*	-13.7813	-1.3653*	-23.5940
Threshold	25.0448*	4.2486	26.9961*	4.5283	24.4137*	11.1670	31.9084*	15.3262	25.0086*	12.9972	28.1640*	18.2504
Price	-5.9545*	-13.3064	-5.1947*	-9.4667	-4.5797*	-29.9577	-5.2748*	-30.1284	-3.8578*	-27.7264	-4.9555*	-36.5022
σ_g					10.2570*	8.7312	10.3102*	8.8531	10.3771*	7.4679	10.8793*	9.2059
σ_p									0.4401*	5.2733	0.0470	0.5324
LLF	-19,426.57				-18,664.99				-15,550.81			
AIC	38,973.14				37,453.98				31,229.62			
BIC	38,858.98				37,335.84				31,107.49			

Note: A single asterisk indicates significance at a 5% level.

Table 6: Simulated Aggregate Data and Threshold Estimates

Brand	Regime	Variable	Estimate	t-ratio	R^2	Brand	Regime	Variable	Estimate	t-ratio	R^2
1	Gains	Constant	-5.0189*	-98.2757	0.064	6	Gains	Constant	-4.1967*	-96.1652	0.069
		Price	-0.9754*	-28.2146				Price	-0.8957*	-29.3968	
	Losses	Constant	-5.7034*	-275.2625	0.546		Losses	Constant	-4.6809*	-242.7848	0.538
		Price	-1.6562*	-118.0478				Price	-1.5636*	-116.0765	
2	Gains	Constant	-4.1433*	-83.4163	0.031	7	Gains	Constant	-3.7355*	-63.7126	0.009
		Price	-0.5698*	-18.9917				Price	-0.3142*	-9.7754	
	Losses	Constant	-5.1578*	-267.5202	0.574		Losses	Constant	-5.4833*	-245.5571	0.438
		Price	-1.1895*	-102.1039				Price	-1.1633*	-95.0441	
3	Gains	Constant	-5.1985*	-144.0421	0.089	8	Gains	Constant	-3.7135*	-61.6557	0.019
		Price	-0.7880*	-33.6591				Price	-0.6556*	-15.2312	
	Losses	Constant	-6.0012*	-293.0278	0.534		Losses	Constant	-5.2063*	-222.8729	0.461
		Price	-1.5301*	-115.2191				Price	-1.6606*	-99.4961	
4	Gains	Constant	-4.8832*	-106.2952	0.031	9	Gains	Constant	-3.8710*	-66.0700	0.045
		Price	-0.4833*	-19.3308				Price	-0.2499*	-7.9767	
	Losses	Constant	-5.7989*	-266.8633	0.431		Losses	Constant	-5.7044*	-262.1489	0.552
		Price	-1.1075*	-93.6971				Price	-1.1377*	-97.7440	
5	Gains	Constant	-4.1522*	-70.4959	0.035	10	Gains	Constant	-5.0361*	-114.0942	0.049
		Price	-0.6971*	-20.4117				Price	-0.5557*	-24.5221	
	Losses	Constant	-5.1220*	-180.4146	0.325		Losses	Constant	-5.5205*	-361.7654	0.557
		Price	-1.2293*	-74.6817				Price	-0.9456*	-120.7701	

Note: A single asterisk indicates significance at a 5% level.

Table 7: Alternate Threshold Model Estimates: Cereal

	Threshold Model: No Volatility Term Model 4				Threshold Model: Volatility, Fixed Coefficient Model 5				Threshold Model: Random Coefficient Model 6			
	Gains		Losses		Gains		Losses		Gains		Losses	
	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
G Cheerios	2.2649*	3.6670	2.3134*	6.3228	2.4619*	4.1128	2.3168*	7.5019	2.4948*	17.8378	2.5427*	24.9681
Private Label	3.1933*	5.1468	3.2786*	8.4853	3.3186*	5.5267	2.4869*	7.8843	3.1795*	22.5869	2.8252*	27.2638
K Raisin Bran	2.1352*	3.4399	2.6426*	6.5776	2.5470*	4.2264	2.6006*	7.2304	3.2055*	22.1586	2.5170*	22.4392
K Frosted Mini-Wheats	2.2396*	3.5890	2.3441*	5.8847	2.3425*	3.8807	2.2706*	6.5703	2.4952*	17.4473	2.2203*	20.4550
Q Cap N Crunch	2.7025*	4.3589	2.4903*	6.5216	2.9906*	4.9814	2.2163*	6.9980	2.9891*	21.1491	2.2373*	21.3440
K Rice Krispies	2.4761*	3.9679	2.4173*	6.3757	2.6046*	4.3127	2.1162*	6.6614	2.7732*	19.3432	2.5721*	24.4230
K Special K	1.9242*	3.0993	1.9505*	5.0297	2.2839*	3.7859	2.1219*	6.0575	2.8272*	19.5670	2.0564*	18.3736
G Chex	1.7717*	2.8667	1.6755*	4.5149	2.0966*	3.4998	1.7107*	5.4229	2.1807*	15.5438	2.7346*	25.5076
P Honey Bunches of Oats	2.6307*	4.1953	2.6794*	7.0829	2.6462*	4.3728	2.3198*	7.3259	2.8445*	19.8744	2.8767*	27.3201
K Frosted Flakes	3.1238*	5.0396	3.5302*	9.4992	3.2228*	5.3603	8.3774*	5.2581	3.1333*	22.2112	3.0210*	28.7811
G Cinnamon Toast Crunch	2.3862*	3.8552	2.2396*	5.9610	2.6288*	4.3835	1.8052*	5.7462	2.5676*	18.2781	2.4423*	23.2748
Q Life	3.1172*	4.9800	3.0294*	8.0981	2.9296*	4.8613	2.7863*	8.8672	3.0317*	21.3929	2.4594*	24.0979
G Lucky Charms	1.9962*	3.2175	2.0107*	5.1368	2.2688*	3.7732	2.2362*	6.4248	2.9262*	20.2230	2.1297*	19.3670
G Reeses Puffs	3.0643*	4.9439	3.0873*	8.1339	3.0237*	5.0435	2.6753*	8.3883	3.0423*	21.6511	2.9558*	28.1517
P Shredded Wheat	2.8167*	4.5322	2.7716*	6.8872	2.7907*	4.6407	2.7492*	7.5991	3.0845*	21.7252	2.6813*	23.7772
K Corn Flakes	2.6027*	4.1855	2.6675*	6.8473	2.8768*	4.7718	1.3845*	4.4183	3.4736*	23.9212	1.6025*	15.5184
P Grape Nuts	1.9123*	3.0972	1.7449*	4.7624	1.9086*	3.1912	1.5730*	5.1122	2.1436*	15.3252	1.8414*	18.0834
K Froot Loops	2.1357*	3.4531	2.2163*	5.9381	2.5212*	4.2051	1.9731*	6.2382	2.9990*	21.2035	2.4915*	23.5431
P Pebbles	2.4211*	3.9127	2.8229*	7.4314	2.6437*	4.4109	2.3412*	7.3666	2.6714*	19.0094	2.6157*	24.9245
Gain / Loss	2.3612*	5.7627	2.7202*	5.6985	2.2872*	5.7228	3.1815*	5.9074	1.9224*	14.3752	1.9070*	11.4103
Display	-0.3802*	-9.6378	0.4663*	10.4118	-0.3962*	-10.7609	0.5083*	10.8924	-0.3404*	-28.3118	0.5681*	40.5645
Feature	-0.0860*	-2.6131	0.7644*	12.4971	-0.1360*	-4.5675	0.4097*	7.6110	-0.0759*	-7.5101	0.3536*	19.7287
Promotion	-1.5750*	-19.4597	-1.2390*	-23.7560	-1.6203*	-20.0124	-0.7765*	-16.8312	-1.6736*	-60.0443	-0.7573*	-55.2694
Last Purchase	-0.5781*	-14.1459	-0.2253*	-5.0558	-0.5283*	-14.6165	-0.2774*	-6.3643	-0.5479*	-48.2602	-0.2903*	-21.9420
Brand Loyalty	7.2531*	44.0095	1.2314*	12.4150	5.3354*	42.1988	0.4872*	5.2900	2.3453*	76.3474	0.0944*	3.4940
Inventory	0.4219*	11.5509	0.2897*	6.1436	0.4115*	12.3455	0.3425*	7.2954	0.3026*	28.8700	0.4291*	29.2250
Store 1	-1.2211*	-1.9681	-1.4598*	-3.9931	-1.2530*	-2.0838	-1.4437*	-4.7361	-1.1056*	-7.8169	-2.0275*	-20.1501
Store 2	-1.9311*	-3.1162	-1.7826*	-4.8934	-1.9690*	-3.2789	-1.7503*	-5.7710	-1.1758*	-8.3272	-1.8364*	-18.2891
Threshold					25.2902*	3.0295	27.2581*	3.0206	29.5879*	12.5708	32.2448*	13.2679
σ_g									11.5540*	9.2482	11.4671*	7.7844
LLF	-21,504.78				-19,645.17				-15,804.01			
AIC	43,117.56				39,402.34				-31,492.02			
BIC	43,015.36				39,296.15				-31,602.19			

Note: A single asterisk indicates significance at a 5% level.

Table 8: Threshold Model Estimates: Yogurt, Coffee, and Detergent

	Yogurt				Coffee				Detergent			
	Sticker-Shock: Two Random Coefficients				Sticker-Shock: Two Random Coefficients				Sticker-Shock: Two Random Coefficients			
	Gains		Losses		Gains		Losses		Gains		Losses	
	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
Brand 1	-2.7651*	-47.7777	-2.5751*	-40.2439	1.8474*	6.0269	2.2358*	7.8202	1.9931*	9.0750	2.3304*	10.4119
Brand 2	-3.0811*	-43.2168	-2.4411*	-32.5413	1.1492*	5.8629	1.2264*	6.3241	0.5832*	5.3945	1.3922*	8.5675
Brand 3	-2.7581*	-52.4556	-2.7411*	-47.9526	1.7141*	9.5706	1.4444*	8.3209	1.0326*	7.1955	2.0462*	5.8944
Brand 4	-2.5341*	-48.1715	-2.4211*	-46.4856	0.4129*	3.1092	0.7859*	5.8004	0.8907*	7.5915	1.2748*	9.3263
Brand 5	-2.6201*	-53.2202	-2.5891*	-56.3284	0.8138*	4.4056	0.8966*	4.2625	0.7128*	5.8902	0.9772*	7.2808
Brand 6	-2.9841*	-48.3237	-2.5301*	-44.3575	0.1794	1.3862	1.0521*	6.3181	0.2547*	2.8100	0.7361*	7.2755
Brand 7	-3.5731*	-52.7351	-3.5191*	-68.0404	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.
Brand 8	-2.6151*	-43.5091	-2.9161*	-48.2449	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.
Brand 9	-2.4401*	-36.2549	-2.8961*	-42.2895	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.
Brand 10	-3.0531*	-71.9130	-2.9441*	-69.3527	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.
Brand 11	-2.8971*	-55.0016	-2.8011*	-56.2909	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.
Brand 12	-3.0621*	-48.8840	-2.6371*	-48.4724	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.
Brand 13	-2.5511*	-46.2356	-2.4331*	-44.8228	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.
Brand 14	-3.3451*	-60.1743	-3.3631*	-60.4952	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.
Brand 15	-2.8501*	-38.2127	-2.6651*	-33.9514	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.
Gain / Loss	5.3059*	6.3807	2.7881*	4.5904	0.1522	0.2699	2.3954*	4.1658	0.4210	0.3521	3.2027*	2.3658
Display	1.0440*	30.8054	0.9109*	19.2922	-0.0651	-1.2338	-0.2594*	-4.3752	-0.2271*	-5.5544	-0.6509*	-11.6617
Feature	0.7839*	17.3543	2.2519*	13.0156	0.0427	0.8584	0.3248*	4.2909	0.3060*	6.2635	0.2979*	4.9674
Promotion	1.5055*	69.7372	1.2369*	58.4441	0.2450*	4.2666	0.2289*	4.5383	-0.2888*	-3.5714	-0.1233	-1.3573
Last Purchase	1.2139*	67.8243	1.6309*	99.9790	-0.0497	-1.0511	-0.1103	-1.9075	-0.2086*	-5.8334	-0.2331*	-4.8739
Inventory	1.0989*	111.0217	0.5059*	48.8370	0.1028*	2.0901	0.0702	1.0591	0.0126*	1.9659	0.0177*	2.3753
Threshold	47.3059*	2.0524	49.3059*	2.1335	25.9699*	4.9889	26.6570*	5.3157	25.3339*	2.2173	27.4809*	2.7555
Price	-5.6911*	-13.0725	-3.0601*	-7.0291	-3.4498*	-9.4289	-2.0062*	-6.0331	-3.2568*	-3.3418	-1.6046	-1.3207
σ_g	10.7549	0.6010	10.3989	0.5809	4.9290	0.6849	-1.9170	-0.2995	5.6067	0.7088	-0.6910	-0.1071
σ_p	0.2345*	4.2704	0.5160*	9.4289	-0.4407	-0.7851	1.5283*	3.6413	0.7015	0.9386	2.3110*	4.2178
LLF	-37,380.44				-4,203.36				-6,180.41			
AIC	74,864.88				8,510.72				12,464.82			
BIC	74,766.66				8,412.50				12,366.60			

Note: A single asterisk indicates significance at a 5% level.